



THE
POWER
TO KNOW.

SAS/IML[®] 9.3

User's Guide



The correct bibliographic citation for this manual is as follows: SAS Institute Inc. 2011. *SAS/IML® 9.3 User's Guide*. Cary, NC: SAS Institute Inc.

SAS/IML® 9.3 User's Guide

Copyright © 2011, SAS Institute Inc., Cary, NC, USA

ISBN 978-1-60764-913-7

All rights reserved. Produced in the United States of America.

For a hard-copy book: No part of this publication may be reproduced, stored in a retrieval system, or transmitted, in any form or by any means, electronic, mechanical, photocopying, or otherwise, without the prior written permission of the publisher, SAS Institute Inc.

For a Web download or e-book: Your use of this publication shall be governed by the terms established by the vendor at the time you acquire this publication.

The scanning, uploading, and distribution of this book via the Internet or any other means without the permission of the publisher is illegal and punishable by law. Please purchase only authorized electronic editions and do not participate in or encourage electronic piracy of copyrighted materials. Your support of others' rights is appreciated.

U.S. Government Restricted Rights Notice: Use, duplication, or disclosure of this software and related documentation by the U.S. government is subject to the Agreement with SAS Institute and the restrictions set forth in FAR 52.227-19, Commercial Computer Software-Restricted Rights (June 1987).

SAS Institute Inc., SAS Campus Drive, Cary, North Carolina 27513.

1st electronic book, July 2011

1st printing, July 2011

SAS® Publishing provides a complete selection of books and electronic products to help customers use SAS software to its fullest potential. For more information about our e-books, e-learning products, CDs, and hard-copy books, visit the SAS Publishing Web site at support.sas.com/publishing or call 1-800-727-3228.

SAS® and all other SAS Institute Inc. product or service names are registered trademarks or trademarks of SAS Institute Inc. in the USA and other countries. ® indicates USA registration.

Other brand and product names are registered trademarks or trademarks of their respective companies.

Contents

Chapter 1.	What's New in SAS/IML 9.3	1
Chapter 2.	Introduction to SAS/IML Software	9
Chapter 3.	Understanding the SAS/IML Language	15
Chapter 4.	Tutorial: A Module for Linear Regression	29
Chapter 5.	Working with Matrices	41
Chapter 6.	Programming Statements	65
Chapter 7.	Working with SAS Data Sets	85
Chapter 8.	File Access	109
Chapter 9.	General Statistics Examples	125
Chapter 10.	Submitting SAS Statements	179
Chapter 11.	Calling Functions in the R Language	189
Chapter 12.	Robust Regression Examples	205
Chapter 13.	Time Series Analysis and Examples	249
Chapter 14.	Nonlinear Optimization Examples	335
Chapter 15.	Graphics Examples	411
Chapter 16.	Window and Display Features	441
Chapter 17.	Storage Features	455
Chapter 18.	Using SAS/IML Software to Generate SAS/IML Statements	461
Chapter 19.	Wavelet Analysis	477
Chapter 20.	Genetic Algorithms	499
Chapter 21.	Sparse Matrix Algorithms	529
Chapter 22.	Further Notes	537
Chapter 23.	Language Reference	543
Chapter 24.	Module Library	1065

Subject Index	1083
----------------------	-------------

Syntax Index	1093
---------------------	-------------

Chapter 1

What's New in SAS/IML 9.3

Contents

Overview	2
Calling SAS Procedures from PROC IML	2
Calling R Functions from PROC IML	2
New Functions and Subroutines	3
ALLCOMB Function	3
ALLPERM Function	3
BIN Function	3
CORR Function	3
COV Function	4
COUNTN Function	4
COUNTMISS Function	4
COUNTUNIQUE Function	4
CUPROD Function	4
DIF Function	4
ELEMENT Function	4
FULL Function	5
LAG Function	5
MEAN Function	5
PROD Function	5
QNTL Call	5
RANCOMB Function	5
RANGE Function	5
RANPERM Function	6
SHAPECOL Function	6
SQRVECH Function	6
STD Function	6
SPARSE Function	6
TABULATE Call	6
VAR Function	6
VECH Function	7
Changes to the IMLMLIB Library	7
Documentation Enhancements	7

Overview

SAS/IML 9.3 includes two new features that are related to calling other languages from within the IML procedure:

- calling SAS procedures and DATA steps from PROC IML
- calling functions in the R statistical programming language from PROC IML

In addition, SAS/IML 9.3 provides several new functions and subroutines.

Calling SAS Procedures from PROC IML

SAS/IML 9.3 supports the `SUBMIT` and `ENDSUBMIT` statements. These statements delimit a block of statements that are sent to another language for processing.

The `SUBMIT` and `ENDSUBMIT` statements enable you to call SAS procedures and DATA steps without leaving the IML procedure. This feature has been very popular in SAS/IML Studio since it was introduced in 2002. The feature is now available in PROC IML.

You can use SAS data sets to transfer data between SAS/IML matrices and SAS procedures. SAS procedures require that data be in a SAS data set.

Calling R Functions from PROC IML

The `SUBMIT` and `ENDSUBMIT` statements also provide an interface to the R statistical programming language, so that you can submit R statements from within your SAS/IML program. To submit statements to R, specify the `R` option in the `SUBMIT` statement.

You can transfer data from SAS/IML matrices and SAS data sets into R matrices and R data frames, and vice versa. Specifically, the following subroutines are available to transfer data from a SAS format into an R format:

Table 1.1 Transferring from a SAS Source to an R Destination

Subroutine	SAS Source	R Destination
<code>ExportDataSetToR</code>	SAS data set	R data frame
<code>ExportMatrixToR</code>	SAS/IML matrix	R matrix

In addition, the following subroutines are available to transfer data from an R format into a SAS format:

Table 1.2 Transferring from an R Source to a SAS Destination

Subroutine	R Source	SAS Destination
<code>ImportDataSetFromR</code>	R expression	SAS data set
<code>ImportMatrixFromR</code>	R expression	SAS/IML matrix

In Table 1.2, an “R expression” can be the name of a data frame, the name of a matrix, or an expression that results in either of these data structures.

New Functions and Subroutines

ALLCOMB Function

The `ALLCOMB` function generates all combinations of n elements taken k at a time.

ALLPERM Function

The `ALLPERM` function generates all permutations of n elements

BIN Function

The `BIN` function divides numeric values into a set of disjoint intervals called bins. The `BIN` function indicates which elements are contained in each bin.

CORR Function

The `CORR` function computes a sample correlation matrix for data. The function supports Pearson’s product-moment correlations, Hoeffding’s D statistics, Kendall’s tau- b coefficients, and Spearman’s correlation coefficients based on the ranks of the variables. The function supports two different methods for dealing with missing values in the data.

COV Function

The **COV function** computes a sample variance-covariance matrix for data. The function supports two different methods for dealing with missing values in the data.

COUNTN Function

The **COUNTN function** counts the number of nonmissing values in a matrix.

COUNTMISS Function

The **COUNTMISS function** counts the number of missing values in a matrix.

COUNTUNIQUE Function

The **COUNTUNIQUE function** counts the number of unique values in a matrix.

CUPROD Function

The **CUPROD function** computes the cumulative product of elements in a matrix.

DIF Function

The **DIF function** computes the differences between data values and one or more lagged (shifted) values for time series data.

ELEMENT Function

The **ELEMENT function** returns a matrix that indicates which elements of one matrix are also elements of a second matrix.

FULL Function

The [FULL function](#) converts a matrix stored in a sparse format into a matrix stored in a dense format. See the [SPARSE function](#) for a description of how sparse matrices are stored.

LAG Function

The [LAG function](#) computes one or more lagged (shifted) values for time series data.

MEAN Function

The [MEAN function](#) computes a sample mean of data. The function can compute arithmetic means, trimmed means, and Winsorized means.

PROD Function

The [PROD function](#) computes the product of elements in one or more matrices.

QNTL Call

The [QNTL subroutine](#) computes sample quantiles for data.

RANCOMB Function

The [RANCOMB function](#) returns random combinations of n elements taken k at a time.

RANGE Function

The [RANGE function](#) returns the range of values for a set of matrices.

RANPERM Function

The `RANPERM` function returns random permutations of n elements.

SHAPECOL Function

The `SHAPECOL` function reshapes and repeats values by columns.

SQRVECH Function

The `SQRVECH` function converts a symmetric matrix which is stored columnwise to a square matrix.

STD Function

The `STD` function computes a sample standard deviation for each column of a data matrix.

SPARSE Function

The `SPARSE` function converts a matrix that contains many zeros into a matrix stored in a sparse format which suitable for use with the `ITSOLVER` subroutine or the `SOLVEIN` subroutine.

TABULATE Call

The `TABULATE` subroutine counts the number of elements in each of the unique categories of the argument.

VAR Function

The `VAR` function computes a sample variance for each column of a data matrix.

VECH Function

The [VECH function](#) creates a vector from the columns of the lower triangular elements of a matrix.

Changes to the IMLMLIB Library

The CORR module has been removed from the IMLMLIB library. In its place is the built-in [CORR function](#).

The MEDIAN, QUARTILE, and STANDARD modules now support missing values in the data argument.

Documentation Enhancements

The first six chapters of the *SAS/IML User's Guide* have been completely rewritten in order to provide new users with a gentle introduction to the SAS/IML language. Two new chapters have been written:

- Chapter 10, “[Submitting SAS Statements](#),” describes how to call SAS procedures from within PROC IML.
- Chapter 11, “[Calling Functions in the R Language](#),” describes how to call R functions from within PROC IML.

Chapter 2

Introduction to SAS/IML Software

Contents

Overview of SAS/IML Software	9
Highlights of SAS/IML Software	10
An Introductory SAS/IML Program	11
PROC IML Statement	12
Conventions Used in This Book	12
Typographical Conventions	12
Output of Examples	13

Overview of SAS/IML Software

SAS/IML software gives you access to a powerful and flexible programming language in a dynamic, interactive environment. The acronym IML stands for “interactive matrix language.”

The fundamental object of the language is a data matrix. You can use SAS/IML software interactively (at the statement level) to see results immediately, or you can submit blocks of statements or an entire program. You can also encapsulate a series of statements by defining a module; you can call the module later to execute all of the statements in the module.

SAS/IML software is powerful. SAS/IML software enables you to concentrate on solving problems because necessary (but distracting) activities such as memory allocation and dimensioning of matrices are performed automatically. You can use built-in operators and call routines to perform complex tasks in numerical linear algebra such as matrix inversion or the computation of eigenvalues. You can define your own functions and subroutines by using SAS/IML modules. You can perform operations on a single value or take advantage of matrix operators to perform operations on an entire data matrix. For example, the following statement adds 1 to every element of the matrix **x**, regardless of the dimensions of **x**:

```
x = x+1;
```

The SAS/IML language contains statements that enable you to manage data. You can read, create, and update SAS data sets in SAS/IML software without using the DATA step. For example, the following statement reads a SAS data set to obtain phone numbers for all individuals whose last name begins with “Smith”:

```
read all var{phone} where(lastname="Smith");
```

The result is **phone**, a vector of phone numbers.

Highlights of SAS/IML Software

SAS/IML provides a high-level programming language.

You can program easily and efficiently with the many features for arithmetic and character expressions in SAS/IML software. You can access a wide variety of built-in functions and subroutines designed to make your programming fast, easy, and efficient. Because SAS/IML software is part of the SAS System, you can access SAS data sets or external files with an extensive set of data processing commands for data input and output, and you can edit existing SAS data sets or create new ones.

SAS/IML software has a complete set of control statements, such as DO/END, START/FINISH, iterative DO, IF-THEN/ELSE, GOTO, LINK, PAUSE, and STOP, giving you all of the commands necessary for execution control and program modularization. See the section “[Control Statements](#)” on page 20 for details.

SAS/IML software operates on matrices.

Functions and statements in most programming languages manipulate and compare a single data element. However, the fundamental data element in SAS/IML software is the matrix, a two-dimensional (row \times column) array of numeric or character values.

SAS/IML software possesses a powerful vocabulary of operators.

You can access built-in matrix operations that require calls to math-library subroutines in other languages. You can access many matrix operators, functions, and subroutines.

SAS/IML software uses operators that apply to entire matrices.

You can add elements of the matrices **A** and **B** with the expression **A+B**. You can perform matrix multiplication with the expression **A*B** and perform elementwise multiplication with the expression **A#B**.

SAS/IML software is interactive.

You can execute SAS/IML statements one at a time and see the results immediately, or you can submit blocks of statements or an entire program. You can also define a module that encapsulates a series of statements. You can interact with an executing module by using the PAUSE statement, which enables you to enter additional statements before continuing execution.

SAS/IML software is dynamic.

You do not need to declare, dimension, or allocate storage for a data matrix. SAS/IML software does this automatically. You can change the dimension or type of a matrix at any time. You can open multiple files or access many libraries. You can reset options or replace modules at any time.

SAS/IML software processes data.

You can read observations from a SAS data set. You can create either multiple vectors (one for each variable in the data set) or a single matrix that contains a column for each data set variable. You can create a new SAS data set, or you can edit or append observations to an existing SAS data set.

An Introductory SAS/IML Program

This section presents a simple introductory SAS/IML program that implements a numerical algorithm that estimates the square root of a number, accurate to three decimal places. The following statements define a function module named `MySqrt` that performs the calculations:

```
proc iml;                                /* begin IML session */

start MySqrt(x);                          /* begin module */
  y = 1;                                  /* initialize y */
  do until(w<1e-3);                       /* begin DO loop */
    z = y;                                /* set z=y */
    y = 0.5#(z+x/z);                      /* estimate square root */
    w = abs(y-z);                         /* compute change in estimate */
  end;                                    /* end DO loop */
  return(y);                              /* return approximation */
finish;                                   /* end module */
```

You can call the `MySqrt` module to estimate the square root of several numbers given in a matrix literal (enclosed in braces) and print the results:

```
t = MySqrt({3,4,7,9});                  /* call function MySqrt */
s = sqrt({3,4,7,9});                    /* compare with true values */
diff = t - s;                           /* compute differences */
print t s diff;                          /* print matrices */
```

Figure 2.1 Approximate Square Roots

	t	s	diff
	1.7320508	1.7320508	0
	2	2	2.22E-15
	2.6457513	2.6457513	4.678E-11
	3	3	1.397E-9

PROC IML Statement

```
PROC IML <SYMSIZE=n1> <WORKSIZE=(n2)> ;  
    <SAS/IML language statements> ;  
QUIT ;
```

You can specify the following options in the PROC IML statement:

SYMSIZE=*n1*

specifies the size of memory, in kilobytes, that is allocated to the PROC IML symbol space.

WORKSIZE=*n2*

specifies the size of memory, in kilobytes, that is allocated to the PROC IML workspace.

If you do not specify any options, PROC IML uses host-dependent defaults. In general, you do not need to be concerned with the details of memory usage because memory allocation is done automatically. However, see the section “[Memory and Workspace](#)” on page 537 for special situations.

Conventions Used in This Book

Typographical Conventions

This book uses several type styles for presenting information. The following list explains the meaning of the typographical conventions used in this book:

text	is the standard type style used for most text.
FUNCTION	is used for the name of SAS/IML functions, subroutines, and statements when they appear in the text. This convention is also used for SAS statements and options. However, you can enter these elements in your own SAS programs in lowercase, uppercase, or a mixture of the two.
SYNTAX	is used in the “Syntax” sections’ initial lists of SAS statements and options.
<i>argument</i>	is used for option values that must be supplied by the user in the syntax definitions.
VariableName	is used for the names of variables and data sets when they appear in the text.
LibName	is used for the names of SAS librefs (such as <i>Sasuser</i>) when they appear in the text.
bold	is used to refer to <i>mathematical</i> matrices and vectors such as in the equation $y = Ax$.

Code	is used to refer to SAS/IML matrices, vectors, and expressions in the SAS/IML language such as the expression $\mathbf{y} = \mathbf{A}\mathbf{x}$. This convention is also used for example code. In most cases, this book uses lowercase type for SAS/IML statements.
<i>italic</i>	is used for terms that are defined in the text, for emphasis, and for references to publications.

Output of Examples

This documentation contains many short examples that illustrate how to use the SAS/IML language. Many examples end with a PRINT statement; the output for these examples appears immediately after the program statements.

Chapter 3

Understanding the SAS/IML Language

Contents

Defining a Matrix	15
Matrix Names and Literals	16
Matrix Names	16
Matrix Literals	16
Creating Matrices from Matrix Literals	17
Scalar Literals	17
Numeric Literals	17
Character Literals	18
Repetition Factors	18
Reassigning Values	19
Assignment Statements	19
Types of Statements	20
Control Statements	20
Functions	21
CALL Statements and Subroutines	23
Command Statements	24
Missing Values	26
Summary	27

Defining a Matrix

A matrix is the fundamental structure in the SAS/IML language. A matrix is a two-dimensional array of numeric or character values. Matrices are useful for working with data and have the following properties:

- Matrices can be either numeric or character. Elements of a numeric matrix are double-precision values. Elements of a character matrix are character strings of equal length.
- The name of a matrix must be a valid SAS name.
- Matrices have dimensions defined by the number of rows and columns.
- Matrices can contain elements that have missing values (see the section “[Missing Values](#)” on page 26).

The dimensions of a matrix are defined by the number of rows and columns. An $n \times p$ matrix has np elements arranged in n rows and p columns. The following nomenclature is standard in this book:

- 1×1 matrices are called *scalars*.
- $1 \times p$ matrices are called *row vectors*.
- $n \times 1$ matrices are called *column vectors*.
- The *type* of a matrix is “numeric” if its elements are numbers; the type is “character” if its elements are character strings. A matrix that has not been assigned values has an “undefined” type.

Matrix Names and Literals

Matrix Names

The name of a matrix must be a valid SAS name: a character string that contains between 1 and 32 characters, begins with a letter or underscore, and contains only letters, numbers, and underscores. You associate a name with a matrix when you create or define the matrix. A matrix name exists independently of values. This means that you can change the values associated with a particular matrix name, change the dimension of the matrix, or even change its type (numeric or character).

Matrix Literals

A *matrix literal* is an enumeration of the values of a matrix. For example, `{1, 2, 3}` is a numeric matrix with three elements. A matrix literal can have a single element (a scalar), or it can be an array of many elements. The matrix can be numeric or character. The dimensions of the matrix are automatically determined by the way you punctuate the values.

Use curly braces (`{ }`) to enclose the values of a matrix. Within the braces, values must be either all numeric or all character. Use commas to separate the rows. If you specify multiple rows, all rows must have the same number of elements.

You can specify any of the following types of elements:

- a number. You can specify numbers with or without decimal points, and in standard or scientific notation. For example, `5`, `3.14`, or `1E-5`.
- a period (`.`), which represents a missing numeric value.
- a number in brackets (`[]`), which represents a repetition factor.

- a character string. Character strings can be enclosed in single quotes (') or double quotes ("), but they do not need to have quotes. Quotes are required when there are no enclosing braces or when you want to preserve case, special characters, or blanks in the string. Special characters include the following: ?, =, *, :, (,), {, and }.

If the string has embedded quotes, you must double them, as shown in the following statements:

```
w1 = "I said, ""Don't fall!""";
w2 = 'I said, "Don't fall!";
```

Creating Matrices from Matrix Literals

You can create a matrix by using matrix literals: simply list the element values inside of curly braces. You can also create a matrix by calling a function, a subroutine, or an assignment statement. The following sections present some simple examples of matrix literals. For more information about matrix literals, see Chapter 5, “Working with Matrices.”

Scalar Literals

The following example statements define scalars as literals. These examples are simple assignment statements with a matrix name on the left-hand side of the equal sign and a value on the right-hand side. Notice that you do not need to use braces when there is only one element.

```
a = 12;
a = . ;
a = 'hi there';
a = "Hello";
```

Numeric Literals

To specify a matrix literal with multiple elements, enclose the elements in braces. Use commas to separate the rows of a matrix. For example, the following statements assign and print matrices of various dimensions:

```
x = {1 . 3 4 5 6};          /* 1 x 6 row vector */
y = {1,2,3,4};              /* 4 x 1 column vector */
z = 3#y;                    /* 3 times the vector y */
w = {1 2, 3 4, 5 6};        /* 3 x 2 matrix */
print x, y z w;
```

Figure 3.1 Matrices Created from Numeric Literals

			x			
	1	.	3	4	5	6
		y	z	w		
		1	3	1	2	
		2	6	3	4	
		3	9	5	6	
		4	12			

Character Literals

You can define a character matrix literal by specifying character strings between braces. If you do not place quotes around the strings, all characters are converted to uppercase. You can use either single or double quotes to preserve case and to specify strings that contain blanks or special characters. For character matrix literals, the length of the elements is determined by the longest element. Shorter strings are padded on the right with blanks. For example, the following statements define and print two 1×2 character matrices with string length 4 (the length of the longer string):

```
a = { abc   defg};           /* no quotes; uppercase */
b = {'abc' 'DEFG'};         /* quotes; case preserved */
print a, b;
```

Figure 3.2 Matrices Created from Character Literals

		a	
		ABC	DEFG
		b	
		abc	DEFG

Repetition Factors

A repetition factor can be placed in brackets before a literal element to have the element repeated. For example, the following two statements are equivalent:

```
answer = {[2] 'Yes', [2] 'No'};
answer = {'Yes' 'Yes', 'No' 'No'};
```

Reassigning Values

You can assign new values to a matrix at any time. The following statements create a 2×3 numeric matrix named **a**, then redefine **a** to be a 1×3 character matrix:

```
a = {1 2 3, 6 5 4};
a = {'Sales' 'Marketing' 'Administration'};
```

Assignment Statements

Assignment statements create matrices by evaluating expressions and assigning the results. The expressions can be composed of operators (for example, matrix multiplication) or functions that operate on matrices (for example, matrix inversion). The resulting matrices automatically acquire appropriate characteristics and values. Assignment statements have the general form *result* = *expression* where *result* is the name of the new matrix and *expression* is an expression that is evaluated.

Functions as Expressions

You can create matrices as a result of a function call. Scalar functions such as **LOG** or **SQRT** operate on each element of a matrix, whereas matrix functions such as **INV** or **RANK** operate on the entire matrix. The following statements are examples of function calls:

```
a = sqrt(b);           /* elementwise square root */
y = inv(x);            /* matrix inversion */
r = rank(x);           /* ranks (order) of elements */
```

The **SQRT** function assigns each element of **a** the square root of the corresponding element of **b**. The **INV** function computes the inverse matrix of **x** and assigns the results to **y**. The **RANK** function creates a matrix **r** with elements that are the ranks of the corresponding elements of **x**.

Operators within Expressions

Three types of operators can be used in assignment statement expressions. The matrices on which an operator acts must have types and dimensions that are conformable to the operation. For example, matrix multiplication requires that the number of columns of the left-hand matrix be equal to the number of rows of the right-hand matrix.

The three types of operators are as follows:

- Prefix operators are placed in front of an operand (**-A**).
- Binary operators are placed between operands (**A*B**).
- Postfix operators are placed after an operand (**A'**).

All operators can work on scalars, vectors, or matrices, provided that the operation makes sense. For example, you can add a scalar to a matrix or divide a matrix by a scalar. The following statement is an example of using operators in an assignment statement:

```
y = x#(x>0);
```

This assignment statement creates a matrix **y** in which each negative element of the matrix **x** is replaced with zero. The statement actually contains two expressions that are evaluated. The expression **x>0** is an operation that compares each element of **x** to zero and creates a temporary matrix of results; an element of the temporary matrix is 1 when the corresponding element of **x** is positive, and 0 otherwise. The original matrix **x** is then multiplied elementwise by the temporary matrix, resulting in the matrix **y**.

See Chapter 23, “[Language Reference](#),” for a complete listing and explanation of operators.

Types of Statements

Statements in the SAS/IML language can be classified into three general categories:

Control statements

direct the flow of execution. For example, the [IF-THEN/ELSE statement](#) conditionally controls statement execution.

Functions and CALL statements

perform special tasks or user-defined operations. For example, the statement [CALL EIGEN](#) computes eigenvalues and eigenvectors.

Command statements

perform special processing, such as setting options, displaying windows, and handling input and output. For example, the [MATTRIB](#) statement associates matrix characteristics with matrix names.

Control Statements

The SAS/IML language has statements that control program execution. You can use control statements to direct the execution of your program and to define DO groups and modules. Some control statements are shown in the following table:

Table 3.1 Control Statements

Statement	Description
DO, END	Specifies a group of statements
Iterative DO, END	Defines an iteration loop
GOTO, LINK	Specifies the next program statement to be executed
IF-THEN/ELSE	Conditionally routes execution
PAUSE	Instructs a module to pause during execution
QUIT	Exits from the IML procedure
RESUME	Instructs a module to resume execution
RETURN	Returns from a LINK statement or module
RUN	Executes a module
START, FINISH	Defines a module
STOP, ABORT	Stops the execution of an IML program

See Chapter 6, “Programming Statements,” for more information about control statements.

Functions

The general form of a function is *result* = FUNCTION(*arguments*) where *arguments* is a list of matrix names, matrix literals, or expressions. Functions always return a single matrix, whereas subroutines can return multiple matrices or no matrices at all. If a function returns a character matrix, the matrix to hold the result is allocated with a string length equal to the longest element, and all shorter elements are padded on the right with blanks.

Categories of Functions

Many functions fall into one of the following general categories:

scalar functions

operate on each element of the matrix argument. For example, the ABS function returns a matrix with elements that are the absolute values of the corresponding elements of the argument matrix.

matrix inquiry functions

return information about a matrix. For example, the ANY function returns a value of 1 if any of the elements of the argument matrix are nonzero.

summary functions

return summary statistics based on all elements of the matrix argument. For example, the SSQ function returns the sum of squares of all elements of the argument matrix.

matrix reshaping functions

manipulate the matrix argument and returns a reshaped matrix. For example, the DIAG function returns a diagonal matrix with values and dimensions that are determined by the argument matrix.

linear algebraic functions

perform matrix algebraic operations on the argument. For example, the TRACE function returns the trace of the argument matrix.

statistical functions

perform statistical operations on the matrix argument. For example, the RANK function returns a matrix that contains the ranks of the argument matrix.

The SAS/IML language also provides functions in the following general categories:

- matrix sorting and BY-group processing
- numerical linear algebra
- optimization
- random number generation
- time series analysis
- wavelet analysis

See the section “[Statements, Functions, and Subroutines by Category](#)” on page 551 for a complete listing of SAS/IML functions.

Exceptions to the SAS DATA Step

The SAS/IML language supports most functions that are supported in the SAS DATA step. These functions almost always accept matrix arguments and usually act elementwise so that the result has the same dimension as the argument. See the section “[Base SAS Functions Accessible from SAS/IML Software](#)” on page 1044 for a list of these functions and also a small list of functions that are not supported by SAS/IML software or that behave differently than their Base SAS counterparts.

The SAS/IML random number functions UNIFORM and NORMAL are built-in functions that produce the same streams as the RANUNI and RANNOR functions, respectively, of the DATA step. For example, you can use the following statement to create a 10×1 vector of random numbers:

```
x = uniform(repeat(0,10,1));
```

SAS/IML software does not support the OF clause of the SAS DATA step. For example, the following statement cannot be interpreted in SAS/IML software:

```
a = mean(of x1-x10); /* invalid in the SAS/IML language */
```

The term **x1-x10** would be interpreted as subtraction of the two matrix arguments rather than its DATA step meaning, the variables X1 through X10.

CALL Statements and Subroutines

Subroutines (also called “CALL statements”) perform calculations, operations, or interact with the SAS system. CALL statements are often used in place of functions when the operation returns multiple results or, in some cases, no result. The general form of the CALL statement is

CALL SUBROUTINE (*arguments*) ;

where *arguments* can be a list of matrix names, matrix literals, or expressions. If you specify several arguments, use commas to separate them. When using output arguments that are computed by a subroutine, always use variable names instead of expressions or literals.

Creating Matrices with CALL Statements

Matrices are created whenever a CALL statement returns one or more result matrices. For example, the following statement returns two matrices (vectors), **val** and **vec**, that contain the eigenvalues and eigenvectors, respectively, of the matrix **A**:

```
call eigen(val,vec,A);
```

You can program your own subroutine by using the **START** and **FINISH** statements to define a module. You can then execute the module with a **CALL** or **RUN** statement. For example, the following statements define a module named **MyMod** which returns matrices that contain the square root and log of each element of the argument matrix:

```
start MyMod(a,b,c);
    a=sqrt(c);
    b=log(c);
finish;
run MyMod(S,L,{1 2 4 9});
```

Execution of the module statements creates matrices **S** and **L** which contain the square roots and natural logs, respectively, of the elements of the third argument.

Interacting with the SAS System

You can use CALL statements to manage SAS data sets or to access the PROC IML graphics system. For example, the following statement deletes the SAS data set named MyData:

```
call delete(MyData);
```

The following statements activate the graphics system and produce a crude scatter plot:

```
x = 0:100;
y = 50 + 50*sin(6.28*x/100);
call gstart;                /* activate the graphics system */
call gopen;                 /* open a new graphics segment */
call gpoint(x,y);           /* plot the points */
call gshow;                 /* display the graph */
call qclose;                /* close the graphics segment */
```

SAS/IML Studio, which is distributed as part of SAS/IML software, contains graphics that are easier to use and more powerful than the older GSTART/GCLOSE graphics in PROC IML. See the *SAS/IML Studio User's Guide* for a description of the graphs in SAS/IML Studio.

Command Statements

Command statements are used to perform specific system actions, such as storing and loading matrices and modules, or to perform special data processing requests. The following table lists some commands and the actions they perform.

Table 3.2 Command Statements

Statement	Description
FREE	Frees memory associated with a matrix
LOAD	Loads a matrix or module from a storage library
MATTRIB	Associates printing attributes with matrices
PRINT	Prints a matrix or message
RESET	Sets various system options
REMOVE	Removes a matrix or module from library storage
SHOW	Displays system information
STORE	Stores a matrix or module in the storage library

These commands play an important role in SAS/IML software. You can use them to control information displayed about matrices, symbols, or modules.

If a certain computation requires almost all of the memory on your computer, you can use commands to store extraneous matrices in the storage library, free the matrices of their values, and reload them later when you need them again. For example, the following statements define several matrices:

```
proc iml;
a = {1 2 3, 4 5 6, 7 8 9};
b = {2 2 2};
show names;
```

Figure 3.3 List of Symbols in RAM

SYMBOL	ROWS	COLS	TYPE	SIZE
a	3	3	num	8
b	1	3	num	8
Number of symbols = 2 (includes those without values)				

Suppose that you want to compute a quantity that does not involve the **a** matrix or the **b** matrix. You can store **a** and **b** in a library storage with the **STORE** command, and release the space with the **FREE** command.

To list the matrices and modules in library storage, use the `SHOW STORAGE` command (or the `STORAGE` function), as shown in the following statements:

```
store a b;           /* store the matrices */
show storage;        /* make sure the matrices are saved */
free a b;           /* free the RAM */
```

The output from the `SHOW STORAGE` statement (see [Figure 3.4](#)) indicates that there are two matrices in storage. (There are no modules in storage for this example.)

Figure 3.4 List of Symbols in Storage

```
Contents of storage library = WORK.IMLSTOR

Matrices:
A                      B

Modules:
```

You can load these matrices from the storage library into RAM with the `LOAD` command, as shown in the following statement:

```
load a b;
```

See Chapter 17, “[Storage Features](#),” for more details about storing modules and matrices.

Data Management Commands

SAS/IML software has many commands that enable you to manage your SAS data sets from within the SAS/IML environment. These data management commands operate on SAS data sets. There are also commands for accessing external files. The following table lists some commands and the actions they perform.

Table 3.3 Data Management Statements

Statement	Description
APPEND	Adds records to an output SAS data set
CLOSE	Closes a SAS data set
CREATE	Creates a new SAS data set
DELETE	Deletes records in an output SAS data set
EDIT	Reads from or writes to an existing SAS data set
FIND	Finds records that satisfy some condition
LIST	Lists records
PURGE	Purges records marked for deletion
READ	Reads records from a SAS data set into IML matrices
SETIN	Sets a SAS data set to be the input data set
SETOUT	Sets a SAS data set to be the output data set
SORT	Sorts a SAS data set
USE	Opens an existing SAS data set for reading

These commands can be used to perform data management. For example, you can read observations from a SAS data set into a target matrix with the `USE` or `EDIT` command. You can edit a SAS data set and append or delete records. If you have a matrix of values, you can output the values to a SAS data set with the `APPEND` command. See Chapter 7, “[Working with SAS Data Sets](#),” and Chapter 8, “[File Access](#),” for more information about these commands.

Missing Values

With SAS/IML software, a numeric element can have a special value called a *missing value*, which indicates that the value is unknown or unspecified. Such missing values are coded, for logical comparison purposes, in the bit pattern of very large negative numbers. A numeric matrix can have any mixture of missing and nonmissing values. A matrix with missing values should not be confused with an empty or unvalued matrix—that is, a matrix with zero rows and zero columns.

In matrix literals, a numeric missing value is specified as a single period (.). In data processing operations that involve a SAS data set, you can append or delete missing values. All operations that move values also move missing values.

However, for efficiency reasons, SAS/IML software does not support missing values in most matrix operations and functions. For example, matrix multiplication of a matrix with missing values is not supported. Furthermore, many linear algebraic operations are not mathematically defined for a matrix with missing values. For example, the inverse of a matrix with missing values is meaningless.

See Chapter 5, “[Working with Matrices](#),” and Chapter 22, “[Further Notes](#),” for more details about missing values.

Summary

This chapter introduced the fundamentals of the SAS/IML language, including the basic data element, the matrix. You learned several ways to create matrices: assignment statements, matrix literals, and CALL statements that return matrix results.

The chapter also introduced various types of programming statements: commands, control statements, iterative statements, module definitions, functions, and subroutines.

Chapter 4, “[Tutorial: A Module for Linear Regression](#),” offers an introductory tutorial that demonstrates how to use SAS/IML software for statistical computations.

Chapter 4

Tutorial: A Module for Linear Regression

Contents

Overview of Linear Regression	29
Example: Solving a System of Linear Equations	30
A Module for Linear Regression	31
Orthogonal Regression	34
Plotting Regression Results	36
Low-Resolution Plots	37
SAS/IML Studio Graphics	39

Overview of Linear Regression

You can use SAS/IML software to solve mathematical problems or implement new statistical techniques and algorithms. Formulas and matrix equations are easily translated in the SAS/IML language. For example, if X is a data matrix and Y is a vector of observed responses, then you might be interested in the solution, b , to the matrix equation $Xb = Y$. In statistics, the data matrices that arise often have more rows than columns and so an exact solution to the linear system is impossible to find. Instead, the statistician often solves a related equation: $X'Xb = X'Y$. The following mathematical formula expresses the solution vector in terms of the data matrix and the observed responses:

$$b = (X'X)^{-1}X'Y$$

This mathematical formula can be translated into the following SAS/IML statement:

```
b = inv(X`*X) * X`*Y;      /* least squares estimates */
```

This assignment statement uses a built-in function (INV) and matrix operators (transpose and matrix multiplication). It is mathematically equivalent to (but less efficient than) the following alternative statement:

```
b = solve(X`*X, X`*Y);    /* more efficient computation */
```

If a statistical method has not been implemented directly in a SAS procedure, you might be able to program it by using the SAS/IML language. The most commonly used mathematical and matrix operations are built directly into the language, so programs that require many statements in other languages require only a few SAS/IML statements.

Example: Solving a System of Linear Equations

Because the syntax of the SAS/IML language is similar to the notation used in linear algebra, it is often possible to directly translate mathematical methods from matrix-algebraic expressions into executable SAS/IML statements. For example, consider the problem of solving three simultaneous equations:

$$\begin{aligned} 3x_1 - x_2 + 2x_3 &= 8 \\ 2x_1 - 2x_2 + 3x_3 &= 2 \\ 4x_1 + x_2 - 4x_3 &= 9 \end{aligned}$$

These equations can be written in matrix form as

$$\begin{bmatrix} 3 & -1 & 2 \\ 2 & -2 & 3 \\ 4 & 1 & -4 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} = \begin{bmatrix} 8 \\ 2 \\ 9 \end{bmatrix}$$

and can be expressed symbolically as

$$\mathbf{Ax} = \mathbf{c}$$

where \mathbf{A} is the matrix of coefficients for the linear system. Because \mathbf{A} is nonsingular, the system has a solution given by

$$\mathbf{x} = \mathbf{A}^{-1}\mathbf{c}$$

This example solves this linear system of equations.

- 1 Define the matrices \mathbf{A} and \mathbf{c} . Both of these matrices are input as matrix literals; that is, you type the row and column values as discussed in Chapter 3, “[Understanding the SAS/IML Language](#).”

```
proc iml;
a = {3  -1  2,
      2  -2  3,
      4   1 -4};
c = {8, 2, 9};
```

- 2 Solve the equation by using the built-in INV function and the matrix multiplication operator. The INV function returns the inverse of a square matrix and $*$ is the operator for matrix multiplication. Consequently, the solution is computed as follows:

```
x = inv(a) * c;
print x;
```

Figure 4.1 The Solution of a Linear System of Equations

x
3
5
2

- 3 Equivalently, you can solve the linear system by using the more efficient SOLVE function, as shown in the following statement:

```
x = solve(a, c);
```

After SAS/IML executes the statements, the rows of the vector **x** contain the x_1 , x_2 , and x_3 values that solve the linear system.

You can end PROC IML by using the QUIT statement:

```
quit;
```

A Module for Linear Regression

The linear systems that arise naturally in statistics are usually *overconstrained*, meaning that the **X** matrix has more rows than columns and that an exact solution to the linear system is impossible to find. Instead, the statistician assumes a linear model of the form

$$\mathbf{y} = \mathbf{X}\mathbf{b} + \mathbf{e}$$

where **y** is the vector of responses, **X** is a design matrix, and **b** is a vector of unknown parameters that are estimated by minimizing the sum of squares of **e**, the error or residual term.

The following example illustrates some programming techniques by using SAS/IML statements to perform linear regression. (The example module does not replace regression procedures such as the REG procedure, which are more efficient for regressions and offer a multitude of diagnostic options.)

Suppose you have response data **y** measured at five values of the independent variable **X** and you want to perform a quadratic regression. In this case, you can define the design matrix **X** and the data vector **y** as follows:

```
proc iml;
x = {1 1 1,
      1 2 4,
      1 3 9,
      1 4 16,
      1 5 25};
y = {1, 5, 9, 23, 36};
```

You can compute the least squares estimate of **b** by using the following statement:

```
b = inv(x`*x) * x`*y;
print b;
```

Figure 4.2 Parameter Estimates

b
2.4
-3.2
2

The predicted values are found by multiplying the data matrix and the parameter estimates; the residuals are the differences between actual and predicted responses, as shown in the following statements:

```
yhat = x*b;
r = y-yhat;
print yhat r;
```

Figure 4.3 Predicted and Residual Values

yhat	r
1.2	-0.2
4	1
10.8	-1.8
21.6	1.4
36.4	-0.4

To estimate the variance of the responses, calculate the sum of squared errors (SSE), the error degrees of freedom (DFE), and the mean squared error (MSE) as follows:

```
sse = ssq(r);
dfe = nrow(x)-ncol(x);
mse = sse/dfe;
print sse dfe mse;
```

Figure 4.4 Statistics for a Linear Model

sse	dfe	mse
6.4	2	3.2

Notice that in computing the degrees of freedom, you use the function **NCOL** to return the number of columns of **X** and the function **NROW** to return the number of rows.

Now suppose you want to solve the problem repeatedly on new data. To do this, you can define a module. Modules begin with a **START statement** and end with a **FINISH statement**, with the program statements in between. The following statements define a module named **Regress** to perform linear regression:


```

start Regress;                                /* begins module      */
  xpxi = inv(x`*x);                            /* inverse of X'X      */
  beta = xpxi * (x`*y);                        /* parameter estimate  */
  yhat = x*beta;                               /* predicted values     */
  resid = y-yhat;                             /* residuals           */

  sse = ssq(resid);                            /* SSE                 */
  n = nrow(x);                                /* sample size         */
  dfe = nrow(x)-ncol(x);                      /* error DF           */
  mse = sse/dfe;                              /* MSE                 */
  cssy = ssq(y-sum(y)/n);                     /* corrected total SS  */
  rsquare = (cssy-sse)/cssy;                  /* RSQUARE             */
  print , "Regression Results", sse dfe mse rsquare;

  stdb = sqrt(vecdiag(xpxi)*mse); /* std of estimates    */
  t = beta/stdb;                          /* parameter t tests   */
  prob = 1-probf(t#t,1,dfe);              /* p-values            */
  print , "Parameter Estimates",, beta stdb t prob;
  print , y yhat resid;
finish Regress;                                /* ends module        */

```

Assuming that the matrices **x** and **y** are defined, you can run the Regress module as follows:

```
run Regress;                                /* executes module    */
```

Figure 4.5 The Results of a Regression Module

Regression Results			
sse	dfe	mse	rsquare
6.4	2	3.2	0.9923518
Parameter Estimates			
beta	stdb	t	prob
2.4	3.8366652	0.6255432	0.5954801
-3.2	2.923794	-1.094468	0.387969
2	0.4780914	4.1833001	0.0526691
y	yhat	resid	
1	1.2	-0.2	
5	4	1	
9	10.8	-1.8	
23	21.6	1.4	
36	36.4	-0.4	

Orthogonal Regression

In the previous section, you ran a module that computes parameter estimates and statistics for a linear regression model. All of the matrices used in the Regress module are global variables because the Regress module does not have any arguments. Consequently, you can use those matrices in additional calculations.

Suppose you want to correlate the parameter estimates. To do this, you can calculate the covariance of the estimates, then scale the covariance into a correlation matrix with values of 1 on the diagonal. You can perform these operations by using the following statements:

```
reset print;                /* turns on auto printing */
covb = xpxi*mse;            /* covariance of estimates */
s = 1/sqrt(vecdiag(covb));  /* standard errors */
corrb = diag(s)*covb*diag(s); /* correlation of estimates */
```

The RESET PRINT statement causes the IML procedure to print the result of each assignment statement, as shown in Figure 4.6. The covariance matrix of the estimates is contained in the **covb** matrix. The vector **s** contains the standard errors of the parameter estimates and is used to compute the correlation matrix of the estimates (**corrb**). These statistics are shown in Figure 4.6.

Figure 4.6 Covariance and Correlation Matrices for Estimates

Regression Results			
sse	dfc	mse	rsquare
6.4	2	3.2	0.9923518
Parameter Estimates			
beta	stdb	t	prob
2.4	3.8366652	0.6255432	0.5954801
-3.2	2.923794	-1.094468	0.387969
2	0.4780914	4.1833001	0.0526691
y	yhat	resid	
1	1.2	-0.2	
5	4	1	
9	10.8	-1.8	
23	21.6	1.4	
36	36.4	-0.4	
covb	3 rows	3 cols	(numeric)
14.72	-10.56	1.6	
-10.56	8.5485714	-1.371429	
1.6	-1.371429	0.2285714	
s	3 rows	1 col	(numeric)

Figure 4.6 *continued*

```

                                0.260643
                                0.3420214
                                2.0916501

                                corrb      3 rows      3 cols      (numeric)

                                1 -0.941376  0.8722784
                                -0.941376      1 -0.981105
                                0.8722784 -0.981105      1

```

You can also use the Regress module to carry out an orthogonalized regression version of the previous polynomial regression. In general, the columns of **X** are not orthogonal. You can use the **ORPOL** function to generate orthogonal polynomials for the regression. Using them provides greater computing accuracy and reduced computing times. When you use orthogonal polynomial regression, you can expect the statistics of fit to be the same and expect the estimates to be more stable and uncorrelated.

To perform an orthogonal regression on the data, you must first create a vector that contains the values of the independent variable x , which is the second column of the design matrix **X**. Then, use the **ORPOL** function to generate orthogonal second degree polynomials. You can perform these operations by using the following statements:

```

x1 = x[,2];                /* data = second column of X */
x = orpol(x1, 2);          /* generates orthogonal polynomials */
reset noprint;            /* turns off auto printing */
run Regress;              /* runs Regress module */

reset print;              /* turns on auto printing */
covb = xpxi*mse;
s = 1 / sqrt(vecdiag(covb));
corrb = diag(s)*covb*diag(s);
reset noprint;

```

Figure 4.7 Covariance and Correlation Matrices for Estimates

```

                                x1      5 rows      1 col      (numeric)

                                1
                                2
                                3
                                4
                                5

                                x      5 rows      3 cols      (numeric)

                                0.4472136 -0.632456  0.5345225
                                0.4472136 -0.316228  -0.267261
                                0.4472136 1.755E-17  -0.534522
                                0.4472136 0.3162278  -0.267261
                                0.4472136 0.6324555  0.5345225

                                Regression Results

```

Figure 4.7 continued

	sse	dfc	mse	rsquare
	6.4	2	3.2	0.9923518
Parameter Estimates				
	beta	stdb	t	prob
	33.093806	1.7888544	18.5	0.0029091
	27.828043	1.7888544	15.556349	0.0041068
	7.4833148	1.7888544	4.1833001	0.0526691
	y	yhat	resid	
	1	1.2	-0.2	
	5	4	1	
	9	10.8	-1.8	
	23	21.6	1.4	
	36	36.4	-0.4	
covb	3 rows	3 cols	(numeric)	
	3.2	0	0	
	0	3.2	0	
	0	0	3.2	
s	3 rows	1 col	(numeric)	
		0.559017		
		0.559017		
		0.559017		
corrb	3 rows	3 cols	(numeric)	
	1	0	0	
	0	1	0	
	0	0	1	

For these data, the off-diagonal values of the **corrb** matrix are displayed as zeros. For some analyses you might find that certain matrix elements are very close to zero but not exactly zero because of the computations of floating-point arithmetic. You can use the RESET FUZZ option to control whether small values are printed as zeros.

Plotting Regression Results

SAS/IML software includes SAS/IML Studio, an environment for developing SAS/IML programs. SAS/IML Studio includes high-level statistical graphics such as scatter plots, histograms, and bar charts. You can use

the SAS/IML Studio graphical user interface (GUI) to create graphs, or you can create and modify graphics by writing programs. The GUI is described in the *SAS/IML Studio User's Guide*. See *SAS/IML Studio for SAS/STAT Users* for an introduction to programming in SAS/IML Studio.

You can also produce high-resolution graphics by using the GXYPLOT module in the IMLMLIB library; see Chapter 24, “[Module Library](#).” Also see Chapter 15, “[Graphics Examples](#),” for more information about high-resolution graphics.

You can create some simple plots in PROC IML by using the [PGRAPH subroutine](#) which produces low-resolution scatter plots.

Low-Resolution Plots

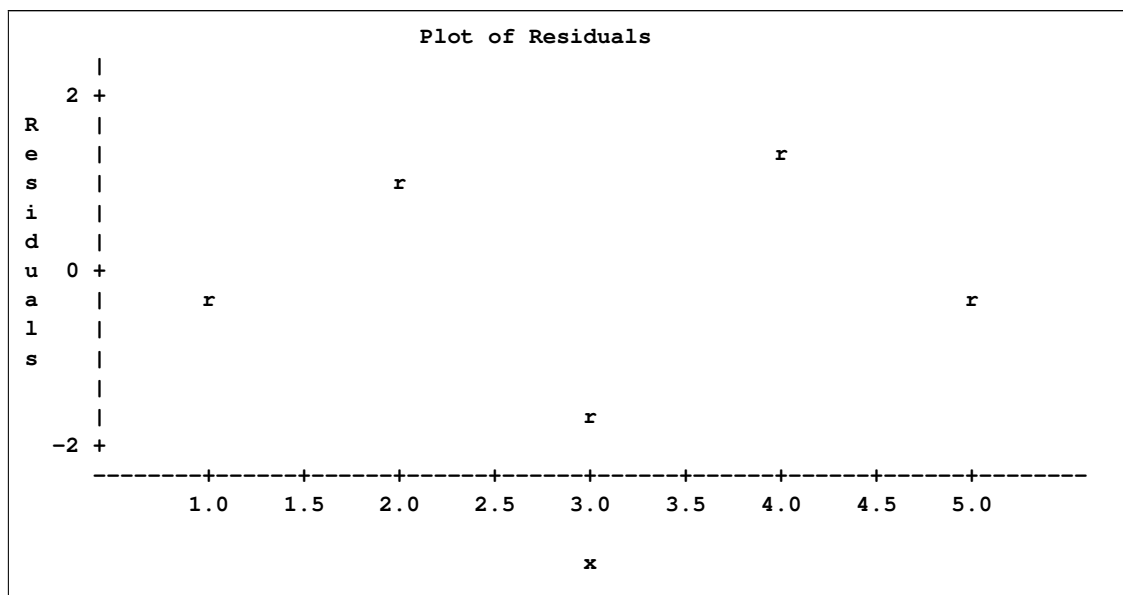
You can continue the example of this chapter by using the [PGRAPH](#) subroutine to create a low-resolution plot.

The following statements plot the residual values versus the explanatory variable:

```
xy = x1 || resid;
reset linesize=78 pagesize=20;
call pgraf(xy, 'r', 'x', 'Residuals', 'Plot of Residuals');
```

The first statement creates a matrix by using the horizontal concatenation operator (||) to concatenate **x1** with **resid**. The two-column matrix **xy** contains the pairs of points that the PGRAPH subroutine plots. The PGRAPH call produces the desired plot, as shown in [Figure 4.8](#).

Figure 4.8 Residual Plot from the PGRAPH Subroutine



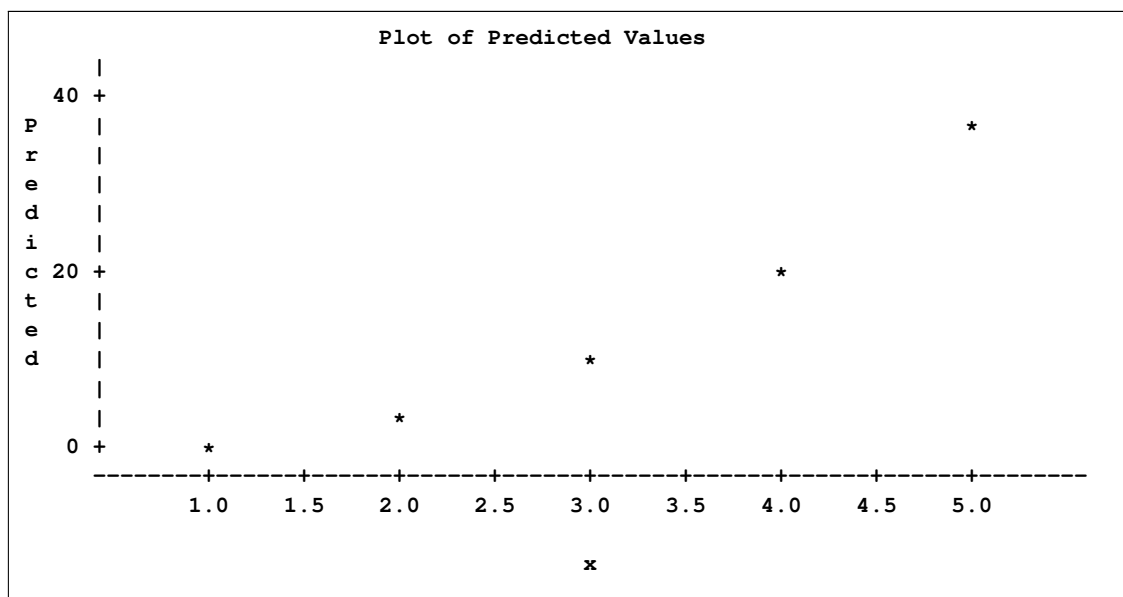
The arguments to PGRAF are as follows:

- an $n \times 2$ matrix that contains the pairs of points
- a plotting symbol
- a label for the X axis
- a label for the Y axis
- a title for the plot

You can also plot the predicted values \hat{y} against x . You can create a matrix (say, **xyh**) that contains the points to plot by concatenating **x1** with **yhat**. The PGRAF subroutine plots the points, as shown in the following statements. The resulting plot is shown in Figure 4.9.

```
xyh = x1 || yhat;
call pgraf(xyh, '*', 'x', 'Predicted', 'Plot of Predicted Values');
```

Figure 4.9 Predicted Value Plot from the PGRAF Subroutine



You can also use the PGRAF subroutine to create a low-resolution plot of the predicted and observed values plotted against the explanatory variable, as shown in the following statements:

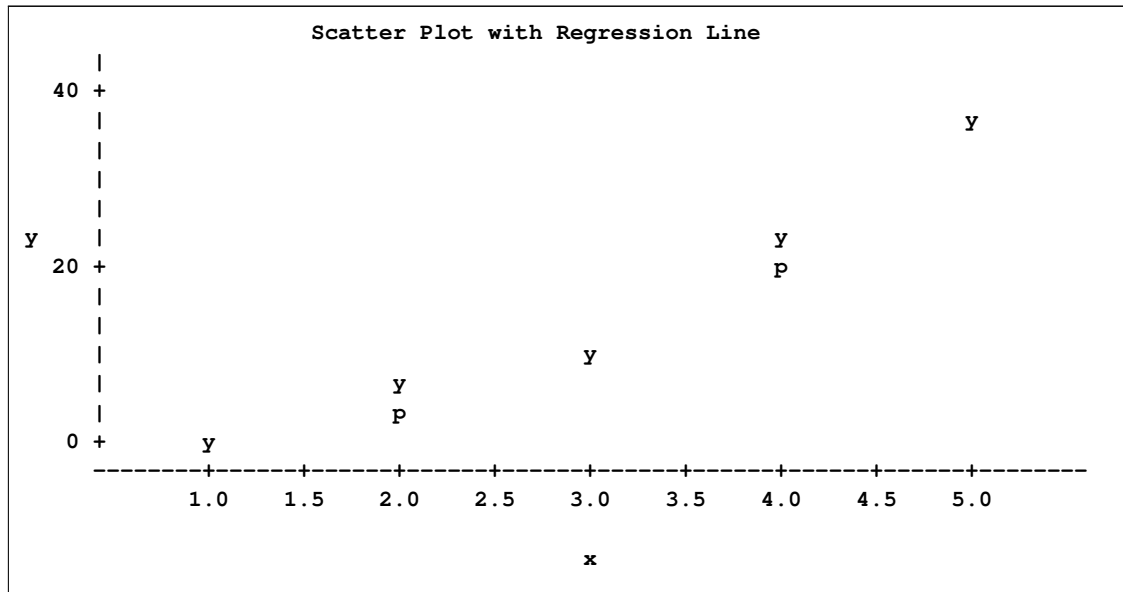
```
n = nrow(x1); /* number of observations */
newxy = (x1//x1) || (y//yhat); /* observed followed by predicted */
label = repeat('y',n,1) // repeat('p',n,1); /* 'y' followed by 'p' */
call pgraf(newxy, label, 'x', 'y', 'Scatter Plot with Regression Line');
```

The **NROW** function returns the number of rows of **x1**. The example creates a matrix **newxy**, which contains the pairs of all observed values, followed by the pairs of predicted values. (Notice that you need to use both the horizontal concatenation operator (**||**) and the vertical concatenation operator (**//**).) The matrix **label** contains the character label for each point: a “y” for each observed point and a “p” for each predicted point.

Finally, the PGRAF subroutine plots the observed and predicted values by using the corresponding symbols, as shown in [Figure 4.9](#).

For several points in [Figure 4.8](#), the observed and predicted values are too close together to be distinguishable in the low-resolution plot.

Figure 4.10 Plot of Predicted and Observed Values



SAS/IML Studio Graphics

If you develop your SAS/IML programs in SAS/IML Studio, you can use high-level statistical graphics. For example, the following statements create three scatter plots that duplicate the low-resolution plots created in the previous section. Two of the plots are shown in [Figure 4.11](#). The main steps in the program are indicated by numbered comments; these steps are explained in the list that follows the program.

```
x = {1 1 1, 1 2 4, 1 3 9, 1 4 16, 1 5 25};          /* 1 */
y = {1, 5, 9, 23, 36};
x1 = x[,2];                                         /* data = second column of X */
x = orpol(x1,2);                                   /* generates orthogonal polynomials */
run Regress;                                       /* runs the Regress module */

declare DataObject dobj;                           /* 2 */
dobj = DataObject.Create("Reg",                    /* 3 */
    {"x" "y" "Residuals" "Predicted"},
    x1 || y || resid || yhat);

declare ScatterPlot p1, p2, p3;
p1 = ScatterPlot.Create(dobj, "x", "Residuals");   /* 4 */
p1.SetTitleText("Plot of Residuals", true);
```

```

p2 = ScatterPlot.Create(dobj, "x", "Predicted"); /* 5 */
p2.SetTitleText("Plot of Predicted Values", true);

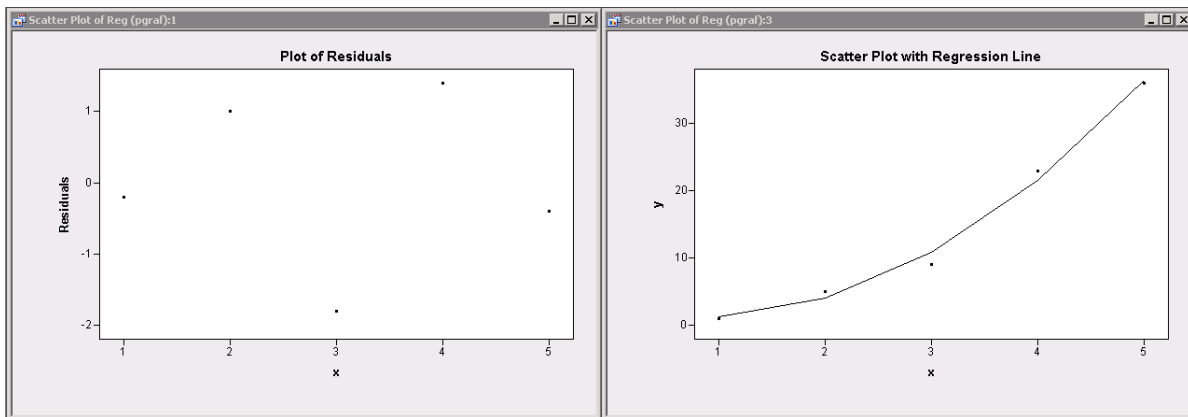
p3 = ScatterPlot.Create(dobj, "x", "y");          /* 6 */
p3.SetTitleText("Scatter Plot with Regression Line", true);
p3.DrawUseDataCoordinates();
p3.DrawLine(x1,yhat);                             /* 7 */

```

To completely understand this program, you should read *SAS/IML Studio for SAS/STAT Users*. The following list describes the main steps of the program:

1. Use SAS/IML to create the data and run the Regress module.
2. Specify that the `dobj` variable is an object of the `DataObject` class. SAS/IML Studio extends the SAS/IML language by adding object-oriented programming techniques.
3. Create an object of the `DataObject` class from SAS/IML vectors.
4. Create a scatter plot of the residuals versus the values of the explanatory variable.
5. Create a scatter plot of the predicted values versus the values of the explanatory variable.
6. Create a scatter plot of the observed responses versus the values of the explanatory variable.
7. Overlay a line for the predicted values.

Figure 4.11 Graphs Created by SAS/IML Studio



Chapter 5

Working with Matrices

Contents

Overview of Working with Matrices	41
Entering Data as Matrix Literals	42
Scalars	42
Matrices with Multiple Elements	43
Using Assignment Statements	44
Simple Assignment Statements	44
Functions That Generate Matrices	45
Index Vectors	49
Using Matrix Expressions	50
Operators	50
Compound Expressions	51
Elementwise Binary Operators	52
Subscripts	53
Subscript Reduction Operators	59
Displaying Matrices with Row and Column Headings	61
The AUTONAME Option in the RESET Statement	61
The ROWNAME= and COLNAME= Options in the PRINT Statement	62
The MATTRIB Statement	62
More about Missing Values	63

Overview of Working with Matrices

SAS/IML software provides many ways to create matrices. You can create matrices by doing any of the following:

- entering data as a matrix literal
- using assignment statements
- using functions that generate matrices
- creating submatrices from existing matrices with subscripts

- using SAS data sets (see Chapter 7, “Working with SAS Data Sets,” for more information)

Chapter 3, “Understanding the SAS/IML Language,” describes some of these techniques.

After you define matrices, you have access to many operators and functions for forming matrix expressions. These operators and functions facilitate programming and enable you to refer to submatrices. This chapter describes how to work with matrices in the SAS/IML language.

Entering Data as Matrix Literals

The simplest way to create a matrix is to define a matrix literal by entering the matrix elements. A matrix literal can contain numeric or character data. A matrix literal can be a single element (called a *scalar*), a single row of data (called a *row vector*), a single column of data (called a *column vector*), or a rectangular array of data (called a *matrix*). The *dimension* of a matrix is given by its number of rows and columns. An $n \times p$ matrix has n rows and p columns.

Scalars

Scalars are matrices that have only one element. You can define a scalar by typing the matrix name on the left side of an assignment statement and its value on the right side. The following statements create and display several examples of scalar literals:

```
proc iml;
x = 12;
y = 12.34;
z = .;
a = 'Hello';
b = "Hi there";
print x y z a b;
```

The output is displayed in Figure 5.1. Notice that you need to use either single quotes (') or double quotes (") when defining a character literal. Using quotes preserves the case and embedded blanks of the literal. It is also always correct to enclose data values within braces ({ }).

Figure 5.1 Examples of Scalar Quantities

x	y	z	a	b
12	12.34	.	Hello	Hi there

Matrices with Multiple Elements

To enter a matrix having multiple elements, use braces (`{ }`) to enclose the data values. If the matrix has multiple rows, use commas to separate them. Inside the braces, all elements must be either numeric or character. You cannot have a mixture of data types within a matrix. Each row must have the same number of elements.

For example, suppose you have one week of data on daily coffee consumption (cups per day) for four people in your office. Create a 4×5 matrix called **coffee** with each person's consumption represented by a row of the matrix and each day represented by a column. The following statements use the **RESET PRINT** command so that the result of each assignment statement is displayed automatically:

```
proc iml;
reset print;
coffee = {4 2 2 3 2,
          3 3 1 2 1,
          2 1 0 2 1,
          5 4 4 3 4};
```

Figure 5.2 A 4×5 Matrix

coffee	4 rows	5 cols	(numeric)	
4	2	2	3	2
3	3	1	2	1
2	1	0	2	1
5	4	4	3	4

Next, you can create a character matrix called **names** with rows that contains the names of the coffee drinkers in your office. Notice in **Figure 5.3** that if you do not use quotes, characters are converted to uppercase.

```
names = {Jenny, Linda, Jim, Samuel};
```

Figure 5.3 A Column Vector of Names

names	4 rows	1 col	(character, size 6)
JENNY			
LINDA			
JIM			
SAMUEL			

Notice that **RESET PRINT** statement produces output that includes the name of the matrix, its dimensions, its type, and (when the type is character) the element size of the matrix. The element size represents the length of each string, and it is determined by the length of the longest string.

Next display the **coffee** matrix using the elements of **names** as row names by specifying the **ROWNAME=** option in the **PRINT** statement:

```
print coffee[rowname=names];
```

Figure 5.4 Rows of a Matrix Labeled by a Vector

coffee					
JENNY	4	2	2	3	2
LINDA	3	3	1	2	1
JIM	2	1	0	2	1
SAMUEL	5	4	4	3	4

Using Assignment Statements

Assignment statements create matrices by evaluating expressions and assigning the results to a matrix. The expressions can be composed of operators (for example, the matrix addition operator (+)), functions (for example, the INV function), and subscripts. Assignment statements have the general form *result = expression* where *result* is the name of the new matrix and *expression* is an expression that is evaluated. The resulting matrix automatically acquires the appropriate dimension, type, and value. Details about writing expressions are described in the section “Using Matrix Expressions” on page 50.

Simple Assignment Statements

Simple assignment statements involve an equation that has a matrix name on the left side and either an expression or a function that generates a matrix on the right side.

Suppose that you want to generate some statistics for the weekly coffee data. If a cup of coffee costs 30 cents, then you can create a matrix with the daily expenses, **dayCost**, by multiplying the per-cup cost with the matrix **coffee**. You can turn off the automatic printing so that you can customize the output with the ROWNAME=, FORMAT=, and LABEL= options in the PRINT statement, as shown in the following statements:

```
reset noprint;
dayCost = 0.30 # coffee; /* elementwise multiplication */
print dayCost[rowname=names format=8.2 label="Daily totals"];
```

Figure 5.5 Daily Cost for Each Employee

Daily totals					
JENNY	1.20	0.60	0.60	0.90	0.60
LINDA	0.90	0.90	0.30	0.60	0.30
JIM	0.60	0.30	0.00	0.60	0.30
SAMUEL	1.50	1.20	1.20	0.90	1.20

You can calculate the weekly total cost for each person by using the matrix multiplication operator (*). First create a 5×1 vector of ones. This vector sums the daily costs for each person when multiplied with the **coffee** matrix. (A more efficient way to do this is by using subscript reduction operators, which are discussed in “Using Matrix Expressions” on page 50.) The following statements perform the multiplication:

```
ones = {1,1,1,1,1};
weektot = dayCost * ones; /* matrix-vector multiplication */
print weektot[rowname=names format=8.2 label="Weekly totals"];
```

Figure 5.6 Weekly Total for Each Employee

Weekly totals	
JENNY	3.90
LINDA	3.00
JIM	1.80
SAMUEL	6.00

You might want to calculate the average number of cups consumed per day in the office. You can use the SUM function, which returns the sum of all elements of a matrix, to find the total number of cups consumed in the office. Then divide the total by 5, the number of days. The number of days is also the number of columns in the **coffee** matrix, which you can determine by using the NCOL function. The following statements perform this calculation:

```
grandtot = sum(coffee);
average = grandtot / ncol(coffee);
print grandtot[label="Total number of cups"],
      average[label="Daily average"];
```

Figure 5.7 Total and Average Number of Cups for the Office

Total number of cups	
	49
Daily average	
	9.8

Functions That Generate Matrices

SAS/IML software has many useful built-in functions that generate matrices. For example, the **J function** creates a matrix with a given dimension and specified element value. You can use this function to initialize a matrix to a predetermined size. Here are several functions that generate matrices:

BLOCK	creates a block-diagonal matrix
DESIGNF	creates a full-rank design matrix
I	creates an identity matrix

J	creates a matrix of a given dimension
REPEAT	creates a new matrix by repeating elements of the argument matrix
SHAPE	shapes a new matrix from the argument

The sections that follow illustrate the functions that generate matrices. The output of each example is generated automatically by using the **RESET PRINT** statement:

```
reset print;
```

The BLOCK Function

The BLOCK function has the following general form:

BLOCK (*matrix1*,< *matrix2*,...*matrix15*>);

The BLOCK function creates a block-diagonal matrix from the argument matrices. For example, the following statements form a block-diagonal matrix:

```
a = {1 1, 1 1};  
b = {2 2, 2 2};  
c = block(a,b);
```

Figure 5.8 A Block-Diagonal Matrix

c	4 rows	4 cols	(numeric)	
	1	1	0	0
	1	1	0	0
	0	0	2	2
	0	0	2	2

The J Function

The J function has the following general form:

J (*nrow* <, *ncol* <, *value* >>);

It creates a matrix that has *nrow* rows, *ncol* columns, and all elements equal to *value*. The *ncol* and *value* arguments are optional; if they are not specified, default values are used. In many statistical applications, it is helpful to be able to create a row (or column) vector of ones. (You did so to calculate coffee totals in the previous section.) You can do this with the J function. For example, the following statement creates a 5 × 1 column vector of ones:

```
ones = j(5,1,1);
```

Figure 5.9 A Vector of Ones

ones	5 rows	1 col	(numeric)
		1	
		1	
		1	
		1	
		1	

The I Function

The I function creates an identity matrix of a given size. It has the following general form:

I (*dimension*) ;

where *dimension* gives the number of rows. For example, the following statement creates a 3×3 identity matrix:

```
I3 = I(3);
```

Figure 5.10 An Identity Matrix

I3	3 rows	3 cols	(numeric)
	1	0	0
	0	1	0
	0	0	1

The DESIGNF Function

The DESIGNF function generates a full-rank design matrix, which is useful in calculating ANOVA tables. It has the following general form:

DESIGNF (*column-vector*) ;

For example, the following statement creates a full-rank design matrix for a one-way ANOVA, where the treatment factor has three levels and there are $n_1 = 3$, $n_2 = 2$, and $n_3 = 2$ observations at the factor levels:

```
d = designf({1,1,1,2,2,3,3});
```

Figure 5.11 A Design Matrix

d	7 rows	2 cols	(numeric)
---	--------	--------	-----------

Figure 5.11 continued

	1	0
	1	0
	1	0
	0	1
	0	1
	-1	-1
	-1	-1

The REPEAT Function

The REPEAT function creates a new matrix by repeating elements of the argument matrix. It has the following syntax:

```
REPEAT (matrix, nrow, ncol) ;
```

The function repeats *matrix* a total of *nrow* × *ncol* times. The argument is repeated *nrow* times in the vertical direction and *ncol* times in the horizontal direction. For example, the following statement creates a 4 × 6 matrix:

```
x = {1 2, 3 4};  
r = repeat(x, 2, 3);
```

Figure 5.12 A Matrix of Repeated Values

	r	4 rows	6 cols	(numeric)	
	1	2	1	2	1
	3	4	3	4	3
	1	2	1	2	1
	3	4	3	4	3

The SHAPE Function

The SHAPE function creates a new matrix by reshaping an argument matrix. It has the following general form:

```
SHAPE (matrix, nrow <, ncol <, pad-value >>) ;
```

The *ncol* and *pad-value* arguments are optional; if they are not specified, default values are used. The following statement uses the SHAPE function to create a 3 × 3 matrix that contains the values 99 and 33. The function cycles back and repeats values to fill in the matrix when no *pad-value* is given.

```
aa = shape({99 33, 33 99}, 3, 3);
```

Figure 5.13 A Matrix of Repeated Values

	aa	3 rows	3 cols	(numeric)
--	----	--------	--------	-----------

Figure 5.13 *continued*

	99	33	33
	99	99	33
	33	99	99

Alternatively, you can specify a value for *pad-value* that is used for filling in the matrix:

```
bb = shape({99 33, 33 99}, 3, 3, 0);
```

Figure 5.14 A Matrix Padded with Zeroes

bb	3 rows	3 cols	(numeric)
	99	33	33
	99	0	0
	0	0	0

The SHAPE function cycles through the argument matrix elements in row-major order and fills in the matrix with zeros after the first cycle through the argument matrix.

Index Vectors

You can create a row vector by using the index operator (:). The following statements show that you can use the index operator to count up, count down, or to create a vector of character values with numerical suffixes:

```
r = 1:5;
s = 10:6;
t = 'abc1':'abc5';
```

Figure 5.15 Row Vectors Created with the Index Operator

r	1 row	5 cols	(numeric)		
1	2	3	4	5	
s	1 row	5 cols	(numeric)		
10	9	8	7	6	
t	1 row	5 cols	(character, size 4)		
abc1 abc2 abc3 abc4 abc5					

To create a vector based on an increment other than 1, use the DO function. For example, if you want a vector that ranges from -1 to 1 by 0.5 , use the following statement:

```
u = do(-1, 1, .5);
```

Figure 5.16 Row Vector Created with the DO Function

u	1 row	5 cols	(numeric)	
-1	-0.5	0	0.5	1

Using Matrix Expressions

A matrix expression is a sequence of names, literals, operators, and functions that perform some calculation, evaluate some condition, or manipulate values. Matrix expressions can appear on either side of an assignment statement.

Operators

Operators used in matrix expressions fall into three general categories:

- Prefix operators are placed in front of operands. For example, $-A$ uses the sign reversal prefix operator ($-$) in front of the matrix A to reverse the sign of each element of A .
- Binary operators are placed between operands. For example, $A + B$ uses the addition binary operator ($+$) between matrices A and B to add corresponding elements of the matrices.
- Postfix operators are placed after an operand. For example, A' uses the transpose postfix operator ($'$) after the matrix A to transpose the matrix.

Matrix operators are described in detail in Chapter 23, “[Language Reference](#).”

Table 5.1 shows the precedence of matrix operators in the SAS/IML language.

Table 5.1 Operator Precedence

Priority Group	Operators					
I (highest)	\wedge	\backslash	subscripts	$-(\text{prefix})$	$\#\#$	$**$
II	$*$	$\#$	$\langle \rangle$	$> \langle$	$/$	$@$
III	$+$	$-$				
IV	\parallel	$//$	$:$			
V	$<$	$<=$	$>$	$>=$	$=$	$\wedge =$
VI	$\&$					
VII (lowest)	$ $					

Compound Expressions

With SAS/IML software, you can write compound expressions that involve several matrix operators and operands. For example, the following statements are valid matrix assignment statements:

```
a = x+y+z;
a = x+y*z` ;
a = (-x) # (y-z) ;
```

The rules for evaluating compound expressions are as follows:

- Evaluation follows the order of operator precedence, as described in [Table 5.1](#). Group I has the highest priority; that is, Group I operators are evaluated first. Group II operators are evaluated after Group I operators, and so forth. Consider the following statement:

```
a = x+y*z;
```

This statement first multiplies matrices **y** and **z** since the ***** operator (Group II) has higher precedence than the **+** operator (Group III). It then adds the result of this multiplication to the matrix **x** and assigns the new matrix to **a**.

- If neighboring operators in an expression have equal precedence, the expression is evaluated from left to right, except for the Group I operators. Consider the following statement:

```
a = x/y/z;
```

This statement first divides each element of matrix **x** by the corresponding element of matrix **y**. Then, using the result of this division, it divides each element of the resulting matrix by the corresponding element of matrix **z**. The operators in Group I, described in [Table 5.1](#), are evaluated from right to left. For example, the following expression is evaluated as $-(\mathbf{X}^2)$:

```
-x**2
```

When multiple prefix or postfix operators are juxtaposed, precedence is determined by their order from inside to outside.

For example, the following expression is evaluated as $(\mathbf{A}^{\text{'}})[i, j]$:

```
a` [i, j]
```

- All expressions enclosed in parentheses are evaluated first, using the two preceding rules. Consider the following statement:

```
a = x/(y/z) ;
```

This statement is evaluated by first dividing elements of **y** by the elements of **z**, then dividing this result into **x**.

Elementwise Binary Operators

Elementwise binary operators produce a result matrix from element-by-element operations on two argument matrices.

Table 5.2 lists the elementwise binary operators.

Table 5.2 Elementwise Binary Operators

Operator	Description
+	Addition; string concatenation
−	Subtraction
#	Elementwise multiplication
##	Elementwise power
/	Division
<>	Element maximum
><	Element minimum
	Logical OR
&	Logical AND
<	Less than
<=	Less than or equal to
>	Greater than
>=	Greater than or equal to
^=	Not equal to
=	Equal to

For example, consider the following two matrices:

$$\mathbf{A} = \begin{bmatrix} 2 & 2 \\ 3 & 4 \end{bmatrix}, \mathbf{B} = \begin{bmatrix} 4 & 5 \\ 1 & 0 \end{bmatrix}$$

The addition operator (+) adds corresponding matrix elements, as follows:

$$\mathbf{A} + \mathbf{B} \text{ is } \begin{bmatrix} 6 & 7 \\ 4 & 4 \end{bmatrix}$$

The elementwise multiplication operator (#) multiplies corresponding elements, as follows:

$$\mathbf{A} \# \mathbf{B} \text{ is } \begin{bmatrix} 8 & 10 \\ 3 & 0 \end{bmatrix}$$

The elementwise power operator (##) raises elements to powers, as follows:

$$\mathbf{A} \# \# 2 \text{ is } \begin{bmatrix} 4 & 4 \\ 9 & 16 \end{bmatrix}$$

The element maximum operator ($<>$) compares corresponding elements and chooses the larger, as follows:

$$\mathbf{A} <> \mathbf{B} \text{ is } \begin{bmatrix} 4 & 5 \\ 3 & 4 \end{bmatrix}$$

The less than or equal to operator ($<=$) returns a 1 if an element of \mathbf{A} is less than or equal to the corresponding element of \mathbf{B} , and returns a 0 otherwise:

$$\mathbf{A} <= \mathbf{B} \text{ is } \begin{bmatrix} 1 & 1 \\ 0 & 0 \end{bmatrix}$$

All operators can work on scalars, vectors, or matrices, provided that the operation makes sense. For example, you can add a scalar to a matrix or divide a matrix by a scalar. For example, the following statement replaces each negative element of the matrix \mathbf{x} with 0:

```
y = x#(x>0) ;
```

The expression $\mathbf{x}>0$ is an operation that compares each element of \mathbf{x} to (scalar) zero and creates a temporary matrix of results; an element of the temporary matrix is 1 when the corresponding element of \mathbf{x} is positive, and 0 otherwise. The original matrix \mathbf{x} is then multiplied elementwise by the temporary matrix, resulting in the matrix \mathbf{y} . To fully understand the intermediate calculations, you can use the [RESET](#) statement with the PRINTALL option to have the temporary result matrices displayed.

Subscripts

Subscripts are special postfix operators placed in square brackets ([]) after a matrix operand. Subscript operations have the general form *operand*[*row,column*] where

<i>operand</i>	is usually a matrix name, but it can also be an expression or literal.
<i>row</i>	refers to a scalar or vector expression that selects one or more rows from the operand.
<i>column</i>	refers to a scalar or vector expression that selects one or more columns from the operand.

You can use subscripts to do any of the following:

- refer to a single element of a matrix
- refer to an entire row or column of a matrix
- refer to any submatrix contained within a matrix
- perform a *reduction* across rows or columns of a matrix. A reduction is a statistical operation (often a sum or mean) applied to the rows or to the columns of a matrix.

In expressions, subscripts have the same (high) precedence as the transpose postfix operator ($'$). When both *row* and *column* subscripts are used, they are separated by a comma. If a matrix has row or column names associated with it from a [MATTRIB](#) or [READ](#) statement, then the corresponding row or column subscript can also be a character matrix whose elements match the names of the rows or columns to be selected.

Selecting a Single Element

You can select a single element of a matrix in several ways. You can use two subscripts (*row*, *column*) to refer to its location, or you can use one subscript to index the elements in row-major order.

For example, for the coffee example used previously in this chapter, there are several ways to find the element that corresponds to the number of cups that Samuel drank on Monday.

First, you can refer to the element by row and column location. In this case, you want the fourth row and first column. The following statements extract the datum and place it in the matrix **c41**:

```
coffee={4 2 2 3 2, 3 3 1 2 1, 2 1 0 2 1, 5 4 4 3 4};
names={Jenny, Linda, Jim, Samuel};
print coffee[rowname=names];
c41 = coffee[4,1];
print c41;
```

Figure 5.17 Datum Extracted from a Matrix

coffee					
JENNY	4	2	2	3	2
LINDA	3	3	1	2	1
JIM	2	1	0	2	1
SAMUEL	5	4	4	3	4
c41					
5					

You can also use row and column names, which can be assigned with an **MATTRIB** statement as follows:

```
mattrib coffee rowname=names
      colname={'MON' 'TUE' 'WED' 'THU' 'FRI'};
cSamMon = coffee['SAMUEL', 'MON'];
print cSamMon;
```

Figure 5.18 Datum Extracted from a Matrix with Assigned Attributes

cSamMon	
5	

You can also look for the element by enumerating the elements of the matrix in row-major order. In this case, you refer to this element as the sixteenth element of **coffee**:

```
c16 = coffee[16];
print c16;
```

Figure 5.19 Datum Extracted from a Matrix by Specifying the Element Number

c16
5

Selecting a Row or Column

To refer to an entire row of a matrix, specify the subscript for the row but omit the subscript for the column. For example, to refer to the row of the **coffee** matrix that corresponds to Jim, you can specify the submatrix that consists of the third row and all columns. The following statements extract and print this submatrix:

```
jim = coffee[3,];
print jim;
```

Alternately, you can use the row names assigned by the **MATTRIB** statement. Both results are shown in [Figure 5.20](#).

```
jim2 = coffee['JIM',];
print jim2;
```

Figure 5.20 Row Extracted from a Matrix

			jim		
2	1	0	2	1	
			jim2		
2	1	0	2	1	

If you want to extract the data for Friday, you can specify the subscript for the fifth column. You omit the row subscript to indicate that the operation applies to all rows. The following statements extract and print this submatrix:

```
friday = coffee[,5];
print friday;
```

Figure 5.21 Column Extracted from a Matrix

	friday
2	
1	
1	
4	

Alternatively, you could also index by the column name as follows:

```
friday = coffee['FRI'];
```

Submatrices

You refer to a submatrix by specifying the rows and columns that determine the submatrix. For example, to create the submatrix of **coffee** that consists of the first and third rows and the second, third, and fifth columns, use the following statements:

```
submat1 = coffee[{1 3}, {2 3 5}];
print submat1;
```

Figure 5.22 Submatrix Extracted from a Matrix

submat1		
2	2	2
1	0	1

The first vector, {1 3}, selects the rows and the second vector, {2 3 5}, selects the columns. Alternately, you can create the vectors of indices and use them to extract the submatrix, as shown in following statements:

```
rows = {1 3};
cols = {2 3 5};
submat1 = coffee[rows, cols];
```

You can also use the row and column names:

```
rows = {'JENNY' 'JIM'};
cols = {'TUE' 'WED' 'FRI'};
submat1 = coffee[rows, cols];
```

You can use index vectors generated by the index creation operator (:) in subscripts to refer to successive rows or columns. For example, the following statements extract the first three rows and last three columns of **coffee**:

```
submat2 = coffee[1:3, 3:5];
print submat2;
```

Figure 5.23 Submatrix of Contiguous Rows and Columns

submat2		
2	3	2
1	2	1
0	2	1

Selecting Multiple Elements

All SAS/IML matrices are stored in row-major order. This means that you can index multiple elements of a matrix by listing the position of the elements in an $n \times p$ matrix. The elements in the first row have positions

1 through p , the elements in the second row have positions $p + 1$ through $2p$, and the elements in the last row have positions $(n - 1)p + 1$ through np .

For example, in the coffee data discussed previously, you might be interested in finding occurrences for which some person (on some day) drank more than two cups of coffee. The LOC function is useful for creating an index vector for a matrix that satisfies some condition. The following statement uses the LOC function to find the data that satisfy the desired criterion:

```
h = loc(coffee > 2);
print h;
```

Figure 5.24 Indices That Correspond to a Criterion

h					
	COL1	COL2	COL3	COL4	COL5
ROW1	1	4	6	7	16
h					
	COL6	COL7	COL8	COL9	
ROW1	17	18	19	20	

The row vector **h** contains indices of the **coffee** matrix that satisfy the criterion. If you want to find the number of cups of coffee consumed on these occasions, you need to subscript the **coffee** matrix with the indices, as shown in the following statements:

```
cups = coffee[h];
print cups;
```

Figure 5.25 Values That Correspond to a Criterion

cups
4
3
3
3
5
4
4
3
4

Notice that SAS/IML software returns a column vector when a matrix is subscripted by a single array of indices. This might surprise you, but clearly the **cups** matrix cannot be the same shape as the **coffee** matrix since it contains a different number of elements. Therefore, the only reasonable alternative is to return either a row vector or a column vector. Either would be a valid choice; SAS/IML software returns a column vector.

Even if the original matrix is a row vector, the subscripted matrix will be a column vector, as the following example shows:

```
v = {-1 2 5 -2 7}; /* v is a row vector */
v2 = v[{1 3 5}]; /* v2 is a column vector */
print v2;
```

Figure 5.26 Column Vector of Extracted Values

v2				
				-1
				5
				7

If you want to index into a row vector and you want the resulting variable also to be a row vector, then use the following technique:

```
v3 = v[ ,{1 3 5}]; /* Select columns. Note the comma. */
print v3;
```

Figure 5.27 Row Vector of Extracted Values

v3				
-1		5		7

Subscripted Assignment

You can assign values into a matrix by using subscripts to refer to the element or submatrix. In this type of assignment, the subscripts appear on the left side of the equal sign. For example, to assign the value 4 in the first row, second column of **coffee**, use subscripts to refer to the appropriate element in an assignment statement, as shown in the following statements and in [Figure 5.27](#):

```
coffee[1,2] = 4;
print coffee;
```

To change the values in the last column of **coffee** to zeros, use the following statements:

```
coffee[,5] = {0,0,0,0}; /* alternatively: coffee[:,5] = 0; */
print coffee;
```

Figure 5.28 Matrices after Assigning Values to Elements

coffee				
4	4	2	3	2
3	3	1	2	1
2	1	0	2	1
5	4	4	3	4

Figure 5.28 *continued*

coffee				
4	4	2	3	0
3	3	1	2	0
2	1	0	2	0
5	4	4	3	0

In the next example, you locate the negative elements of a matrix and set these elements to zero. (This can be useful in situations where negative elements might indicate errors.) The LOC function is useful for creating an index vector for a matrix that satisfies some criterion. The following statements use the LOC function to find and replace the negative elements of the matrix **T**:

```
t = {3  2 -1,
      6 -4  3,
      2  2  2 };
i = loc(t<0);
print i;
t[i] = 0;
print t;
```

Figure 5.29 Results of Finding and Replacing Negative Values

i		
3	5	
t		
3	2	0
6	0	3
2	2	2

Subscripts can also contain expressions. For example, the previous example could have been written as follows:

```
t[loc(t<0)] = 0;
```

If you use a noninteger value as a subscript, only the integer portion is used. Using a subscript value less than one or greater than the dimension of the matrix results in an error.

Subscript Reduction Operators

A reduction operator is a statistical operation (for example, a sum or a mean) that returns a matrix of a smaller dimension. Reduction operators are often encountered in frequency tables: the marginal frequencies represent the sum of the frequencies across rows or down columns.

In SAS/IML software, you can use reduction operators in place of values for subscripts to get reductions across all rows or columns. Table 5.3 lists operators for subscript reduction.

Table 5.3 Subscript Reduction Operators

Operator	Description
+	Addition
#	Multiplication
<>	Maximum
><	Minimum
<:>	Index of maximum
>:<	Index of minimum
:	Mean
##	Sum of squares

For example, to get row sums of a matrix **x**, you can sum across the columns with the syntax **x[,+]**. Omitting the first subscript specifies that the operator apply to all rows. The second subscript (+) specifies that summation reduction take place across the columns. The elements in each row are added, and the new matrix consists of one column that contains the row sums.

To give a specific example, consider the coffee data from earlier in the chapter. The following statements use the summation reduction operator to compute the sums for each row:

```
coffee={4 2 2 3 2, 3 3 1 2 1, 2 1 0 2 1, 5 4 4 3 4};
names={Jenny, Linda, Jim, Samuel};
mattrib coffee rowname=names colname={'MON' 'TUE' 'WED' 'THU' 'FRI'};
Total = coffee[,+];
print coffee Total;
```

Figure 5.30 Summation across Columns to Find the Row Sums

coffee	MON	TUE	WED	THU	FRI	Total
JENNY	4	2	2	3	2	13
LINDA	3	3	1	2	1	10
JIM	2	1	0	2	1	6
SAMUEL	5	4	4	3	4	20

You can use these reduction operators to reduce the dimensions of rows, columns, or both. When both rows and columns are reduced, row reduction is done first.

For example, the expression **A[+, <>]** results in the maximum (<>) of the column sums (+).

You can repeat reduction operators. To get the sum of the row maxima, use the expression **A[, <>][+,]**, or, equivalently, **A[, <>][+,]**.

A subscript such as **A[{2 3}, +]** first selects the second and third rows of **A** and then finds the row sums of that submatrix.

The following examples demonstrate how to use the operators for subscript reduction. Consider the following matrix:

$$\mathbf{A} = \begin{bmatrix} 0 & 1 & 2 \\ 5 & 4 & 3 \\ 7 & 6 & 8 \end{bmatrix}$$

The following statements are true:

$$\mathbf{A}[\{2\ 3\}, +] \text{ is } \begin{bmatrix} 12 \\ 21 \end{bmatrix} \text{ (row sums for rows 2 and 3)}$$

$$\mathbf{A}[+, < >] \text{ is } \begin{bmatrix} 13 \end{bmatrix} \text{ (maximum of column sums)}$$

$$\mathbf{A}[< >, +] \text{ is } \begin{bmatrix} 21 \end{bmatrix} \text{ (sum of column maxima)}$$

$$\mathbf{A}[> <][+,] \text{ is } \begin{bmatrix} 9 \end{bmatrix} \text{ (sum of row minima)}$$

$$\mathbf{A}[< : >] \text{ is } \begin{bmatrix} 3 \\ 1 \\ 3 \end{bmatrix} \text{ (indices of row maxima)}$$

$$\mathbf{A}[> : <,] \text{ is } \begin{bmatrix} 1 & 1 & 1 \end{bmatrix} \text{ (indices of column minima)}$$

$$\mathbf{A}[:] \text{ is } \begin{bmatrix} 4 \end{bmatrix} \text{ (mean of all elements)}$$

Displaying Matrices with Row and Column Headings

You can customize the way matrices are displayed with the AUTONAME option, with the ROWNAME= and COLNAME= options, or with the MATTRIB statement.

The AUTONAME Option in the RESET Statement

You can use the RESET statement with the AUTONAME option to automatically display row and column headings. If your matrix has n rows and p columns, the row headings are ROW1 to ROW n and the column headings are COL1 to COL p . For example, the following statements produce the subsequent matrix:

```
coffee={4 2 2 3 2, 3 3 1 2 1, 2 1 0 2 1, 5 4 4 3 4};
reset autoname;
print coffee;
```

Figure 5.31 Result of the AUTONAME Option

	coffee				
	COL1	COL2	COL3	COL4	COL5
ROW1	4	2	2	3	2
ROW2	3	3	1	2	1
ROW3	2	1	0	2	1
ROW4	5	4	4	3	4

The ROWNAME= and COLNAME= Options in the PRINT Statement

You can specify your own row and column headings. The easiest way is to create vectors that contain the headings and then display the matrix by using the ROWNAME= and COLNAME= options in the PRINT statement. For example, the following statements display row names and column names for a matrix:

```
names={Jenny, Linda, Jim, Samuel};
days={Mon Tue Wed Thu Fri};
mattrib coffee rowname=names colname=days;
print coffee;
```

Figure 5.32 Result of the ROWNAME= and COLNAME= Options

	coffee				
	MON	TUE	WED	THU	FRI
JENNY	4	2	2	3	2
LINDA	3	3	1	2	1
JIM	2	1	0	2	1
SAMUEL	5	4	4	3	4

The MATTRIB Statement

The MATTRIB statement associates printing characteristics with matrices. You can use the MATTRIB statement to display `coffee` with row and column headings. In addition, you can format the displayed numeric output and assign a label to the matrix name. The following example shows how to customize your displayed output:

```
mattrib coffee rowname=names
          colname=days
          label='Weekly Coffee'
          format=2.0;
print coffee;
```

Figure 5.33 Result of the MATTRIB Statement

	Weekly Coffee				
	MON	TUE	WED	THU	FRI
JENNY	4	2	2	3	2
LINDA	3	3	1	2	1
JIM	2	1	0	2	1
SAMUEL	5	4	4	3	4

More about Missing Values

Missing values in matrices are discussed in Chapter 3, “[Understanding the SAS/IML Language](#).” You should carefully read that chapter and Chapter 22, “[Further Notes](#),” so that you are aware of the way SAS/IML software handles missing values. The following examples show how missing values are handled for elementwise operations and for subscript reduction operators.

Consider the following two matrices **X** and **Y**:

$$\mathbf{X} = \begin{bmatrix} 1 & 2 & . \\ . & 5 & 6 \\ 7 & . & 9 \end{bmatrix} \quad \mathbf{Y} = \begin{bmatrix} 4 & . & 2 \\ 2 & 1 & 3 \\ 6 & . & 5 \end{bmatrix}$$

The following operations handle missing values in matrices:

Matrix addition: $\mathbf{X} + \mathbf{Y}$ is $\begin{bmatrix} 5 & . & . \\ . & 6 & 9 \\ 13 & . & 14 \end{bmatrix}$

Elementwise multiplication: $\mathbf{X} \# \mathbf{Y}$ is $\begin{bmatrix} 4 & . & . \\ . & 5 & 18 \\ 42 & . & 45 \end{bmatrix}$

Subscript reduction: $\mathbf{X}[+,]$ is $\begin{bmatrix} 8 & 7 & 15 \end{bmatrix}$

Chapter 6

Programming Statements

Contents

Overview of Programming Statements	65
Selection Statements	66
Compound Statements	67
Iteration Statements	68
Jump Statements	70
Statements That Define and Execute Modules	72
Defining and Executing a Module	72
Understanding Symbol Tables	73
Modules with No Arguments	74
Modules with Arguments	74
Nesting Modules	78
Understanding Argument Passing	80
Storing and Loading Modules	82
Termination Statements	82
PAUSE Statement	82
STOP Statement	84
ABORT Statement	84
QUIT Statement	84

Overview of Programming Statements

The SAS/IML programming language has control statements that enable you to control the path of execution in a program. The control statements in the SAS/IML language are similar to the corresponding statements in the SAS DATA step. This chapter describes the following concepts:

- selection statements
- compound statements
- iteration statements
- jump statements

- statements that define and execute modules
- termination statements

Selection Statements

Selection statements choose one of several control paths in a program. The SAS/IML language supports the IF-THEN and the IF-THEN/ELSE statements. You can use an IF-THEN statement to test an expression and to conditionally perform an operation. You can also optionally specify an ELSE statement. The general form of the IF-THEN/ELSE statement is as follows:

```
IF expression THEN statement1 ;
```

```
ELSE statement2 ;
```

The expression is evaluated first. If the value of expression is true (which means nonzero and nonmissing), the THEN statement is executed. If the value of expression is false (which means zero or missing), the ELSE statement (if present) is executed. If an ELSE statement is not present, control passes to the next statement in the program.

The expression in an IF-THEN statement is often a comparison, as in the following example:

```
a = {17 22, 13 10};
if max(a)<20 then
  p = 1;
else p = 0;
```

The IF clause evaluates the expression **max**(**a**)<20. If all values of the matrix **a** are less than 20, **p** is set to 1. Otherwise, **p** is set to 0. For the given values of **a**, the IF condition is false, since **a**[1,2] is not less than 20.

You can nest IF-THEN statements within the clauses of other IF-THEN or ELSE statements. Any number of nesting levels is allowed. The following is an example of nested IF-THEN statements:

```
w = 0;
if n>0 then
  if x>y then w = x;
  else w = y;
```

There is an ambiguity associated with the previous statements. Is the ELSE statement associated with the first IF-THEN statement or the second? As the indenting indicates, an ELSE statement is associated with the closest previous IF-THEN statement. (If you want the ELSE statement to be associated with the first IF-THEN statement, you need to use a DO group, as described in the next section.)

When the condition to be evaluated is a matrix expression, the result of the evaluation is a temporary matrix of zeros, ones, and possibly missing values. If all values of the result matrix are nonzero and nonmissing, the condition is true; if any element in the result matrix is zero or missing, the condition is false. This evaluation is equivalent to using the ALL function. For example, the following two statements produce the same result:

```

if x<y then      statement;
if all(x<y) then statement;

```

If you are testing whether at least one element in **x** is less than the corresponding element in **y**, use the [ANY function](#), as shown in the following statement:

```

if any(x<y) then statement;

```

Compound Statements

Several statements can be grouped together into a compound statement (also called a *block* or a DO group). You use a DO statement to define the beginning of a DO group and an END statement to define the end. DO groups have two principal uses:

- to group a set of statements so that they are executed as a unit
- to group a set of statements for a conditional (IF-THEN/ELSE) clause

DO groups have the following general form:

```

DO ;
    statements ;
END ;

```

As with IF-THEN/ELSE statements, you can nest DO groups to any number of levels. The following is an example of nested DO groups:

```

do;
    statements;
    do;
        statements;
    end;
    statements;
end;

```

It is a good programming convention to indent the statements in DO groups as shown, so that each statement's position indicates its level of nesting.

For IF-THEN/ELSE conditionals, DO groups can be used as units for either the THEN or ELSE clauses so that you can perform many statements as part of the conditional action, as shown in the following statements:

```

if x<y then
do;
    z1 = abs(x+y);

```

```

        z2 = abs(x-y) ;
    end;
else
    do;
        z1 = abs(x-y) ;
        z2 = abs(x+y) ;
    end;

```

An alternative formulation that requires less indented space is to write the DO statement on the same line as the THEN or ELSE clause, as shown in following statements:

```

if x<y then do;
    z1 = abs(x+y) ;
    z2 = abs(x-y) ;
end;
else do;
    z1 = abs(x-y) ;
    z2 = abs(x+y) ;
end;

```

For some programming applications, you must use either a DO group or a module. For example, [LINK](#) and [GOTO](#) statements must be programmed inside a DO group or a module.

Iteration Statements

The DO statement supports clauses that iterate over compound statements. With an iterative DO statement, you can repeatedly execute a set of statements until some condition stops the execution. The following table lists the different kinds of iteration statements in the SAS/IML language:

Clause	DO Statement
DATA	DO DATA statement
<i>variable</i> = <i>start</i> TO <i>stop</i> < BY <i>increment</i> >	Iterative DO statement
WHILE(<i>expression</i>)	DO WHILE statement
UNTIL(<i>expression</i>)	DO UNTIL statement

A DO statement can have any combination of these four iteration clauses, but the clauses must be specified in the order listed in the preceding table.

DO DATA Statements

The general form of the DO DATA statement is as follows:

```
DO DATA ;
```

The DATA keyword specifies that iteration stops when an end-of-file condition occurs. Other DO specifications exit after tests are performed at the top or bottom of a loop.

See Chapter 7, “Working with SAS Data Sets,” and Chapter 8, “File Access,” for more information about processing data.

You can use the DO DATA statement to read data from an external file or to process observations from a SAS data set. In the DATA step in Base SAS software, the iteration is usually implied. The DO DATA statement simulates this iteration until the end of a file is reached.

The following example reads data from an external file named *MyData.txt* that contains the following data:

Rick	2.40	3.30
Robert	3.90	4.00
Simon	3.85	4.25

The data values are read one at a time into the scalar variables Name, x, and y.

```
filename MyFile 'MyData.txt';
infile MyFile;                /* infile statement */
do data;                      /* begin read loop */
    input Name $6. x y;        /* read a data value */
    /* do something with each value */
end;
closefile MyFile;
```

Iterative DO Statements

The general form of the iterative DO statement is as follows:

DO *variable*=*start* **TO** *stop* <**BY** *increment*> ;

The value of the *variable* matrix is initialized to the value of the *start* matrix. This value is then incremented by the *increment* value (or by 1 if *increment* is not specified) until it is greater than or equal to the *stop* value. (If *increment* is negative, then the iterations stop when the value is less than or equal to *stop*.)

For example, the following statement specifies a DO loop that initializes *i* to the value 1 and increments *i* by 2 after each loop. The loop ends when the value of *i* is greater than 10.

```
y = 0;
do i = 1 to 10 by 2;
    y = y + i;
end;
```

DO WHILE Statements

The general form of the DO WHILE statement is as follows:

DO WHILE *expression* ;

With a WHILE clause, the expression is evaluated at the beginning of each loop, with iterations continuing until the expression is false (that is, until the expression contains a zero or a missing value). Note that if the expression is false the first time it is evaluated, the loop is not executed.

For example, the following statements initialize `count` to 1 and then increment `count` four times:

```
count = 1;
do while(count<5);
    count = count+1;
end;
```

DO UNTIL Statements

The general form of the DO UNTIL statement is as follows:

DO UNTIL *expression* ;

The UNTIL clause is like the WHILE clause except that the expression is evaluated at the bottom of the loop. This means that the loop always executes at least once.

For example, the following statements initialize `count` to 1 and then increment `count` five times:

```
count = 1;
do until(count>5);
    count = count+1;
end;
```

Jump Statements

During normal execution, each statement in a program is executed in sequence, one after another. The GOTO and LINK statements cause a SAS/IML program to jump from one statement in a program to another statement without executing intervening statements. The place to which execution jumps is identified by a *label*, which is a name followed by a colon placed before an executable statement. You can program a jump by using either the GOTO statement or the LINK statement:

GOTO *label* ;

LINK *label* ;

Both the GOTO and LINK statements instruct SAS/IML software to jump immediately to a labeled statement. However, if you use a LINK statement, then the program returns to the statement following the LINK statement when the program executes a RETURN statement. The GOTO statement does not have this feature. Thus, the LINK statement provides a way of calling sections of code as if they were subroutines. The statements that define the subroutine begin with the label and end with a RETURN statement. LINK statements can be nested within other LINK statements; any number of nesting levels is allowed.

NOTE: The GOTO and LINK statements must be inside a module or DO group. These statements must be able to resolve the referenced label within the current unit of statements. Although matrix symbols can be shared across modules, statement labels cannot. Therefore, all GOTO statement labels and LINK statement labels must be local to the DO group or module.

The GOTO and LINK statements are not often used because you can usually write more understandable programs by using DO groups and modules. The following statements shows an example of using the GOTO statement, followed by an equivalent set of statements that do not use the GOTO statement:

```
x = -2;
do;
    if x<0 then goto negative;
    y = sqrt(x);
    print y;
    goto TheEnd;
negative:
    print "Sorry, value is negative";
TheEnd:
end;

/* same logic, but without using a GOTO statement */
if x<0 then print "Sorry, value is negative";
else do;
    y = sqrt(x);
    print y;
end;
```

The output of each section of the program is identical. It is shown in [Figure 6.1](#).

Figure 6.1 Output That Demonstrates the GOTO Statement

Sorry, value is negative
Sorry, value is negative

The following statements show an example of using the LINK statements. You can also rewrite the statements in a way that avoids using the LINK statement.

```
x = -2;
do;
    if x<0 then link negative;
    y = sqrt(x);
    print y;
    goto TheEnd;
negative:
    print "Using absolute value of x";
    x = abs(x);
    return;
TheEnd:
end;
```

The output of the program is shown in [Figure 6.2](#).

Figure 6.2 Output That Demonstrates the LINK Statement

```

Using absolute value of x

y
1.4142136

```

Statements That Define and Execute Modules

Modules are used for two purposes:

- to create a user-defined subroutine or function. That is, you can define a group of statements that can be called from anywhere in the program.
- to define variables that are local to the module. That is, you can create a separate environment with its own symbol table (see “[Understanding Symbol Tables](#)” on page 73).

A module always begins with a **START** statement and ends with a **FINISH** statement. A module is either a function or a subroutine. When a module returns a single parameter, it is called a function. A function is invoked by its name in an assignment statement. Otherwise, a module is a subroutine. You can execute a subroutine by using either the **RUN** statement or the **CALL** statement.

Defining and Executing a Module

A module definition begins with a **START** statement, which has the following general form:

```
START < name > < ( arguments ) > < GLOBAL ( arguments ) > ;
```

A module definition ends with a **FINISH** statement, which has the following general form:

```
FINISH < name > ;
```

If no name appears in the **START** statement, the name of the module defaults to **MAIN**. If no name appears on the **FINISH** statement, the name of the most recently defined module is used.

There are two ways you can execute a module: you can use either a **RUN** statement or a **CALL** statement. The general forms of these statements are as follows:

```
RUN name < ( arguments ) > ;
```

```
CALL name < ( arguments ) > ;
```

The only difference between the **RUN** and **CALL** statements is the order of resolution. The **RUN** statement is resolved in the following order:

1. user-defined module
2. SAS/IML built-in subroutine

In contrast, the CALL statement is resolved in the opposite order:

1. SAS/IML built-in subroutine
2. user-defined module

In other words, if you define a module with the same name as a SAS/IML subroutine, you can use the RUN statement to call the user-defined module and the CALL statement to call the built-in subroutine.

The RUN and CALL statements must have arguments that correspond to the ones defined in the START statement. A module can call other modules provided that it never recursively calls itself.

After the last statement in a module is executed, control returns to the statement that initially called the module. You can also force a return from a module by using the RETURN statement.

Understanding Symbol Tables

The *scope* of a variable is the set of locations in a program where a variable can be referenced. A variable defined outside of any module is said to exist at the program's *main scope*. For a variable defined inside a module, the scope of the variable is the body of the module.

A *symbol* is the name of a SAS/IML matrix. For example, if **x** and **y** are matrices, then the names 'x' and 'y' are the symbols. Whenever a matrix is defined, its symbol is stored in a *symbol table*. There are two kinds of symbol tables. When a matrix is defined at the main scope, its name is stored in the *global symbol table*. In contrast, each module with arguments is given its own *local symbol table* that contains all symbols used inside the module.

There can be many local symbol tables, one for each module with arguments. (Modules without arguments are described in the next section.) You can have a symbol 'x' in the global table and the same symbol in a local table, but these correspond to separate matrices. By default, the value of the matrix at global scope is independent from the value of a local matrix of the same name that is defined inside a module. Similarly, you can have two modules that each use the matrix **x**, and these matrices are not related. You can force a module to use a variable at main scope by using a GLOBAL clause as described in [“Using the GLOBAL Clause”](#) on page 77.

Values of symbols in a local table are temporary; that is, they exist only while the module is executing. You can no longer access the value of a local variable after the module exits.

Modules with No Arguments

The previous section emphasized that modules with arguments are given a local symbol table. In contrast, a module that has no arguments shares the global symbol table. All variables in such a module are global, which implies that if you modify the value of a matrix inside the module, that change persists when the module exits.

The following example shows a module with no arguments:

```
/* module without arguments, all symbols are global. */
proc iml;
a = 10;                      /* a is global    */
b = 20;                      /* b is global    */
c = 30;                      /* c is global    */
start Mod1;                 /* begin module   */
  p = a+b;                  /* p is global    */
  c = 40;                  /* c already global */
finish;                     /* end module     */

run Mod1;                   /* run the module */
print a b c p;
```

Figure 6.3 Output from Module with Global Variables

a	b	c	p
10	20	40	30

Notice that after the module exits, the following conditions exist:

- **a** is still 10.
- **b** is still 20.
- **c** has been changed to 40.
- **p** is created, added to the global symbol table, and set to 30.

Modules with Arguments

Most modules contain one or more arguments, and therefore contain a separate local symbol table. The following statements apply to modules with arguments:

- You can specify arguments as variable names, expressions, or literal values.
- If you specify several arguments, use commas to separate them.

- Arguments are passed by reference, not by value. This means that a module can change the value of an argument. An argument that is modified by a module is called an *output argument*.
- If you have both output arguments and input arguments, the SAS/IML convention is to list the output arguments first.
- When a module is run, the input arguments can be a matrix name, expression, or literal. However, you should specify only matrix names for output arguments.

When a module is run, the value for each argument is transferred from the global symbol table to the local symbol table. For example, consider the module Mod2 defined in the following statements:

```
proc iml;
a = 10;
b = 20;
c = 30;
start Mod2(x,y);          /* begin module */
    p = x+y;
    x = 100;              /* change the value of an argument */
    c = 25;
finish Mod2;              /* end module */

run Mod2(a,b);
print a b c;
```

The first three statements are submitted in the main scope and define the variables **a**, **b**, and **c**. The values of these variables are stored in the global symbol table. The **START** statement begins the definition of Mod2 and lists two variables (**x** and **y**) as arguments. This creates a local symbol table for Mod2. All symbols used inside the module (**x**, **y**, **p**, and **c**) are in the local symbol table. There is also a correspondence between the arguments in the **RUN** statement (**a** and **b**) and the arguments in the **START** statement (**x** and **y**). Also note that **a** and **b** exist only in the global symbol table, whereas **x**, **y**, and **p** exist only in the local symbol table. The symbol **c** exists in both symbol tables, but the values are completely independent.

When Mod2 is executed with the **RUN** statement, the local variable **x** becomes the “owner” of the data in the global matrix **a**. Similarly, the local variable **y** becomes the owner of the data in **b**. Because **c** is not an argument, there is no correspondence between the value of **c** in the global table and the value of **c** in the local table. When the module finishes execution, the variables **a** and **b** at main scope regain ownership of the data in **x** and **y**, respectively. The local symbol table that contains **x** and **y** is deleted. If the data were modified within the module, the values of **a** and **b** reflect the change, as shown in [Figure 6.4](#).

Figure 6.4 Output from Module with Arguments

a	b	c
100	20	30

Notice that after the module is executed, the following are true:

- **a** is changed to 100 since the corresponding argument, **x**, was changed to 100 inside the module.

- **b** is still 20.
- **c** is still 30. Inside the module, the local symbol **c** was set to 25, but there is no correspondence between the global symbol **c** and the local symbol **c**.

Also note that, inside the module, the symbols **a** and **b** do not exist. Outside the module, the symbols **p**, **x**, and **y** do not exist.

Defining Function Modules

Functions are special modules that return a single value. To write a function module, include a RETURN statement that specifies the value to return. The RETURN statement is necessary for a module to be a function. You can use a function module in an assignment statement, as you would a built-in function.

The symbol-table logic described in the preceding section also applies to function modules. In the following function module, the value of **c** in the local symbol table is assigned to the symbol **z** at main scope:

```
proc iml;
a = 10;
b = 20;
c = 30;
start Mod3(x,y);
    c = 2#x + y;
    return (c);          /* return function value */
finish Mod3;

z = Mod3(a,b);          /* call function          */
print a b c z;
```

Figure 6.5 Output from a Function Module

a	b	c	z
10	20	30	40

Notice the following about this example:

- **a** is still 10 and **b** is still 20.
- **c** is still 30. The symbol **c** in the global table has no connection with the symbol **c** in the local table.
- **z** assigned the value 40, which is the value returned by the module.

Again notice that, inside the module, the symbols **a**, **b**, and **z** do not exist. Outside the module, the symbols **x** and **y** do not exist.

In the next example, you define your own function module, Add, which adds its two arguments:

```

proc iml;
start Add(x,y);
    sum = x+y;
    return(sum);
finish;

a = {9 2, 5 7};
b = {1 6, 8 10};
c = Add(a,b);
print c;

```

Figure 6.6 Output from a Function Module

c	
10	8
13	17

Function modules can also be called as arguments to other modules or to built-in functions. For example, in the following statements, the Add module is called twice, and the results from those calls are used as arguments to call the Add module a third time:

```

d = Add(Add({1 2},{3 4}), Add({5 6}, {7 8}));
print d;

```

Figure 6.7 Output from a Nested Module Call

d	
16	20

Functions are resolved in the following order:

1. SAS/IML built-in functions
2. user-defined function modules
3. SAS DATA step functions

Because of this order of resolution, it is an error to try to define a function module that has the same name as a SAS/IML built-in function.

Using the GLOBAL Clause

For modules with arguments, the variables used inside the module are local and have no connection with any variables that exist outside the module in the global table. However, it is possible to specify that certain variables not be placed in the local symbol table but rather be accessed from the global table. The GLOBAL clause specifies variables that you want to share between local and global symbol tables. The following

is an example of a module that uses a GLOBAL clause to define the symbol `c` as global. This defines a one-to-one correspondence between the value of `c` in the global symbol table and the value of `c` in the local symbol table.

```
proc iml;
a = 10;
b = 20;
c = 30;
start Mod4(x,y) global (c);
    x = 100;
    c = 40;
    b = 500;
finish Mod4;

run Mod4(a,b);
print a b c;
```

The output is shown in Figure 6.8.

Figure 6.8 Output from a Module with a GLOBAL Clause

a	b	c
100	20	40

After the module is called, the following facts are true:

- `a` is changed to 100.
- `b` is still 20 and not 500, since `b` exists independently in the global and local symbol tables.
- `c` is changed to 40 because it was declared to be a global variable. The matrix `c` inside the module is the same matrix as the one outside the module.

Because every module with arguments has its own local table, it is possible to have many local tables. You can use the GLOBAL clause with many (or all) modules to share a single global variable among many local symbol tables.

Nesting Modules

You can nest one module within another. You must make sure that each nested module is completely contained inside the parent module. Each module is defined independently of the others. When you nest modules, it is a good idea to indent the statements relative to the nesting level, as shown in the following example:

```

start ModA;
  start ModB;
    x = 1;
  finish ModB;
  run ModB;
finish ModA;

run ModA;

```

In this example, SAS/IML software starts parsing statements for a module called ModA. In the middle of this module, it recognizes the start of a new module called ModB. It parses ModB until it encounters the first FINISH statement. It then finishes parsing ModA. Thus, it behaves the same as if ModB were parsed prior to ModA, as follows:

```

start ModB;
  x = 1;
finish ModB;

start ModA;
  run ModB;
finish ModA;

run ModA;

```

In particular, you can call the ModB module from the program's main scope. It is *not* the case that ModB is a “local module” known only to module ModA. There is no such thing as a local module.

Calling a Module from Another Module

Consider the following example of calling one module from another module:

```

proc iml;
start Mod5(a,b);
  c = a+b;
  d = a-b;
  run Mod6(c,d);
  print "In Mod5:" c d;
finish;

start Mod6(x,y);
  x = x#y;
finish;

run Mod5({1 2}, {3 4});

```

When one module calls another, you can pass in any symbol defined in the scope of the calling module. In the previous example, the Mod5 module calls the Mod6 module and passes in the local variables **c** and **d**. The Mod6 module multiplies its arguments and overwrites the first argument, as shown in [Figure 6.9](#).

Figure 6.9 Output from Nested Modules

	c		d	
In Mod5:	-8	-12	-2	-2

The variables in the local symbol table of Mod5 are available to pass into Mod6. If Mod6 changes the values of an argument, those values are also changed in the environment from which Mod6 was called. For the previous example, this means that the local variable `c` is modified by Mod6.

If a module has no arguments, it can access variables in the environment from which it is called. For example, consider the following modules:

```
x = 123;

start Mod7;
  print "In Mod7:" x;
finish;

start Mod8(p);
  print "In Mod8:" p;
  run Mod7;
finish;

run Mod8(x);
```

In this example, module Mod7 is called from module Mod8. Therefore, the variables available to Mod7 are those defined in the scope of Mod8. There is no variable named `x` in the environment of Mod8. Therefore an error occurs on the PRINT statement in Mod7, as shown in Figure 6.10. An error would not occur if you call Mod7 from the main scope, because `x` is defined at main scope.

Figure 6.10 Error Message When a Variable Is Not Defined in a Module

```
NOTE: IML Ready
NOTE: Module MOD7 defined.
NOTE: Module MOD8 defined.
ERROR: Matrix x has not been set to a value.

statement : PRINT at line 1550 column 4
traceback : module MOD7 at line 1550 column 4
           module MOD8 at line 1555 column 4

NOTE: Paused in module MOD7.
```

Understanding Argument Passing

You can use expressions and subscripted matrices as arguments to a module, but it is important to understand the way the SAS/IML software passes the results to the module. Expressions are evaluated, and the evaluated

values are stored in temporary variables. Similarly, submatrices are created from subscripted variables and stored in temporary variables. The temporary variables are passed to the module. In the following example, notice that the matrix **x** does not change; you might expect **x** to contain the squared values of **y**.

```

start Square(a,b);
  a = b##2;
finish;

x = {. .};           /* initialize with missing values */
y = {3 4};
reset printall;      /* print all intermediate results */
do i = 1 to 2;        /* pass elements of matrix to modules */
  run Square(x[i],y[i]); /* WRONG: x[i] is not changed */
end;
print x;              /* show that x is unchanged */

```

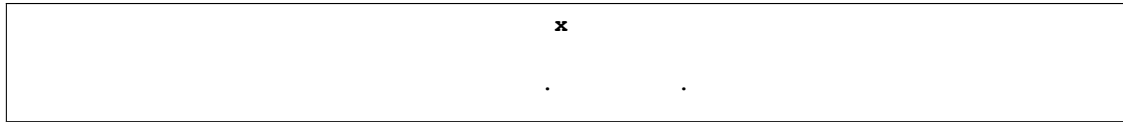
The output is shown in Figure 6.11. The names of the temporary matrices created by the subscript operators are **_TEM1001** and **_TEM1002**. These are the matrices passed into the square module. The module assigns the value 9 to the local matrix **a**, and this value is returned to main scope in the temporary matrix **_TEM1001**, which promptly vanishes! The same sequence of operations repeats for the next call to the Square module.

Figure 6.11 Temporary and Local Matrices in a Module

i	1 row	1 col	(numeric)
		1	
_TEM1002	1 row	1 col	(numeric)
		3	
_TEM1001	1 row	1 col	(numeric)
		.	
a	1 row	1 col	(numeric)
		9	
_TEM1002	1 row	1 col	(numeric)
		4	
_TEM1001	1 row	1 col	(numeric)
		.	
a	1 row	1 col	(numeric)
		16	

Consequently, the values of **x** remain unchanged by the previous calls, as shown in [Figure 6.12](#). The lesson to learn from this example is this: do not pass in an expression or literal as an output argument to a module. Use only matrix names for output arguments. For example, the correct way to call the Square module is to eliminate the loop and simply use the statement **run Square(x, y);**.

Figure 6.12 An Unchanged Matrix



Storing and Loading Modules

You can store and reload modules by using the [STORE](#) statement. The STORE statement saves the module in a storage library. The stored module persists even when you exit PROC IML or exit the SAS System. After a module is stored, you can use the module in other SAS/IML programs by using the [LOAD](#) statement prior to calling the module. The syntax of the STORE and LOAD statements are as follows:

STORE MODULE= *name* ;

LOAD MODULE= *name* ;

You can view the names of the modules in storage with the SHOW statement, as follows:

show storage;

See Chapter 17, “[Storage Features](#),” for details about using the library storage facilities.

Termination Statements

You can stop execution with a [PAUSE](#), [STOP](#), or [ABORT](#) statement. The [QUIT](#) statement is also a termination statement, but it causes the IML procedure to immediately exit. The other termination statements do not cause PROC IML to exit until the statements are executed. The following sections describe the PAUSE, STOP, ABORT, and QUIT statements.

PAUSE Statement

The general form of the PAUSE statement is as follows:

PAUSE *< message >* *< * >* ;

The PAUSE statement does the following:

- stops execution of a module
- remembers where it stopped
- prints a message that you can specify
- sets the current program environment and symbol table to be that of the module that contains the PAUSE statement. This means that you can type statements that reference local variables in the module. For example, you might want to use a PAUSE statement while debugging a module so that you can print the value of local variables.

A RESUME statement enables you to continue execution at the location of the most recent PAUSE statement.

You can use a STOP statement as an alternative to the RESUME statement to remove the paused state and to return to the main scope outside the module. You can specify a message in the PAUSE statement. This message is displayed in the output window when the PAUSE statement is executed. For example, the following PAUSE statements each display a message:

```
pause "Please enter an assignment for X, then enter RESUME;";

msg = "Please enter an assignment for X, then enter RESUME;";
pause msg;
```

The PAUSE statement also writes a note to the SAS log. To suppress the note, use the * option, as shown in the following statement:

```
pause *;
```

When you use a PAUSE, RESUME, STOP, or ABORT statement, keep in mind the following details:

- The PAUSE statement must be used from inside a module.
- It is an error to execute a RESUME statement without any outstanding pauses.
- You can define and execute modules while paused within another module.
- If a run-time error occurs inside a module, a PAUSE statement is automatically executed. This gives you an opportunity to correct the error and resume execution of the module with a RESUME statement. Alternately, you can submit a STOP statement to exit from the module environment, or an ABORT statement to exit PROC IML.
- You cannot reenter or redefine an active (paused) module.
- When paused, you can run another module that also pauses. The paused environments are stacked.
- You can put a RESUME statement inside a module. For example, suppose you are paused in module A and then run module B, which executes a RESUME statement. Execution is resumed in module A and does not return to module B.
- You can use the PAUSE and RESUME statements in both subroutine and function modules.

- If you pause in a subroutine module that has its own symbol table, then the statements executed while paused use this symbol table. You must use a `RESUME` or a `STOP` statement to return to the global symbol table environment.
- You can use the `PAUSE` and `RESUME` statements, in conjunction with the `PUSH`, `QUEUE`, and `EXECUTE` subroutines described in Chapter 18, “[Using SAS/IML Software to Generate SAS/IML Statements](#),” to execute SAS/IML statements that you generate within a module.

STOP Statement

The general form of the `STOP` statement is as follows:

STOP ;

The `STOP` statement clears all pauses and returns to the main scope.

ABORT Statement

The general form of the `ABORT` statement is as follows:

ABORT ;

The `ABORT` statement stops execution and exits from PROC IML, much like a `QUIT` statement. The difference is that the `ABORT` statement is an executable statement that can be used in IF-THEN statements and in modules. For example, you might want to exit PROC IML if a certain error occurs. You can check for the error in a module and execute the `ABORT` statement if the error occurs.

QUIT Statement

The syntax of the `QUIT` statement is as follows:

QUIT ;

The `QUIT` statement stops execution and exits from PROC IML. The `QUIT` statement is executed as soon as the statement is parsed. Consequently, you cannot use `QUIT` in a module or as part of an IF-THEN/ELSE statement.

Chapter 7

Working with SAS Data Sets

Contents

Overview	85
Opening a SAS Data Set	87
Making a SAS Data Set Current	88
Displaying SAS Data Set Information	88
Referring to a SAS Data Set	89
Listing Observations	89
Specifying a Range of Observations	90
Selecting a Set of Variables	92
Selecting Observations	93
Reading Observations from a SAS Data Set	95
Using the READ Statement with the VAR Clause	96
Using the READ Statement with the VAR and INTO Clauses	96
Using the READ Statement with the WHERE Clause	97
Editing a SAS Data Set	98
Updating Observations	98
Deleting Observations	99
Creating a SAS Data Set from a Matrix	101
Using the CREATE Statement with the FROM Option	101
Using the CREATE Statement with the VAR Clause	102
Understanding the End-of-File Condition	103
Producing Summary Statistics	103
Sorting a SAS Data Set	104
Indexing a SAS Data Set	104
Data Set Maintenance Functions	105
Summary of Commands	106
Comparison with the SAS DATA Step	107
Summary	107

Overview

SAS/IML software has many statements for passing data from SAS data sets to matrices and from matrices to SAS data sets. You can create matrices from the variables and observations of a SAS data set in several

ways. You can create a column vector for each data set variable, or you can create a matrix where columns correspond to data set variables. You can use all the observations in a data set or use a subset of them.

You can also create a SAS data set from a matrix. The columns correspond to data set variables and the rows correspond to observations. Data management commands enable you to edit, append, rename, or delete SAS data sets from within the SAS/IML environment.

When reading a SAS data set, you can read any number of observations into a matrix either sequentially, directly by record number, or conditionally according to conditions in a **WHERE** clause. You can also index a SAS data set. The indexing capability facilitates retrievals by the indexed variable.

Operations on SAS data sets are performed with straightforward, consistent, and powerful statements. For example, the **LIST statement** can perform the following tasks:

- list the next record
- list a specified record
- list any number of specified records
- list the whole file
- list records satisfying one or more conditions
- list specified variables or all variables

If you want to read values into a matrix, use the **READ statement** instead of the **LIST statement** with the same operands and features as the **LIST statement**. You can specify operands that control which records and variables are used indirectly, as matrices, so that you can dynamically program the records, variables, and conditional values you want.

In this chapter, you use the SAS data set **CLASS**, which contains the variables **NAME**, **SEX**, **AGE**, **HEIGHT**, and **WEIGHT**, to learn about the following:

- opening a SAS data set
- examining the contents of a SAS data set
- displaying data values with the **LIST statement**
- reading observations from a SAS data set into matrices
- editing a SAS data set
- creating a SAS data set from a matrix
- displaying matrices with row and column headings
- producing summary statistics
- sorting a SAS data set
- indexing a SAS data set

- similarities and differences between the data set and the SAS DATA step

Throughout this chapter, the right angle brackets (>) indicate statements that you submit; responses from Interactive Matrix Language follow.

First, invoke the IML procedure by using the following statement:

```
> proc iml;

IML Ready
```

Opening a SAS Data Set

Before you can access a SAS data set, you must first submit a command to open it. There are three ways to open a SAS data set:

- To simply read from an existing data set, submit a USE statement to open it for Read access. The general form of the USE statement is as follows:

USE *SAS-data-set* < *VAR operand* > < *WHERE(expression)* > ;

With Read access, you can use the FIND, INDEX, LIST, and READ statements with the data set.

- To read and write to an existing data set, use the EDIT statement. The general form of the EDIT statement is as follows:

EDIT *SAS-data-set* < *VAR operand* > < *WHERE(expression)* > ;

This statement enables you to use both the reading statements (LIST, READ, INDEX, and FIND) and the writing statements (REPLACE, APPEND, DELETE, and PURGE).

- To create a new data set, use the CREATE statement to open a new data set for both output and input. The general form of the CREATE statement is as follows:

CREATE *SAS-data-set* < *VAR operand* > ;

CREATE *SAS-data-set* *FROM* *from-name* ;

< [*COLNAME=column-name* *ROWNAME=row-name*] > ; ;

Use the APPEND statement to place the matrix data into the newly created data set. If you do not use the APPEND statement, the new data set has no observations.

If you want to list observations and create matrices from the data in the SAS data set named CLASS, you must first submit a statement to open the CLASS data set. Because CLASS already exists, specify the USE statement.

Making a SAS Data Set Current

IML data processing commands work on the current data set. This feature makes it unnecessary for you to specify the data set as an operand each time. There are two current data sets, one for input and one for output. IML makes a data set the current one as it is opened. You can also make a data set current by using two setting statements, SETIN and SETOUT:

- The USE and SETIN statements make a data set current for input.
- The SETOUT statement makes a data set current for output.
- The CREATE and EDIT statements make a data set current for both input and output.

If you issue a USE, EDIT, or CREATE statement for a data set that is already open, the data set is made the current data set. To find out which data sets are open and which are current input and current output data sets, use the SHOW DATASETS statement.

The current observation is set by the last operation that performed input/output (I/O). If you want to set the current observation without doing any I/O, use the SETIN (or SETOUT) statement with the POINT option. After a data set is opened, the current observation is set to 0. If you attempt to list or read the current observation, the current observation is converted to 1. You can make the CLASS data set current for input and position the pointer at the 10th observation with the following statement:

```
> setin class point 10;
```

Displaying SAS Data Set Information

You can use SHOW statements to display information about your SAS data sets. The SHOW DATASETS statement lists all open SAS data sets and their status. The SHOW CONTENTS statement displays the variable names and types, the size, and the number of observations in the current input data set. For example, to get information for the CLASS data set, issue the following statements:

```
> use class;
> show datasets;
```

LIBNAME	MEMNAME	OPEN MODE	STATUS
-----	-----	-----	-----
WORK	.CLASS	Input	Current Input

```
> show contents;
```

VAR NAME	TYPE	SIZE
NAME	CHAR	8
SEX	CHAR	8


```

AGE          NUM          8
HEIGHT       NUM          8
WEIGHT       NUM          8
Number of Variables:      5
Number of Observations: 19

```

As you can see, CLASS is the only data set open. The USE statement opens it for input, and it is the current input data set. The full name for CLASS is WORK.CLASS. The libref is the default, WORK. The next section tells you how to change the libref to another name.

Referring to a SAS Data Set

The USE, EDIT, and CREATE statements take as their first operand the data set name. This name can have either one or two levels. If it is a two-level name, the first level refers to the name of the SAS data library; the second name is the data set name. If the libref is WORK, the data set is stored in a directory for temporary data sets; these are automatically deleted at the end of the session. Other librefs are associated with SAS data libraries by using the LIBNAME statement.

If you specify only a single name, then IML supplies a default libref. At the beginning of an IML session, the default libref is SASUSER if SASUSER is defined as a libref or WORK otherwise. You can reset the default libref by using the RESET DEFLIB statement. If you want to create a permanent SAS data set, you must specify a two-level name by using the RESET DEFLIB statement (see the chapter on SAS files in *SAS Language Reference: Concepts* for more information about permanent SAS data sets):

```
> reset deflib=name;
```

Listing Observations

You can list variables and observations in a SAS data set with the LIST statement. The general form of the LIST statement is as follows:

```
LIST < range > < VAR operand > < WHERE(expression) > ;
```

where

range specifies a range of observations.

operand selects a set of variables.

expression is an expression that is evaluated as being true or false.

The next three sections discuss how to use each of these clauses with the CLASS data set.

Specifying a Range of Observations

You can specify a range of observations with a keyword or by record number by using the POINT option. You can use the *range* operand with the data management statements DELETE, FIND, LIST, READ, and REPLACE.

You can specify *range* with any of the following keywords:

ALL	specifies all observations.
CURRENT	specifies the current observation.
NEXT < <i>number</i> >	specifies the next observation or next <i>number</i> of observations.
AFTER	specifies all observations after the current one.
POINT <i>operand</i>	specifies observations by number, where <i>operand</i> can be one of the following:

Operand	Example
a single record number	point 5
a literal giving several record numbers	point {2 5 10}
the name of a matrix that contains record numbers	point p
an expression in parentheses	point (p+1)

If you want to list all observations in the CLASS data set, use the keyword ALL to indicate that the range is all observations. The following example demonstrates the use of this keyword:

```
> list all;
```

OBS	NAME	SEX	AGE	HEIGHT	WEIGHT
1	JOYCE	F	11.0000	51.3000	50.5000
2	THOMAS	M	11.0000	57.5000	85.0000
3	JAMES	M	12.0000	57.3000	83.0000
4	JANE	F	12.0000	59.8000	84.5000
5	JOHN	M	12.0000	59.0000	99.5000
6	LOUISE	F	12.0000	56.3000	77.0000
7	ROBERT	M	12.0000	64.8000	128.0000
8	ALICE	F	13.0000	56.5000	84.0000
9	BARBARA	F	13.0000	65.3000	98.0000
10	JEFFREY	M	13.0000	62.5000	84.0000
11	CAROL	F	14.0000	62.8000	102.5000
12	HENRY	M	14.0000	63.5000	102.5000
13	ALFRED	M	14.0000	69.0000	112.5000
14	JUDY	F	14.0000	64.3000	90.0000
15	JANET	F	15.0000	62.5000	112.5000
16	MARY	F	15.0000	66.5000	112.0000
17	RONALD	M	15.0000	67.0000	133.0000
18	WILLIAM	M	15.0000	66.5000	112.0000
19	PHILIP	M	16.0000	72.0000	150.0000

Without a *range* specification, the LIST statement lists only the current observation, which in this example is now the last observation because of the previous LIST statement. Here is the result of using the LIST statement:

```
> list;
```

OBS	NAME	SEX	AGE	HEIGHT	WEIGHT
19	PHILIP	M	16.0000	72.0000	150.0000

Use the POINT keyword with record numbers to list specific observations. You can follow the keyword POINT with a single record number or with a literal giving several record numbers. Here are two examples:

```
> list point 5;
```

OBS	NAME	SEX	AGE	HEIGHT	WEIGHT
5	JOHN	M	12.0000	59.0000	99.5000

```
> list point {2 4 9};
```

OBS	NAME	SEX	AGE	HEIGHT	WEIGHT
2	THOMAS	M	11.0000	57.5000	85.0000
4	JANE	F	12.0000	59.8000	84.5000
9	BARBARA	F	13.0000	65.3000	98.0000

You can also indicate the range indirectly by creating a matrix that contains the records you want to list, as in the following example:

```
> p={2 4 9};
> list point p;
```

OBS	NAME	SEX	AGE	HEIGHT	WEIGHT
2	THOMAS	M	11.0000	57.5000	85.0000
4	JANE	F	12.0000	59.8000	84.5000
9	BARBARA	F	13.0000	65.3000	98.0000

The *range* operand is usually listed first when you are using the access statements DELETE, FIND, LIST, READ, and REPLACE. The following table shows access statements and their default ranges:

Statement	Default Range
LIST	current
READ	current
FIND	all
REPLACE	current
APPEND	always at end
DELETE	current

Selecting a Set of Variables

You can use the VAR clause to select a set of variables. The general form of the VAR clause is as follows:

VAR *operand* ;

where *operand* can be specified by using one of the following items:

- a literal that contains variable names
- the name of a matrix that contains variable names
- an expression in parentheses yielding variable names
- one of the following keywords:

`_ALL_` for all variables
`_CHAR_` for all character variables
`_NUM_` for all numeric variables

The following examples show all possible ways you can use the VAR clause:

```
var {time1 time5 time9}; /* a literal giving the variables */
var time;                /* a matrix that contains the names */
var('time1':'time9');   /* an expression */
var _all_;                /* a keyword */
```

For example, to list students' names from the CLASS data set, use the VAR clause with a literal, as in the following statement:

```
> list point p var{name};
```

```
      OBS  NAME
-----  -----
      2  THOMAS
      4   JANE
      9  BARBARA
```

To list AGE, HEIGHT, and WEIGHT, you can use the VAR clause with a matrix giving the variables, as in the following statements:

```
> v={age height weight};
> list point p var v;
```

```
      OBS      AGE      HEIGHT      WEIGHT
-----  -----  -----  -----
      2   11.0000   57.5000   85.0000
      4   12.0000   59.8000   84.5000
      9   13.0000   65.3000   98.0000
```

The VAR clause can be used with the following statements for the tasks described:

Statement	VAR Clause Function
APPEND	specifies which IML variables contain data to append to the data set
CREATE	specifies the variables to go in the data set
EDIT	limits which variables are accessed
LIST	specifies which variables to list
READ	specifies which variables to read
REPLACE	specifies which data set variable's data values to replace with corresponding IML variable data values
USE	limits which variables are accessed

Selecting Observations

The WHERE clause conditionally selects observations, within the *range* specification, according to conditions given in the *expression*. The general form of the WHERE clause is as follows:

WHERE *variable comparison-op operand* ;

where

variable is a variable in the SAS data set.

comparison-op is one of the following comparison operators:

<	less than
<=	less than or equal to
=	equal to
>	greater than
>=	greater than or equal to
^=	not equal to
?	contains a given string
^?	does not contain a given string
=:	begins with a given string
=*	sounds like or is spelled like a given string

operand is a literal value, a matrix name, or an expression in parentheses.

WHERE comparison arguments can be matrices. For the following operators, the WHERE clause succeeds if *all* the elements in the matrix satisfy the condition:

^= ^? < <= > >=

For the following operators, the WHERE clause succeeds if *any* of the elements in the matrix satisfy the condition:

= ? =: =*

Logical expressions can be specified within the WHERE clause by using the AND (&) and OR (!) operators. The general form is as follows:

clause&*clause* (for an AND clause)
clause | *clause* (for an OR clause)

where *clause* can be a comparison, a parenthesized clause, or a logical expression clause that is evaluated by using operator precedence.

For example, to list the names of all males in the data set CLASS, use the following statement:

```
> list all var{name} where(sex='M');
```

OBS	NAME
2	THOMAS
3	JAMES
5	JOHN
7	ROBERT
10	JEFFREY
12	HENRY
13	ALFRED
17	RONALD
18	WILLIAM
19	PHILIP

The WHERE comparison arguments can be matrices. In the following cases that use the *= operator, the comparison is made to each name to find a string that sounds like or is spelled like the given string or strings:

```
> n={name sex age};
> list all var n where(name={ "ALFRED", "CAROL", "JUDY" });
```

OBS	NAME	SEX	AGE
11	CAROL	F	14.0000
13	ALFRED	M	14.0000
14	JUDY	F	14.0000

```
> list all var n where(name={ "JON", "JAN" });
```

OBS	NAME	SEX	AGE
4	JANE	F	12.0000
5	JOHN	M	12.0000

To list AGE, HEIGHT, and WEIGHT for all students in their teens, use the following statement:

```
> list all var v where(age>12);
```

OBS	AGE	HEIGHT	WEIGHT
8	13.0000	56.5000	84.0000
9	13.0000	65.3000	98.0000
10	13.0000	62.5000	84.0000
11	14.0000	62.8000	102.5000
12	14.0000	63.5000	102.5000
13	14.0000	69.0000	112.5000
14	14.0000	64.3000	90.0000
15	15.0000	62.5000	112.5000
16	15.0000	66.5000	112.0000
17	15.0000	67.0000	133.0000
18	15.0000	66.5000	112.0000
19	16.0000	72.0000	150.0000

NOTE: In the WHERE clause, the expression on the left side refers to values of the data set variables, and the expression on the right side refers to matrix values. You cannot use comparisons that involve more than one data set variable in a single comparison; for example, you cannot use either of the following expressions:

```
list all where (height>weight);
list all where (weight-height>0);
```

You could use the first statement if WEIGHT were a matrix name already defined rather than a variable in the SAS data set.

Reading Observations from a SAS Data Set

Transferring data from a SAS data set to a matrix is done by using the READ statement. The SAS data set you want to read data from must already be open. You can open a SAS data set with either the USE or the EDIT statement. If you already have several data sets open, you can point to the one you want with the SETIN statement, making it the current input data set. The general form of the READ statement is as follows:

```
READ <range> <VAR operand> <WHERE(expression)>;
      <INTO name>;
```

where

range specifies a range of observations.
operand selects a set of variables.
expression is an expression that is evaluated as being true or false.
name names a target matrix for the data.

Using the READ Statement with the VAR Clause

Use the **READ statement** with the VAR clause to read variables from the current SAS data set into column vectors of the VAR clause. Each variable in the VAR clause becomes a column vector with the same name as the variable in the SAS data set. The number of rows is equal to the number of observations processed, depending on the range specification and the WHERE clause. For example, to read the numeric variables AGE, HEIGHT, and WEIGHT for all observations in the CLASS data set, use the following statements:

```
> read all var {age height weight};
```

Now use the **SHOW NAMES statement** to display all the matrices you have created so far in this chapter:

```
> show names;
```

```

AGE          19 rows      1 col  num      8
HEIGHT       19 rows      1 col  num      8
N            1 row        3 cols char     4
P            1 row        3 cols num      8
V            1 row        3 cols char     6
WEIGHT       19 rows      1 col  num      8
Number of symbols = 8  (includes those without values)
```

You see that, with the **READ statement**, you have created the three numeric vectors **AGE**, **HEIGHT**, and **WEIGHT**. (Notice that the matrices you created earlier, **N**, **P**, and **V**, are also listed.) You can select the variables that you want to access with a VAR clause in the **USE statement**. The two previous statements can also be written as follows:

```

use class var{age height weight};
read all;
```

Using the READ Statement with the VAR and INTO Clauses

Sometimes you want to have all of the numeric variables in the same matrix so that you can determine correlations. Use the READ statement with the INTO clause and the VAR clause to read the variables listed in the VAR clause into the single matrix named in the INTO clause. Each variable in the VAR clause becomes a column of the target matrix. If there are p variables in the VAR clause and n observations are processed, the target matrix in the INTO clause is an $n \times p$ matrix.

The following statement creates a matrix **X** that contains the numeric variables of the CLASS data set. Notice the use of the keyword **_NUM_** in the VAR clause to specify that all numeric variables be read.


```
> read all var _num_ into x;
> print x;
```

	X	
11	51.3	50.5
11	57.5	85
12	57.3	83
12	59.8	84.5
12	59	99.5
12	56.3	77
12	64.8	128
13	56.5	84
13	65.3	98
13	62.5	84
14	62.8	102.5
14	63.5	102.5
14	69	112.5
14	64.3	90
15	62.5	112.5
15	66.5	112
15	67	133
15	66.5	112
16	72	150

Using the READ Statement with the WHERE Clause

Use the WHERE clause as you did with the [LIST statement](#), to conditionally select observations from within the specified range. If you want to create a matrix **FEMALE** that contains the variables AGE, HEIGHT, and WEIGHT for females only, use the following statements:

```
> read all var _num_ into female where(sex="F");
> print female;
```

	FEMALE	
11	51.3	50.5
12	59.8	84.5
12	56.3	77
13	56.5	84
13	65.3	98
14	62.8	102.5
14	64.3	90
15	62.5	112.5
15	66.5	112

Now try some special features of the WHERE clause to find values that begin with certain characters (the `=:` operator) or that contain certain strings (the `?` operator). To create a matrix **J** that contains the students whose names begin with the letter “J,” use the following statements:

```
> read all var{name} into j where(name=: "J");
```

```
> print j;
```

```
J
JOYCE
JAMES
JANE
JOHN
JEFFREY
JUDY
JANET
```

To create a matrix **AL** of children with names that contains the string “AL,” use the following statement:

```
> read all var{name} into al where(name?"AL");
> print al;
```

```
AL
ALICE
ALFRED
RONALD
```

Editing a SAS Data Set

You can edit a SAS data set by using the EDIT statement. You can update values of variables, mark observations for deletion, delete the marked observations, and save the changes you make. The general form of the EDIT statement is as follows:

```
EDIT SAS-data-set < VAR operand > < WHERE(expression) > ;
```

where

SAS-data-set names an existing SAS data set.

operand selects a set of variables.

expression is an expression that is evaluated as being true or false.

Updating Observations

Suppose you have updated data and want to change some values in the CLASS data set. For instance, suppose the student named Henry has had a birthday since the data were added to the CLASS data set. You can do the following:

- make the CLASS data set current for input and output
- read the data

- change the appropriate data value
- replace the changed data in the data set

First, submit an EDIT statement to make the CLASS data set current for input and output. Then use the FIND statement, which finds observation numbers and stores them in a matrix, to find the observation number of the data for Henry and store it in the matrix **d**. Here are the statements:

```
> edit class;
> find all where(name={'HENRY'}) into d;
> print d;
```

```
      D
      12
```

The following statement lists the observation that contains the data for Henry:

```
> list point d;
```

OBS	NAME	SEX	AGE	HEIGHT	WEIGHT
12	HENRY	M	14.0000	63.5000	102.5000

As you see, the observation number is 12. Now read the value for AGE into a matrix and update its value. Finally, replace the value in the CLASS data set and list the observation that contains the data for Henry again. Here are the statements:

```
> age=15;
> replace;
```

```
      1 observations replaced.
```

```
> list point 12;
```

OBS	NAME	SEX	AGE	HEIGHT	WEIGHT
12	HENRY	M	15.0000	63.5000	102.5000

Deleting Observations

Use the DELETE statement to mark an observation to be deleted. The general form of the DELETE statement is as follows:

```
DELETE <range> <WHERE(expression)> ;
```

where

range specifies a range of observations.

expression is an expression that is evaluated as being true or false.

The following are examples of valid uses of the DELETE statement:

Statement	Description
<code>delete;</code>	deletes the current observation
<code>delete point 10;</code>	deletes observation 10
<code>delete all where (age>12);</code>	deletes all observations where AGE is greater than 12

If a file accumulates a number of observations marked as deleted, you can clean out these observations and renumber the remaining observations by using the PURGE statement.

Suppose the student named John has moved and you want to update the CLASS data set. You can remove the observation by using the EDIT and DELETE statements. First, find the observation number of the data for John and store it in the matrix **d** by using the FIND statement. Then submit a DELETE statement to mark the record for deletion. A deleted observation is still physically in the file and still has an observation number, but it is excluded from processing. The deleted observations appear as gaps when you list the file by observation number, as in the following example:

```
> find all where(name={'JOHN'}) into d;
> print d;
```

```
D
5
```

```
> delete point d;
```

```
1 observation deleted.
```

```
> list all;
```

OBS	NAME	SEX	AGE	HEIGHT	WEIGHT
1	JOYCE	F	11.0000	51.3000	50.5000
2	THOMAS	M	11.0000	57.5000	85.0000
3	JAMES	M	12.0000	57.3000	83.0000
4	JANE	F	12.0000	59.8000	84.5000
6	LOUISE	F	12.0000	56.3000	77.0000
7	ROBERT	M	12.0000	64.8000	128.0000
8	ALICE	F	13.0000	56.5000	84.0000
9	BARBARA	F	13.0000	65.3000	98.0000
10	JEFFREY	M	13.0000	62.5000	84.0000
11	CAROL	F	14.0000	62.8000	102.5000
12	HENRY	M	15.0000	63.5000	102.5000
13	ALFRED	M	14.0000	69.0000	112.5000
14	JUDY	F	14.0000	64.3000	90.0000
15	JANET	F	15.0000	62.5000	112.5000
16	MARY	F	15.0000	66.5000	112.0000
17	RONALD	M	15.0000	67.0000	133.0000
18	WILLIAM	M	15.0000	66.5000	112.0000
19	PHILIP	M	16.0000	72.0000	150.0000

Notice that there is a gap in the data where the deleted observation was (observation 5). To renumber the observations and close the gaps, submit the PURGE statement. Note that the PURGE statement deletes any indexes associated with a data set. Here is the statement:

```
> purge;
```

Creating a SAS Data Set from a Matrix

SAS/IML software provides the capability to create a new SAS data set from a matrix. You can use the CREATE and APPEND statements to create a SAS data set from a matrix, where the columns of the matrix become the data set variables and the rows of the matrix become the observations. Thus, an $n \times m$ matrix produces a SAS data set with m variables and n observations. The CREATE statement opens the new SAS data set for both input and output, and the APPEND statement writes to (outputs to) the data set.

Using the CREATE Statement with the FROM Option

You can create a SAS data set from a matrix by using the CREATE statement with the FROM option. This form of the CREATE statement is as follows:

```
CREATE SAS-data-set FROM matrix ;  
      < [COLNAME=column-name ROWNAME=row-name] > ;
```

where

<i>SAS-data-set</i>	names the new data set.
<i>matrix</i>	names the matrix that contains the data.
<i>column-name</i>	names the variables in the data set.
<i>row-name</i>	adds a variable that contains row titles to the data set.

Suppose you want to create a SAS data set named **RATIO** that contains a variable with the height-to-weight ratios for each student. You first create a matrix that contains the ratios from the matrices **HEIGHT** and **WEIGHT** that you have already defined. Next, use the CREATE and APPEND statements to open a new SAS data set called **RATIO** and append the observations, naming the data set variable **HTWT** instead of **COL1**.

```
htwt=height/weight;  
create ratio from htwt[colname='htwt'];  
append from htwt;
```

Now submit the SHOW DATASETS and SHOW CONTENTS statements:

```
> show datasets;
```

LIBNAME	MEMNAME	OPEN MODE	STATUS
WORK	.CLASS	Update	
WORK	.RATIO	Update	Current Input Current Output

```
> show contents;
```

VAR NAME	TYPE	SIZE
HTWT	NUM	8
Number of Variables:		1
Number of Observations:		18

```
> close ratio;
```

As you can see, the new SAS data set RATIO has been created. It has 18 observations and 1 variable (recall that you deleted 1 observation earlier).

Using the CREATE Statement with the VAR Clause

You can use a VAR clause with the CREATE statement to select the variables you want to include in the new data set. In the previous example, the new data set RATIO had one variable. If you want to create a similar data set but include the second variable NAME, you use the VAR clause. You could not do this with the FROM option because the variable HTWT is numeric and the variable NAME is character. The following statements create a new data set RATIO2 having the variables NAME and HTWT:

```
> create ratio2 var{name htwt};
> append;
> show contents;
```

VAR NAME	TYPE	SIZE
NAME	CHAR	8
HTWT	NUM	8
Number of Variables:		2
Number of Observations:		18

```
> close ratio2;
```

Notice that now the variable NAME is in the data set.

Understanding the End-of-File Condition

If you try to read past the end of a data set or point to an observation greater than the number of observations in the data set, you create an end-of-file condition. If an end-of-file condition occurs inside a DO DATA iteration group, IML transfers control to the next statement outside the current DO DATA group.

The following example uses a DO DATA loop while reading the CLASS data set. It reads the variable WEIGHT in one observation at a time and accumulates the weights of the students in the IML matrix SUM. When the data are read, the total class weight is stored in the matrix SUM.

```
setin class point 0;
sum=0;
do data;
  read next var{weight};
  sum=sum+weight;
end;
print sum;
```

Producing Summary Statistics

Summary statistics on the numeric variables of a SAS data set can be obtained with the SUMMARY statement. These statistics can be based on subgroups of the data by using the CLASS clause in the SUMMARY statement. The SAVE option in the OPT clause enables you to save the computed statistics in matrices for later perusal. For example, consider the following statement.

```
> summary var {height weight} class {sex} stat{mean std} opt{save};
```

SEX	Nobs	Variable	MEAN	STD
F	9	HEIGHT	60.58889	5.01833
		WEIGHT	90.11111	19.38391
M	9	HEIGHT	64.45556	4.90742
		WEIGHT	110.00000	23.84717
All	18	HEIGHT	62.52222	5.20978
		WEIGHT	100.05556	23.43382

This summary statement gives the mean and standard deviation of the variables HEIGHT and WEIGHT for the two subgroups (male and female) of the data set CLASS. Since the SAVE option is set, the statistics of the variables are stored in matrices under the name of the corresponding variables: each column corresponds to a statistic and each row corresponds to a subgroup. Two other vectors, SEX and _NOBS_, are created. The

vector `SEX` contains the two distinct values of the `CLASS` variable `SEX` used in forming the two subgroups. The vector `_NOBS_` has the number of observations in each subgroup.

Note that the combined means and standard deviations of the two subgroups are displayed but not saved.

More than one `CLASS` variable can be used, in which case a subgroup is defined by the combination of the values of the `CLASS` variables.

Sorting a SAS Data Set

The observations in a SAS data set can be ordered (sorted) by specific key variables. To sort a SAS data set, close the data set if it is currently open, and issue a `SORT` statement for the variables by which you want the observations to be ordered. Specify an output data set name if you want to keep the original data set. For example, the following statement creates a new SAS data set named `SORTED`:

```
> sort class out=sorted by name;
```

The new data set has the observations from the data set `CLASS`, ordered by the variable `NAME`.

The following statement sorts in place the data set `CLASS` by the variable `NAME`:

```
> sort class by name;
```

However, when the `SORT` statement is finished executing, the original data set is replaced by the sorted data set.

You can specify as many key variables as needed, and, optionally, each variable can be preceded by the keyword `DESCENDING`, which denotes that the variable that follows is to be sorted in descending order.

Indexing a SAS Data Set

Searching through a large data set for information about one or more specific observations can take a long time because the procedure must read each record. You can reduce this search time by first indexing the data set by a variable. The `INDEX` statement builds a special companion file that contains the values and record numbers of the indexed variables. Once the index is built, IML can use the index for queries with `WHERE` clauses if it decides that indexed retrieval is more efficient. Any number of variables can be indexed, but only one index is in use at a given time. Note that purging a data set with the `PURGE` statement results in the loss of all associated indexes.

Once you have indexed a data set, IML can use this index whenever a search is conducted with respect to the indexed variables. The indexes are updated automatically whenever you change values in indexed variables. When an index is in use, observations cannot be randomly accessed by their physical location

numbers. This means that the POINT range cannot be used when an index is in effect. However, if you purge the observations marked for deletion, or sort the data set in place, the indexes become invalid and IML automatically deletes them.

For example, if you want a list of all female students in the CLASS data set, you can first index CLASS by the variable SEX. Then use the LIST statement with a WHERE clause. Of course, the CLASS data set is small, and indexing does little if anything to speed queries with the WHERE clause. If the data set had thousands of students, though, indexing could save search time.

To index the data set by the variable SEX, submit the following statement:

```
> index sex;
```

NOTE: Variable SEX indexed.

NOTE: Retrieval by SEX.

Now list all students by using the following statement. Notice the ordering of the special file built by indexing by the variable SEX. Retrievals by SEX will be quick.

```
> list all;
```

OBS	NAME	SEX	AGE	HEIGHT	WEIGHT
1	JOYCE	F	11.0000	51.3000	50.5000
4	JANE	F	12.0000	59.8000	84.5000
6	LOUISE	F	12.0000	56.3000	77.0000
8	ALICE	F	13.0000	56.5000	84.0000
9	BARBARA	F	13.0000	65.3000	98.0000
11	CAROL	F	14.0000	62.8000	102.5000
14	JUDY	F	14.0000	64.3000	90.0000
15	JANET	F	15.0000	62.5000	112.5000
16	MARY	F	15.0000	66.5000	112.0000
2	THOMAS	M	11.0000	57.5000	85.0000
3	JAMES	M	12.0000	57.3000	83.0000
7	ROBERT	M	12.0000	64.8000	128.0000
10	JEFFREY	M	13.0000	62.5000	84.0000
12	HENRY	M	15.0000	63.5000	102.5000
13	ALFRED	M	14.0000	69.0000	112.5000
17	RONALD	M	15.0000	67.0000	133.0000
18	WILLIAM	M	15.0000	66.5000	112.0000
19	PHILIP	M	16.0000	72.0000	150.0000

Data Set Maintenance Functions

Two functions and two subroutines are provided to perform data set maintenance:

DATASETS function obtains members in a data library. This function returns a character matrix that contains the names of the SAS data sets in a library.

CONTENTS function	obtains variables in a member. This function returns a character matrix that contains the variable names for the SAS data set specified by <i>libname</i> and <i>memname</i> . The variable list is returned in alphabetical order.
RENAME subroutine	renames a SAS data set member in a specified library.
DELETE subroutine	deletes a SAS data set member in a specified library.

See [Chapter 23](#) for details and examples of these functions and routines.

Summary of Commands

You have seen that IML has an extensive set of commands that operate on SAS data sets. [Table 7.1](#) summarizes the data management commands you can use to perform management tasks for which you might normally use the SAS DATA step.

Table 7.1 Data Management Commands

Command	Description
APPEND	adds observations to the end of a SAS data set
CLOSE	closes a SAS data set
CREATE	creates and opens a new SAS data set for input and output
DELETE	marks observations for deletion in a SAS data set
EDIT	opens an existing SAS data set for input and output
FIND	finds observations
INDEX	indexes variables in a SAS data set
LIST	lists observations
PURGE	purges all deleted observations from a SAS data set
READ	reads observations into IML variables
REPLACE	writes observations back into a SAS data set
RESET DEFLIB	names default libname
SAVE	saves changes and reopens a SAS data set
SETIN	selects an open SAS data set for input
SETOUT	selects an open SAS data set for output
SHOW CONTENTS	shows contents of the current input SAS data set
SHOW DATASETS	shows SAS data sets currently open
SORT	sorts a SAS data set
SUMMARY	produces summary statistics for numeric variables
USE	opens an existing SAS data set for input

Comparison with the SAS DATA Step

If you want to remain in the IML environment and mimic DATA step processing, you need to learn the basic differences between IML and the SAS DATA step:

- With SAS/IML software, you start with a `CREATE` statement instead of a `DATA` statement. You must explicitly set up all your variables with the correct attributes before you create a data set. This means that you must define character variables to have the desired string length beforehand. Numeric variables are the default, so any variable not defined as character is assumed to be numeric. In the DATA step, the variable attributes are determined from context across the whole step.
- With SAS/IML software, you must use an `APPEND` statement to output an observation; in the DATA step, you either use an `OUTPUT` statement or let the DATA step output it automatically.
- With SAS/IML software, you iterate with a `DO DATA` loop. In the DATA step, the iterations are implied.
- With SAS/IML software, you have to close the data set with a `CLOSE` statement unless you plan to exit the IML environment with a `QUIT` statement. The DATA step closes the data set automatically at the end of the step.
- The DATA step usually executes faster than IML.

In short, the DATA step treats the problem with greater simplicity, allowing shorter programs. However, IML has more flexibility because it is interactive and has a powerful matrix-handling capability.

Summary

In this chapter, you have learned many ways to interact with SAS data sets from within the IML environment. You learned how to open and close a SAS data set, how to make it current for input and output, how to list observations by specifying a range of observations to process, a set of variables to use, and a condition for subsetting observations. You also learned summary statistics. You also know how to read observations and variables from a SAS data set into matrices as well as create a SAS data set from a matrix of values.

Chapter 8

File Access

Contents

Overview of File Access	109
Referring to an External File	110
Types of External Files	111
Reading from an External File	111
Using the INFILE Statement	111
Using the INPUT Statement	112
Writing to an External File	120
Using the FILE Statement	120
Using the PUT Statement	121
Examples	121
Listing Your External Files	123
Closing an External File	124
Summary	124

Overview of File Access

In this chapter you learn about external files and how to refer to an external file, whether it is a text file or a binary file. You learn how to read data from a file by using the **INFILE** and **INPUT** statements and how to write data to an external file by using the **FILE** and **PUT** statements.

With external files, you must know the format in which the data are stored or to be written. This is in contrast to SAS data sets, which are specialized files with a structure that is already known to the SAS System.

The SAS/IML statements used to access files are very similar to the corresponding statements in the SAS DATA step. The following table summarizes the IML statements and their functions.

Statement	Function
CLOSEFILE	closes an external file
FILE	opens an external file for output
INFILE	opens an external file for input
INPUT	reads from the current input file
PUT	writes to the current output file
SHOW: FILES	Shows all open files, their attributes, and their status (current input and output files)

Referring to an External File

Suppose that you have data for students in a class. You have recorded the values for the variables NAME, SEX, AGE, HEIGHT, and WEIGHT for each student and have stored the data in an external text file named USER.TEXT.CLASS. If you want to read these data into IML variables, you need to indicate where the data are stored. In other words, you need to name the input file. If you want to write data from matrices to a file, you also need to name an output file.

There are two ways to refer to an input or output file: a *pathname* and a *filename*. A pathname is the name of the file as it is known to the operating system. A filename is an indirect SAS reference to the file made by using the FILENAME statement. You can identify a file in either way by using the FILE and INFILE statements.

For example, you can refer to the input file where the class data are stored by using a literal pathname—that is, a quoted string. The following statement opens the file USER.TEXT.CLASS for input:

```
infile 'user.text.class';
```

Similarly, if you want to output data to the file USER.TEXT.NEWCLASS, you need to reference the output file with the following statement:

```
file 'user.text.newclass';
```

You can also refer to external files by using a filename. When using a filename as the operand, simply give the name. The name must be one already associated with a pathname by a previously issued FILENAME statement.

For example, suppose you want to reference the file with the class data by using a FILENAME statement. First, you must associate the pathname with an alias (called a *fileref*), such as INCLASS. Then you can refer to USER.TEXT.CLASS with the fileref INCLASS.

The following statements achieve the same result as the previous INFILE statement with the quoted pathname:

```
filename inclass 'user.text.class';  
infile inclass;
```

You can use the same technique for output files. The following statements have the same effect as the previous FILE statement:

```
filename outclass 'user.text.newclass';  
file outclass;
```

Three filenames have special meaning to IML: CARDS, LOG, and PRINT. These refer to the standard input and output streams for all SAS sessions, as follows:

CARDS is a special filename for instream input data.
LOG is a special filename for log output.
PRINT is a special filename for standard print output.

When the pathname is specified, there is a limit of 64 characters to the operand.

Types of External Files

Most files that you work with are *text files*, which means that they can be edited and displayed without any special program. Text files under most host environments have special characters, called carriage-control characters or end-of-line characters, to separate one record from the next.

If your file does not adhere to these conventions, it is called a *binary file*. Typically, binary files do not have the usual record separators, and they can use any binary codes, including unprintable control characters. If you want to read a binary file, you must specify RECFM=N in the INFILE statement and use the byte operand (<) in the INPUT statement to specify the length of each item you want read. Treating a file as binary enables you to have direct access to a file position by byte address by using the byte operand (>) in the INPUT or PUT statement.

You write data to an external file by using the FILE and PUT statements. The output file can be text or binary. If your output file is binary, you must specify RECFM=N in the FILE statement. One difference between binary files and text files in output is that with binary files, the PUT statement does not put the record-separator characters at the end of each record written.

Reading from an External File

After you have chosen a method to refer to the external file you want to read, you need an INFILE statement to open it for input and an INPUT statement to tell IML how to read the data.

The next several sections cover how to use an INFILE statement and how to specify an INPUT statement so that you can input data from an external file.

Using the INFILE Statement

An INFILE statement identifies an external file that contains data that you want to read. It opens the file for input or, if the file is already open, makes it the current input file. This means that subsequent INPUT statements are read from this file until another file is made the current input file.

The following options can be used with the INFILE statement:

FLOWOVER

enables the INPUT statement to go to the next record to obtain values for the variables.

LENGTH=variable

names a variable that contains the length of the current record, where the value is set to the number of bytes used after each INPUT statement.

MISSOEVER

prevents reading from the next input record when an INPUT statement reaches the end of the current record without finding values for all variables. It assigns missing values to all values that are expected but not found.

RECFM=N

specifies that the file is to be read in as a pure binary file rather than as a file with record-separator characters. You must use the byte operands (< and >) to get new records rather than separate INPUT statements or the new line operator (/).

STOPOVER

stops reading when an INPUT statement reaches the end of the current record without finding values for all variables in the statement. It treats going past the end of a record as an error condition, triggering an end-of-file condition. The STOPOVER option is the default.

The FLOWOVER, MISSOEVER, and STOPOVER options control how the INPUT statement works when you try to read past the end of a record. You can specify only one of these options. Read these options carefully so that you understand them completely.

The following example uses the INFILE statement with a FILENAME statement to read the class data file. The MISSOEVER option is used to prevent reading from the next record if values for all variables in the INPUT statement are not found.

```
filename inclass 'user.text.class';
infile inclass missover;
```

You can specify the pathname with a quoted literal also. The preceding statements could be written as follows:

```
infile 'user.text.class' missover;
```

Using the INPUT Statement

Once you have referenced the data file that contains your data with an INFILE statement, you need to tell IML the following information about how the data are arranged:

- the number of variables and their names
- each variable's type, either numeric or character

- the format of each variable's values
- the columns that correspond to each variable

In other words, you must tell IML how to read the data.

The INPUT statement describes the arrangement of values in an input record. The INPUT statement reads records from a file specified in the previously executed INFILE statement, reading the values into IML variables.

There are two ways to describe a record's values in an IML INPUT statement:

- list (or scanning) input
- formatted input

Following are several examples of valid INPUT statements for the class data file, depending, of course, on how the data are stored.

If the data are stored with a blank or a comma between fields, then list input can be used. For example, the INPUT statement for the class data file might look as follows:

```
infile inclass;
input name $ sex $ age height weight;
```

These statements tell IML the following:

- There are five variables: NAME, SEX, AGE, HEIGHT and WEIGHT.
- Data fields are separated by commas or blanks.
- NAME and SEX are character variables, as indicated by the dollar sign (\$).
- AGE, HEIGHT, and WEIGHT are numeric variables, the default.

The data must be stored in the same order in which the variables are listed in the INPUT statement. Otherwise, you can use formatted input, which is column specific. Formatted input is the most flexible and can handle any data file. Your INPUT statement for the class data file might look as follows:

```
infile inclass;
input @1 name $char8. @10 sex $char1. @15 age 2.0
      @20 height 4.1 @25 weight 5.1;
```

These statements tell IML the following:

- NAME is a character variable; its value begins in column 1 (indicated by @1) and occupies eight columns (\$CHAR8.).
- SEX is a character variable; its value is found in column 10 (\$CHAR1.).

- AGE is a numeric variable; its value is found in columns 15 and 16 and has no decimal places (2.0).
- HEIGHT is a numeric variable found in columns 20 through 23 with one decimal place implied (4.1).
- WEIGHT is a numeric variable found in columns 25 through 29 with one decimal place implied (5.1).

The next sections discuss these two modes of input.

List Input

If your data are recorded with a comma or one or more blanks between data fields, you can use list input to read your data. If you have missing values—that is, unknown values—they must be represented by a period (.) rather than a blank field.

When IML looks for a value, it skips past blanks and tab characters. Then it scans for a delimiter to the value. The delimiter is a blank, a comma, or the end of the record. When the ampersand (&) format modifier is used, IML looks for two blanks, a comma, or the end of the record.

The general form of the INPUT statement for list input is as follows:

```
INPUT variable <$> <&> <... variable <$> > <&> ;
```

where

<i>variable</i>	names the variable to be read by the INPUT statement.
\$	indicates that the preceding variable is character.
&	indicates that a character value can have a single embedded blank. Because a blank normally indicates the end of a data value, use the ampersand format modifier to indicate the end of the value with at least two blanks or a comma.

With list input, IML scans the input lines for values. Consider using list input in the following cases:

- when blanks or commas separate input values
- when periods rather than blanks represent missing values

List input is the default in several situations. Descriptions of these situations and the behavior of IML follow:

- If no input format is specified for a variable, IML scans for a number.
- If a single dollar sign or ampersand format modifier is specified, IML scans for a character value. The ampersand format modifier enables single embedded blanks to occur.
- If a format is given with width unspecified or zero, IML scans for the first blank or comma.

If the end of a record is encountered before IML finds a value, then the behavior is as described by the record overflow options in the INFILE statement discussed in the section “[Using the INFILE Statement](#)” on page 111.

When you read with list input, the order of the variables listed in the INPUT statement must agree with the order of the values in the data file. For example, consider the following data:

Alice	f	10	61	97
Beth	f	11	64	105
Bill	m	12	63	110

You can use list input to read these data by specifying the following INPUT statement:

```
input name $ sex $ age height weight;
```

NOTE: This statement implies that the variables are stored in the order given. That is, each line of data contains a student's name, sex, age, height, and weight in that order and separated by at least one blank or by a comma.

Formatted Input

The alternative to list input is formatted input. An INPUT statement reading formatted input must have a SAS informat after each variable. An *informat* gives the data type and field width of an input value. Formatted input can be used with pointer controls and format modifiers. Note, however, that neither pointer controls nor format modifiers are necessary for formatted input.

Pointer Control Features

Pointer controls reset the pointer's column and line positions and tell the INPUT statement where to go to read the data value. You use pointer controls to specify the columns and lines from which you want to read:

- *Column pointer controls* move the pointer to the column you specify.
- *Line pointer controls* move the pointer to the next line.
- *Line hold controls* keep the pointer on the current input line.
- *Binary file indicator controls* indicate that the input line is from a binary file.

Column Pointer Controls

Column pointer controls indicate in which column an input value starts. Column pointer controls begin with either an at sign (@) or a plus sign (+). A complete list follows:

@ <i>n</i>	moves the pointer to column <i>n</i> .
@ <i>point-variable</i>	moves the pointer to the column given by the current value of <i>point-variable</i> .
@(<i>expression</i>)	moves the pointer to the column given by the value of the <i>expression</i> . The <i>expression</i> must evaluate to a positive integer.
+ <i>n</i>	moves the pointer <i>n</i> columns.

- +*point-variable* moves the pointer the number of columns given by the value of *point-variable*.
- +(*expression*) moves the pointer the number of columns given by the value of *expression*. The value of *expression* can be positive or negative.

Here are some examples of using column pointer controls:

Example	Meaning
@12	go to column 12
@N	go to the column given by the value of N
@(N-1)	go to the column given by the value of N-1
+5	skip 5 spaces
+N	skip N spaces
+(N+1)	skip N+1 spaces

In the earlier example that used formatted input, you used several pointer controls. Here are the statements:

```
infile inclass;
input @1 name $char8. @10 sex $char1. @15 age 2.0
      @20 height 4.1 @25 weight 5.1;
```

The @1 moves the pointer to column 1, the @10 moves it to column 10, and so on. You move the pointer to the column where the data field begins and then supply an informat specifying how many columns the variable occupies. The INPUT statement could also be written as follows:

```
input @1 name $char8. +1 sex $char1. +4 age 2. +3 height 4.1
      +1 weight 5.1;
```

In this form, you move the pointer to column 1 (@1) and read eight columns. The pointer is now at column 9. Now, move the pointer +1 columns to column 10 to read SEX. The \$char1. informat says to read a character variable occupying one column. After you read the value for SEX, the pointer is at column 11, so move it to column 15 with +4 and read AGE in columns 15 and 16 (the 2. informat). The pointer is now at column 17, so move +3 columns and read HEIGHT. The same idea applies for reading WEIGHT.

Line Pointer Control

The line pointer control (/) directs IML to skip to the next line of input. You need a line pointer control when a record of data takes more than one line. You use the new line pointer control (/) to skip to the next line and continue reading data. In the example reading the class data, you do not need to skip a line because each line of data contains all the variables for a student.

Line Hold Control

The trailing at sign (@), when at the end of an INPUT statement, directs IML to hold the pointer on the current record so that you can read more data with subsequent INPUT statements. You can use it to read several records from a single line of data. Sometimes, when a record is very short—say, 10 columns or so—you can save space in your external file by coding several records on the same line.

Binary File Indicator Controls

When the external file you want to read is a binary file (RECFM=N is specified in the INFILE statement), you must tell IML how to read the values by using the following binary file indicator controls:

<code>>n</code>	start reading the next record at the byte position <i>n</i> in the file.
<code>>point-variable</code>	start reading the next record at the byte position in the file given by <i>point-variable</i> .
<code>>(expression)</code>	start reading the next record at the byte position in the file given by <i>expression</i> .
<code><n</code>	read the number of bytes indicated by the value of <i>n</i> .
<code><point-variable</code>	read the number of bytes indicated by the value of <i>point-variable</i> .
<code><(expression)</code>	read the number of bytes indicated by the value of <i>expression</i> .

Pattern Searching

You can have the input mechanism search for patterns of text by using the at sign (@) with a character operand. IML starts searching at the current position, advances until it finds the pattern, and leaves the pointer at the position immediately after the found pattern in the input record. For example, the following statement searches for the pattern **NAME=** and then uses list input to read the value after the found pattern:

```
input @ 'NAME=' name $;
```

If the pattern is not found, then the pointer is left past the end of the record, and the rest of the INPUT statement follows the conventions based on the options MISSOEVER, STOPOVER, and FLOWOVER described in the section “Using the INFILE Statement” on page 111. If you use pattern searching, you usually specify the MISSOEVER option so that you can control for the occurrences of the pattern not being found.

Notice that the MISSOEVER feature enables you to search for a variety of items in the same record, even if some of them are not found. For example, the following statements are able to read in the ADDR variable even if **NAME=** is not found (in which case, NAME is unvalued):

```
infile in1 missover;
input @1 @ "NAME=" name $
      @1 @ "ADDR=" addr &
      @1 @ "PHONE=" phone $;
```

The pattern operand can use any characters except for the following:

% \$ [] { } < > — ? * # @ ^ ` (backquote)

Record Directives

Each INPUT statement goes to a new record except in the following special cases:

- An at sign (@) at the end of an INPUT statement specifies that the record is to be held for future INPUT statements.

- Binary files (RECFM=N) always hold their records until the > directive.

As discussed in the syntax of the INPUT statement, the line pointer operator (/) instructs the input mechanism to go immediately to the next record. For binary (RECFM=N) files, the > directive is used instead of the /.

Blanks

For character values, the informat determines the way blanks are interpreted. For example, the \$CHAR w . format reads blanks as part of the whole value, while the BZ w . format turns blanks into zeros. See *SAS Language Reference: Dictionary* for more information about informats.

Missing Values

Missing values in formatted input are represented by blanks or a single period for a numeric value and by blanks for a character value.

Matrix Use

Data values are either character or numeric. Input variables always result in scalar (one row by one column) values with type (character or numeric) and length determined by the input format.

End-of-File Condition

End of file is the condition of trying to read a record when there are no more records to read from the file. The consequences of an end-of-file condition are described as follows.

- All the variables in the INPUT statement that encountered end of file are freed of their values. You can use the NROW or NCOL function to test if this has happened.
- If end of file occurs inside a DO DATA loop, execution is passed to the statement after the END statement in the loop.

For text files, end of file is encountered first as the end of the last record. The next time input is attempted, the end-of-file condition is raised.

For binary files, end of file can result in the input mechanism returning a record that is shorter than the requested length. In this case IML still attempts to process the record, using the rules described in the section “[Using the INFILE Statement](#)” on page 111.

The DO DATA mechanism provides a convenient mechanism for handling end of file.

For example, to read the class data from the external file USER.TEXT.CLASS into a SAS data set, you need to perform the following steps:

1. Establish a *fileref* referencing the data file.
2. Use an INFILE statement to open the file for input.
3. Initialize any character variables by setting the length.
4. Create a new SAS data set with a CREATE statement. You want to list the variables you plan to input in a VAR clause.
5. Use a DO DATA loop to read the data one line at a time.
6. Write an INPUT statement telling IML how to read the data.
7. Use an APPEND statement to add the new data line to the end of the new SAS data set.
8. End the DO DATA loop.
9. Close the new data set.
10. Close the external file with a CLOSEFILE statement.

Your statements should look as follows:

```
filename inclass 'user.text.class';
infile inclass missover;
name="12345678";
sex="1";
create class var{name sex age height weight};
do data;
    input name $ sex $ age height weight;
    append;
end;
close class;
closefile inclass;
```

Note that the APPEND statement is not executed if the INPUT statement reads past the end of file since IML escapes the loop immediately when the condition is encountered.

Differences with the SAS DATA Step

If you are familiar with the SAS DATA step, you will notice that the following features are supported differently or are not supported in IML:

- The pound sign (#) directive supporting multiple current records is not supported.
- Grouping parentheses are not supported.
- The colon (:) format modifier is not supported.
- The byte operands (< and >) are new features supporting binary files.

- The ampersand (&) format modifier causes IML to stop reading data if a comma is encountered. Use of the ampersand format modifier is valid with list input only.
- The RECFM=F option is not supported.

Writing to an External File

If you have data in matrices and you want to write these data to an external file, you need to reference, or point to, the file (as discussed in the section “[Referring to an External File](#)” on page 110). The FILE statement opens the file for output so that you can write data to it. You need to specify a PUT statement to direct how the data are output. These two statements are discussed in the following sections.

Using the FILE Statement

The FILE statement is used to refer to an external file. If you have values stored in matrices, you can write these values to a file. Just as with the INFILE statement, you need a fileref to point to the file you want to write to. You use a FILE statement to indicate that you want to write to rather than read from a file.

For example, if you want to output to the file USER.TEXT.NEWCLASS, you can specify the file with a quoted literal pathname. Here is the statement:

```
> file 'user.text.newclass';
```

Otherwise, you can first establish a fileref and then refer to the file by its fileref, as follows:

```
> filename outclass 'user.text.class';
> file outclass;
```

There are two options you can use in the FILE statement:

- | | |
|-----------------------|---|
| RECFM=N | specifies that the file is to be written as a pure binary file without record-separator characters. |
| LRECL= <i>operand</i> | specifies the size of the buffer to hold the records. |

The FILE statement opens a file for output or, if the file is already open, makes it the current output file so that subsequent PUT statements write to the file. The FILE statement is similar in syntax and operation to the INFILE statement.

Using the PUT Statement

The PUT statement writes lines to the SAS log, to the SAS output file, or to any external file specified in a FILE statement. The file associated with the most recently executed FILE statement is the *current output file*.

You can use the following arguments with the PUT statement:

<i>variable</i>	names the IML variable with a value that is put to the current pointer position in the record. The variable must be scalar valued. The put variable can be followed immediately by an output format.
<i>literal</i>	gives a literal to be put to the current pointer position in the record. The literal can be followed immediately by an output format.
<i>(expression)</i>	must produce a scalar-valued result. The expression can be immediately followed by an output format.
<i>format</i>	names the output formats for the values.
<i>pointer-control</i>	moves the output pointer to a line or column.

Pointer Control Features

Most PUT statements need the added flexibility obtained with pointer controls. IML keeps track of its position on each output line with a pointer. With specifications in the PUT statement, you can control pointer movement from column to column and line to line. The pointer controls available are discussed in the section “Using the INPUT Statement” on page 112.

Differences with the SAS DATA Step

If you are familiar with the SAS DATA step, you will notice that the following features are supported differently or are not supported:

- The pound sign (#) directive supporting multiple current records is not supported.
- Grouping parentheses are not supported.
- The byte operands (< and >) are a new feature supporting binary files.

Examples

Writing a Matrix to an External File

If you have data stored in an $n \times m$ matrix and you want to output the values to an external file, you need to write out the matrix element by element.

For example, suppose you have a matrix **X** that contains data that you want written to the file **USER.MATRIX**. Suppose also that **X** contains ones and zeros so that the format for output can be one column. You need to do the following:

1. Establish a fileref, such as **OUT**.
2. Use a **FILE** statement to open the file for output.
3. Specify a **DO** loop for the rows of the matrix.
4. Specify a **DO** loop for the columns of the matrix.
5. Use a **PUT** statement to specify how to write the element value.
6. End the inner **DO** loop.
7. Skip a line.
8. End the outer **DO** loop.
9. Close the file.

Your statements should look as follows:

```
filename out 'user.matrix';
file out;
do i = 1 to nrow(x);
    do j = 1 to ncol(x);
        put (x[i,j]) 1.0 +2 @;
    end;
    put;
end;
closefile out;
```

The output file contains a record for each row of the matrix. For example, if your matrix is 4×4 , then the file might look as follows:

```
1  1  0  1
1  0  0  1
1  1  1  0
0  1  0  1
```

Quick Printing to the PRINT File

You can use the **FILE PRINT** statement to route output to the standard print file. The following statements generate data that are output to the **PRINT** file:

```

> file print;
> do a = 0 to 6.28 by .2;
>   x = sin(a);
>   p = (x+1)#30;
>   put @1 a 6.4 +p x 8.4;
> end;

```

Here is the resulting output:

```

0.0000          0.0000
0.2000          0.1987
0.4000          0.3894
0.6000          0.5646
0.8000          0.7174
1.0000          0.8415
1.2000          0.9320
1.4000          0.9854
1.6000          0.9996
1.8000          0.9738
2.0000          0.9093
2.2000          0.8085
2.4000          0.6755
2.6000          0.5155
2.8000          0.3350
3.0000          0.1411
3.2000         -0.0584
3.4000         -0.2555
3.6000         -0.4425
3.8000         -0.6119
4.0000         -0.7568
4.2000         -0.8716
4.4000         -0.9516
4.6000         -0.9937
4.8000         -0.9962
5.0000         -0.9589
5.2000         -0.8835
5.4000         -0.7728
5.6000         -0.6313
5.8000         -0.4646
6.0000         -0.2794
6.2000         -0.0831

```

Listing Your External Files

To list all open files and their current input or current output status, use the `SHOW FILES` statement.

Closing an External File

The CLOSEFILE statement closes files opened by an INFILE or FILE statement. You specify the CLOSEFILE statement just as you do the INFILE or FILE statement. For example, the following statements open the external file USER.TEXT.CLASS for input and then close it:

```
filename in 'user.text.class';  
infile in;  
closefile in;
```

Summary

In this chapter, you learned how to refer to, or point to, an external file by using a FILENAME statement. You can use the FILENAME statement whether you want to read from or write to an external file. The file can also be referenced by a quoted literal pathname. You also learned about the difference between a text file and a binary file.

You learned how to read data from an external file with the INFILE and INPUT statements, using either list or formatted input. You learned how to write your matrices to an external file by using the FILE and PUT statements. Finally, you learned how to close your files.

Chapter 9

General Statistics Examples

Contents	
Overview	125
General Statistics Examples	126
Example 9.1: Correlation	126
Example 9.2: Newton’s Method for Solving Nonlinear Systems of Equations	127
Example 9.3: Regression	129
Example 9.4: Alpha Factor Analysis	132
Example 9.5: Categorical Linear Models	134
Example 9.6: Regression of Subsets of Variables	138
Example 9.7: Response Surface Methodology	144
Example 9.8: Logistic and Probit Regression for Binary Response Models	147
Example 9.9: Linear Programming	150
Example 9.10: Quadratic Programming	155
Example 9.11: Regression Quantiles	157
Example 9.12: Simulations of a Univariate ARMA Process	161
Example 9.13: Parameter Estimation for a Regression Model with ARMA Errors	163
Example 9.14: Iterative Proportional Fitting	170
Example 9.15: Full-Screen Nonlinear Regression	172
References	177

Overview

SAS/IML software has many linear operators that perform high-level operations commonly needed in applying linear algebra techniques to data analysis. The similarity of the Interactive Matrix Language notation and matrix algebra notation makes translation from algorithm to program a straightforward task. The examples in this chapter show a variety of matrix operators at work.

You can use these examples to gain insight into the more complex problems you might need to solve. Some of the examples perform the same analyses as performed by procedures in SAS/STAT software and are not meant to replace them. The examples are included as learning tools.

General Statistics Examples

Example 9.1: Correlation

The following statements show how you can define modules to compute correlation coefficients between numeric variables and standardized values for a set of data. For more efficient computations, use the built-in `CORR` function and the `STD` function.

```
proc iml;
  /* Module to compute correlations */
  start corr;
    n = nrow(x);                                /* number of observations */
    sum = x[+,] ;                               /* compute column sums */
    xpx = t(x)*x-t(sum)*sum/n;                  /* compute sscp matrix */
    s = diag(1/sqrt(vecdiag(xpx)));             /* scaling matrix */
    corr = s*xpx*s;                             /* correlation matrix */
    print "Correlation Matrix",,corr[rowname=nm colname=nm] ;
  finish corr;

  /* Module to standardize data */
  start std;
    mean = x[+,] /n;                            /* means for columns */
    x = x-repeat(mean,n,1);                     /* center x to mean zero */
    ss = x[##,] ;                               /* sum of squares for columns */
    std = sqrt(ss/(n-1));                       /* standard deviation estimate*/
    x = x*diag(1/std);                          /* scaling to std dev 1 */
    print , "Standardized Data",,X[colname=nm] ;
  finish std;

  /* Sample run */
  x = { 1 2 3,
        3 2 1,
        4 2 1,
        0 4 1,
        24 1 0,
        1 3 8};
  nm={age weight height};
  run corr;
  run std;
```

The results are shown in [Output 9.1.1](#).

Output 9.1.1 Correlation Coefficients and Standardized Values

Correlation Matrix			
corr			
	AGE	WEIGHT	HEIGHT
AGE	1	-0.717102	-0.436558
WEIGHT	-0.717102	1	0.3508232
HEIGHT	-0.436558	0.3508232	1
Standardized Data			
	x		
	AGE	WEIGHT	HEIGHT
	-0.490116	-0.322749	0.2264554
	-0.272287	-0.322749	-0.452911
	-0.163372	-0.322749	-0.452911
	-0.59903	1.6137431	-0.452911
	2.0149206	-1.290994	-0.792594
	-0.490116	0.6454972	1.924871

Example 9.2: Newton's Method for Solving Nonlinear Systems of Equations

This example solves a nonlinear system of equations by Newton's method. Let the nonlinear system be represented by

$$F(\mathbf{x}) = 0$$

where \mathbf{x} is a vector and F is a vector-valued, possibly nonlinear function.

In order to find \mathbf{x} such that F goes to 0, an initial estimate \mathbf{x}_0 is chosen, and Newton's iterative method for converging to the solution is used:

$$\mathbf{x}_{n+1} = \mathbf{x}_n - \mathbf{J}^{-1}(\mathbf{x}_n)F(\mathbf{x}_n)$$

where $\mathbf{J}(\mathbf{x})$ is the Jacobian matrix of partial derivatives of F with respect to \mathbf{x} . (For more efficient computations, use the built-in [NLPNRA subroutine](#).)

For optimization problems, the same method is used, where $F(\mathbf{x})$ is the gradient of the objective function and $\mathbf{J}(\mathbf{x})$ becomes the Hessian (Newton-Raphson).

In this example, the system to be solved is

$$\begin{aligned} \mathbf{x}_1 + \mathbf{x}_2 - \mathbf{x}_1\mathbf{x}_2 + 2 &= 0 \\ \mathbf{x}_1 \exp(-\mathbf{x}_2) - 1 &= 0 \end{aligned}$$

The following statements are organized into three modules: NEWTON, FUN, and DERIV.

```

/*      Newton's Method to Solve a Nonlinear Function      */
/* The user must supply initial values,                    */
/* and the FUN and DERIV functions.                         */
/* On entry: FUN evaluates the function f in terms of x    */
/* initial values are given to x                           */
/* DERIV evaluates jacobian j                              */
/* tuning variables: CONVERGE, MAXITER.                    */
/* On exit: solution in x, function value in f close to 0  */
/* ITER has number of iterations.                          */
proc iml;
start newton;
  run fun;          /* evaluate function at starting values */
  do iter = 1 to maxiter          /* iterate until maxiter */
  while(max(abs(f))>converge); /* iterations or convergence */
    run deriv;          /* evaluate derivatives in j */
    delta = -solve(j,f); /* solve for correction vector */
    x = x+delta;          /* the new approximation */
    run fun;          /* evaluate the function */
  end;
finish newton;

maxiter = 15;          /* default maximum iterations */
converge = .000001;    /* default convergence criterion */

/* User-supplied function evaluation */
start fun;
  x1 = x[1] ;
  x2 = x[2] ;          /* extract the values */
  f = (x1+x2-x1*x2+2) //
      (x1*exp(-x2)-1); /* evaluate the function */
finish fun;

/* User-supplied derivatives of the function */
start deriv;
  /* evaluate jacobian */
  j = ((1-x2) || (1-x1) ) // (exp(-x2) || (-x1*exp(-x2)));
finish deriv;

do;
  print "Solving the system: X1+X2-X1*X2+2=0, X1*EXP(-X2)-1=0" ,;
  x={.1, -2};          /* starting values */
  run newton;
  print x f;
end;

```


The results are shown in [Output 9.2.1](#).

Output 9.2.1 Newton's Method: Results

Solving the system: $X_1 + X_2 - X_1 \cdot X_2 + 2 = 0$, $X_1 \cdot \text{EXP}(-X_2) - 1 = 0$	
x	f
0.0977731	5.3523E-9
-2.325106	6.1501E-8

Example 9.3: Regression

This example shows a regression module that calculates statistics that are associated with a linear regression.

```

/*          Regression Routine          */
/* Given X and Y, this fits  $Y = X B + E$  */
/* by least squares.                    */
proc iml;
start reg;
  n = nrow(x);          /* number of observations */
  k = ncol(x);          /* number of variables */
  xpx = x`*x;           /* crossproducts */
  xpy = x`*y;
  xpxi = inv(xpx);      /* inverse crossproducts */
  b = xpxi*xpy;         /* parameter estimates */
  yhat = x*b;           /* predicted values */
  resid = y-yhat;       /* residuals */
  sse = resid`*resid;   /* sum of squared errors */
  dfe = n-k;            /* degrees of freedom error */
  mse = sse/dfe;        /* mean squared error */
  rmse = sqrt(mse);     /* root mean squared error */
  covb = xpxi#mse;      /* covariance of estimates */
  stdb = sqrt(vecdiag(covb)); /* standard errors */
  t = b/stdb;           /* ttest for estimates=0 */
  probt = 1-probf(t#t,1,dfe); /* significance probability */
  print name b stdb t probt;
  s = diag(1/stdb);
  corrb = s*covb*s;     /* correlation of estimates */
  print , "Covariance of Estimates", covb[r=name c=name] ,
        "Correlation of Estimates", corrb[r=name c=name] ;

  if nrow(tval)=0 then return; /* is a t value specified? */
  projx = x*xpxi*x`;      /* hat matrix */
  vresid = (i(n)-projx)*mse; /* covariance of residuals */
  vpred = projx#mse;      /* covariance of predicted values */
  h = vecdiag(projx);     /* hat leverage values */
  lowerm = yhat-tval#sqrt(h*mse); /* low. conf lim for mean */
  upperm = yhat+tval#sqrt(h*mse); /* upper lim. for mean */

```

```

    lower = yhat-tval#sqrt(h*mse+mse); /* lower lim. for indiv*/
    upper = yhat+tval#sqrt(h*mse+mse); /* upper lim. for indiv */
    print , "Predicted Values, Residuals, and Limits" , ,
    y yhat resid h lowerm upperm lower upper;
finish reg;

/* Routine to test a linear combination of the estimates */
/* given L, this routine tests hypothesis that LB = 0. */

start test;
    dfn=nrow(L);
    Lb=L*b;
    vLb=L*xpxi*L`;
    q=Lb`*inv(vLb)*Lb /dfn;
    f=q/mse;
    prob=1-probf(f,dfn,dfe);
    print ,f dfn dfe prob;
finish test;

/* Run it on population of U.S. for decades beginning 1790 */

x= { 1 1 1,
      1 2 4,
      1 3 9,
      1 4 16,
      1 5 25,
      1 6 36,
      1 7 49,
      1 8 64 };

y= {3.929,5.308,7.239,9.638,12.866,17.069,23.191,31.443};
name={"Intercept", "Decade", "Decade**2" };
tval=2.57; /* for 5 df at 0.025 level to get 95% conf. int. */
reset fw=7;
run reg;
do;
    print , "TEST Coef for Linear";
    L={0 1 0 };
    run test;
    print , "TEST Coef for Linear,Quad";
    L={0 1 0,0 0 1};
    run test;
    print , "TEST Linear+Quad = 0";
    L={0 1 1 };
    run test;
end;

```

The results are shown in [Output 9.3.1](#).

Output 9.3.1 Regression Results

name	b	stdb	t	probt
Intercept	5.06934	0.96559	5.24997	0.00333
Decade	-1.1099	0.4923	-2.2546	0.07385
Decade**2	0.53964	0.0534	10.106	0.00016

Covariance of Estimates

	covb		
	Intercept	Decade	Decade**2
Intercept	0.93237	-0.4362	0.04277
Decade	-0.4362	0.24236	-0.0257
Decade**2	0.04277	-0.0257	0.00285

Correlation of Estimates

	corrb		
	Intercept	Decade	Decade**2
Intercept	1	-0.9177	0.8295
Decade	-0.9177	1	-0.9762
Decade**2	0.8295	-0.9762	1

Predicted Values, Residuals, and Limits

y	yhat	resid	h	lowerm	upperm	lower	upper
3.929	4.49904	-0.57	0.70833	3.00202	5.99606	2.17419	6.82389
5.308	5.00802	0.29998	0.27976	4.06721	5.94883	2.99581	7.02023
7.239	6.59627	0.64273	0.23214	5.73926	7.45328	4.62185	8.57069
9.638	9.26379	0.37421	0.27976	8.32298	10.2046	7.25158	11.276
12.866	13.0106	-0.1446	0.27976	12.0698	13.9514	10.9984	15.0228
17.069	17.8367	-0.7677	0.23214	16.9797	18.6937	15.8622	19.8111
23.191	23.742	-0.551	0.27976	22.8012	24.6828	21.7298	25.7542
31.443	30.7266	0.71638	0.70833	29.2296	32.2236	28.4018	33.0515

TEST Coef for Linear

f	dfn	dfe	prob
5.08317	1	5	0.07385

TEST Coef for Linear,Quad

f	dfn	dfe	prob
666.511	2	5	8.54E-7

TEST Linear+Quad = 0

Output 9.3.1 *continued*

	f	dfn	dfe	prob
	1.67746	1	5	0.25184

Example 9.4: Alpha Factor Analysis

This example shows how an algorithm for computing alpha factor patterns (Kaiser and Caffrey 1965) is implemented in the SAS/IML language.

You can store the following ALPHA subroutine in a catalog and load it when needed.

```

/*              Alpha Factor Analysis              */
/* Ref: Kaiser et al., 1965 Psychometrika, pp. 12-13 */
/* r correlation matrix (n.s.) already set up      */
/* p number of variables                          */
/* q number of factors                            */
/* h communalities                                */
/* m eigenvalues                                  */
/* e eigenvectors                                 */
/* f factor pattern                              */
/* (IQ,H2,HI,G,MM) temporary use. freed up        */
/*
proc iml;
start alpha;
  p = ncol(r);
  q = 0;
  h = 0;
  h2 = i(p)-diag(1/vecdiag(inv(r)));
  do while(max(abs(h-h2))>.001); /* initialize */
    h = h2;
    hi = diag(sqrt(1/vecdiag(h)));
    g = hi*(r-i(p))*hi+i(p);
    call eigen(m,e,g); /* smcs */
    if q=0 then do;
      q = sum(m>1); /* iterate until converges */
      iq = 1:q;
    end;
    mm = diag(sqrt(m[iq,])); /* number of factors */
    e = e[,iq]; /* index vector */
    h2 = h*diag((e*mm) [,##]); /* collapse eigvals */
    /* collapse eigvecs */
    /* new communalities */
  end;
  hi = sqrt(h);
  h = vecdiag(h2);
  f = hi*e*mm; /* resulting pattern */
  free iq h2 hi g mm; /* free temporaries */
finish;

/* Correlation Matrix from Harmon, Modern Factor Analysis, */

```

```

/* Second edition, page 124, "Eight Physical Variables" */

r={1.000 .846 .805 .859 .473 .398 .301 .382 ,
   .846 1.000 .881 .826 .376 .326 .277 .415 ,
   .805 .881 1.000 .801 .380 .319 .237 .345 ,
   .859 .826 .801 1.000 .436 .329 .327 .365 ,
   .473 .376 .380 .436 1.000 .762 .730 .629 ,
   .398 .326 .319 .329 .762 1.000 .583 .577 ,
   .301 .277 .237 .327 .730 .583 1.000 .539 ,
   .382 .415 .345 .365 .629 .577 .539 1.000};
nm = {Var1 Var2 Var3 Var4 Var5 Var6 Var7 Var8};
run alpha;
print , "EIGENVALUES" , m;
print , "COMMUNALITIES" , h[rowname=nm];
print , "FACTOR PATTERN", f[rowname=nm];

```

The results are shown in [Output 9.4.1](#).

Output 9.4.1 Alpha Factor Analysis: Results

EIGENVALUES	
m	
	5.937855
	2.0621956
	0.1390178
	0.0821054
	0.018097
	-0.047487
	-0.09148
	-0.100304
COMMUNALITIES	
h	
VAR1	0.8381205
VAR2	0.8905717
VAR3	0.81893
VAR4	0.8067292
VAR5	0.8802149
VAR6	0.6391977
VAR7	0.5821583
VAR8	0.4998126
FACTOR PATTERN	

Output 9.4.1 *continued*

	f	
VAR1	0.813386	-0.420147
VAR2	0.8028363	-0.49601
VAR3	0.7579087	-0.494474
VAR4	0.7874461	-0.432039
VAR5	0.8051439	0.4816205
VAR6	0.6804127	0.4198051
VAR7	0.620623	0.4438303
VAR8	0.6449419	0.2895902

Example 9.5: Categorical Linear Models

This example fits a linear model to a function of the response probabilities

$$\mathbf{K} \log \pi = \mathbf{X}_c + e$$

where \mathbf{K} is a matrix that compares each response category to the last. Data are from Kastenbaum and Lamphiear (1959). First, the Grizzle-Starmer-Koch (1969) approach is used to obtain generalized least squares estimates of π . These form the initial values for the Newton-Raphson solution for the maximum likelihood estimates. The CATMOD procedure can also be used to analyze these binary data (see Cox (1970)). Here is the program.

```

/* Categorical Linear Models */
/* by Least Squares and Maximum Likelihood */
/* CATLIN */
/* Input: */
/*   n the s by p matrix of response counts */
/*   x the s by r design matrix */

proc iml ;
start catlin;

/*---find dimensions---*/
s = nrow(n); /* number of populations */
r = ncol(n); /* number of responses */
q = r-1; /* number of function values */
d = ncol(x); /* number of design parameters */
qd = q*d; /* total number of parameters */

/*---get probability estimates---*/
rown = n[,+]; /* row totals */
pr = n/(rown*repeat(1,1,r)); /* probability estimates */
p = shape(pr[,1:q] ,0,1); /* cut and shaped to vector */
print "INITIAL PROBABILITY ESTIMATES" ,pr;

/* estimate by the GSK method */

/* function of probabilities */

```

```

f = log(p)-log(pr[,r])@repeat(1,q,1);

/* inverse covariance of f */
si = (diag(p)-p*p`)#(diag(rown)@repeat(1,q,q));
z = x@i(q); /* expanded design matrix */
h = z`*si*z; /* crossproducts matrix */
g = z`*si*f; /* cross with f */
beta = solve(h,g); /* least squares solution */
stderr = sqrt(vecdiag(inv(h))); /* standard errors */
run prob;
print , "GSK ESTIMATES" , beta stderr , pi;

/* iterations for ML solution */
crit = 1;
do it = 1 to 8 while(crit>.0005); /* iterate until converge*/

/* block diagonal weighting */
si = (diag(pi)-pi*pi`)#(diag(rown)@repeat(1,q,q));
g = z`*(rown@repeat(1,q,1)#(p-pi)); /* gradient */
h = z`*si*z; /* hessian */
delta = solve(h,g); /* solve for correction */
beta = beta+delta; /* apply the correction */
run prob; /* compute prob estimates */
crit = max(abs(delta)); /* convergence criterion */
end;
stderr = sqrt(vecdiag(inv(h))); /* standard errors */
print , "ML Estimates", beta stderr, pi;
print , "Iterations" it "Criterion" crit;
finish catlin;

/* subroutine to compute new prob estimates @ parameters */
start prob;
la = exp(x*shape(beta,0,q));
pi = la/((1+la[,+])*repeat(1,1,q));
pi = shape(pi,0,1);
finish prob;

/*---prepare frequency data and design matrix---*/
n= { 58 11 05,
      75 19 07,
      49 14 10,
      58 17 08,
      33 18 15,
      45 22 10,
      15 13 15,
      39 22 18,
      04 12 17,
      05 15 08}; /* frequency counts*/

x= { 1 1 1 0 0 0,
      1 -1 1 0 0 0,
      1 1 0 1 0 0,
      1 -1 0 1 0 0,
      1 1 0 0 1 0,

```

```

1 -1 0 0 1 0,
1 1 0 0 0 1,
1 -1 0 0 0 1,
1 1 -1 -1 -1 -1,
1 -1 -1 -1 -1 -1};    /* design matrix*/

run catlin;

```

The maximum likelihood estimates are shown in [Output 9.5.1](#).

Output 9.5.1 Maximum Likelihood Estimates

INITIAL PROBABILITY ESTIMATES		
pr		
0.7837838	0.1486486	0.0675676
0.7425743	0.1881188	0.0693069
0.6712329	0.1917808	0.1369863
0.6987952	0.2048193	0.0963855
0.5	0.2727273	0.2272727
0.5844156	0.2857143	0.1298701
0.3488372	0.3023256	0.3488372
0.4936709	0.278481	0.2278481
0.1212121	0.3636364	0.5151515
0.1785714	0.5357143	0.2857143
GSK ESTIMATES		
beta	stderr	
0.9454429	0.1290925	
0.4003259	0.1284867	
-0.277777	0.1164699	
-0.278472	0.1255916	
1.4146936	0.267351	
0.474136	0.294943	
0.8464701	0.2362639	
0.1526095	0.2633051	
0.1952395	0.2214436	
0.0723489	0.2366597	
-0.514488	0.2171995	
-0.400831	0.2285779	

Output 9.5.1 *continued*

pi	
0.7402867	
0.1674472	
0.7704057	
0.1745023	
0.6624811	
0.1917744	
0.7061615	
0.2047033	
0.516981	
0.2648871	
0.5697446	
0.2923278	
0.3988695	
0.2589096	
0.4667924	
0.3034204	
0.1320359	
0.3958019	
0.1651907	
0.4958784	
ML Estimates	
beta	stderr
0.9533597	0.1286179
0.4069338	0.1284592
-0.279081	0.1156222
-0.280699	0.1252816
1.4423195	0.2669357
0.4993123	0.2943437
0.8411595	0.2363089
0.1485875	0.2635159
0.1883383	0.2202755
0.0667313	0.236031
-0.527163	0.216581
-0.414965	0.2299618

Output 9.5.1 *continued*

pi		
0.7431759		
0.1673155		
0.7723266		
0.1744421		
0.6627266		
0.1916645		
0.7062766		
0.2049216		
0.5170782		
0.2646857		
0.5697771		
0.292607		
0.3984205		
0.2576653		
0.4666825		
0.3027898		
0.1323243		
0.3963114		
0.165475		
0.4972044		
		crit
it		
Iterations		3 Criterion 0.0004092

Example 9.6: Regression of Subsets of Variables

This example performs regression with variable selection. Some of the methods used in this example are also used in the REG procedure. Here is the program.

```
proc iml;

/*-----Initialization-----*/
| c,csave the crossproducts matrix |
| n      number of observations      |
| k      total number of variables to consider |
| l      number of variables currently in model |
| in     a 0-1 vector of whether variable is in |
| b      print collects results (L MSE RSQ BETAS ) |
/*-----*/
start initial;
  n=nrow(x); k=ncol(x); k1=k+1; ik=1:k;
  bnames={nparm mse rsquare} ||varnames;

/*---correct by mean, adjust out intercept parameter---*/
y=y-y[+,]/n; /* correct y by mean */
x=x-repeat(x[+,]/n,n,1); /* correct x by mean */
xpy=x`*y; /* crossproducts */
```

```

ypy=y`*y;
xpx=x`*x;
free x y;                                /* no longer need the data*/
csave=(xpx || xpy) //
      (xpy` || ypy);                      /* save copy of crossproducts*/
finish;

/*-----forward method-----*/
start forward;
print "FORWARD SELECTION METHOD";
free bprint;
c=csave; in=repeat(0,k,1); L=0;          /* no variables are in */
dfe=n-1; mse=ypy/dfe;
sprob=0;

do while(sprob<.15 & l<k);
  indx=loc(^in);                        /* where are the variables not in?*/
  cd=vecdiag(c)[indx,];                 /* xpx diagonals */
  cb=c[indx,k1];                        /* adjusted xpy */
  tsqr=cb#cb/(cd#mse);                  /* squares of t tests */
  imax=tsqr[<:,];                       /* location of maximum in indx */
  sprob=(1-probt(sqrt(tsqr[imax,]),dfe))*2;
  if sprob<.15 then do;                 /* if t-test significant */
    ii=indx[,imax];                    /* pick most significant */
    run swp;                           /* routine to sweep */
    run bpr;                           /* routine to collect results */
  end;
end;

print bprint[colname=bnames] ;
finish;

/*-----backward method-----*/
start backward;
print "BACKWARD ELIMINATION ";
free bprint;
c=csave; in=repeat(0,k,1);
ii=1:k; run swp; run bpr;              /* start with all variables in*/
sprob=1;

do while(sprob>.15 & L>0);
  indx=loc(in);                        /* where are the variables in? */
  cd=vecdiag(c)[indx,];                 /* xpx diagonals */
  cb=c[indx,k1];                        /* bvalues */
  tsqr=cb#cb/(cd#mse);                  /* squares of t tests */
  imin=tsqr[>:,];                       /* location of minimum in indx */
  sprob=(1-probt(sqrt(tsqr[imin,]),dfe))*2;
  if sprob>.15 then do;                 /* if t-test nonsignificant */
    ii=indx[,imin];                    /* pick least significant */
    run swp;                           /* routine to sweep in variable*/
    run bpr;                           /* routine to collect results */
  end;
end;

```

```

    end;
end;

print bprint[colname=bnames] ;
finish;

/*-----stepwise method-----*/
start stepwise;
print "STEPWISE METHOD";
free bprint;
c=csave; in=repeat(0,k,1); L=0;
dfe=n-1; mse=ypy/dfe;
sprob=0;

do while(sprob<.15 & L<k);
    indx=loc(^in);          /* where are the variables not in? */
    nindx=loc(in);          /* where are the variables in?   */
    cd=vecdiag(c)[indx,];   /* xpx diagonals                */
    cb=c[indx,k1];          /* adjusted xpy                 */
    tsqr=cb#cb/cd/mse;      /* squares of t tests           */
    imax=tsqr[<:,];         /* location of maximum in indx  */
    sprob=(1-probt(sqrt(tsqr[imax,]),dfe))*2;
    if sprob<.15 then do;   /* if t-test significant        */
        ii=indx[,imax];    /* find index into c            */
        run swp;           /* routine to sweep             */
        run backstep;      /* check if remove any terms    */
        run bpr;           /* routine to collect results   */
    end;
end;

print bprint[colname=bnames] ;
finish;

/*----routine to backwards-eliminate for stepwise--*/
start backstep;
if nrow(nindx)=0 then return;
bprob=1;
do while(bprob>.15 & L<k);
    cd=vecdiag(c)[nindx,]; /* xpx diagonals                */
    cb=c[nindx,k1];        /* bvalues                      */
    tsqr=cb#cb/(cd#mse);   /* squares of t tests           */
    imin=tsqr[>:,];        /* location of minimum in nindx */
    bprob=(1-probt(sqrt(tsqr[imin,]),dfe))*2;
    if bprob>.15 then do;
        ii=nindx[,imin];
        run swp;
        run bpr;
    end;
end;

finish;

```

```

/*-----search all possible models-----*/
start all;
  /*---use method of schatzoff et al. for search technique---*/
  betak=repeat(0,k,k); /* record estimates for best l-param model*/
  msek=repeat(1e50,k,1); /* record best mse per # parms */
  rsqk=repeat(0,k,1); /* record best rsquare */
  ink=repeat(0,k,k); /* record best set per # parms */
  limit=2##k-1; /* number of models to examine */

  c=csave; in=repeat(0,k,1); /* start out with no variables in model*/

  do kk=1 to limit;
    run ztrail; /* find which one to sweep */
    run swp; /* sweep it in */
    bb=bb/(L||mse||rsq||(c[ik,k1]#in)`);
    if mse<msek[L,] then do; /* was this best for L parms? */
      msek[L,]=mse; /* record mse */
      rsqk[L,]=rsq; /* record rsquare */
      ink[,L]=in; /* record which parms in model*/
      betak[L,]=(c[ik,k1]#in)`; /* record estimates */
    end;
  end;

  print "ALL POSSIBLE MODELS IN SEARCH ORDER";
  print bb[colname=bnames]; free bb;

  bprint=ik`||mse||rsq||betak;
  print "THE BEST MODEL FOR EACH NUMBER OF PARAMETERS";
  print bprint[colname=bnames];
finish;

/*-subroutine to find number of trailing zeros in binary number*/
/* on entry: kk is the number to examine */
/* on exit: ii has the result */
/*-----*/
start ztrail;
  ii=1; zz=kk;
  do while(mod(zz,2)=0); ii=ii+1; zz=zz/2; end;
finish;

/*-----subroutine to sweep in a pivot-----*/
/* on entry: ii has the position(s) to pivot */
/* on exit: in, L, dfe, mse, rsq recalculated */
/*-----*/
start swp;
  if abs(c[ii,ii])<1e-9 then do; print "failure", c;stop;end;
  c=sweep(c,ii);
  in[ii,]^in[ii,];
  L=sum(in); dfe=n-1-L;
  sse=c[k1,k1];
  mse=sse/dfe;

```

```

        rsq=1-sse/ypy;
finish;

/*-----subroutine to collect bprint results-----*/
/* on entry: L,mse,rsq, and c set up to collect */
/* on exit:  bprint has another row */
/*-----*/
start bpr;
    bprint=bprint//(L||mse||rsq||(c[ik,k1]#in)`);
finish;

/*-----stepwise methods-----*/
/* after a call to the initial routine, which sets up*/
/* the data, four different routines can be called */
/* to do four different model-selection methods. */
/*-----*/
start seq;
    run initial;          /* initialization */
    run all;              /* all possible models */
    run forward;          /* forward selection method */
    run backward;         /* backward elimination method*/
    run stepwise;         /* stepwise method */
finish;

/*-----data on physical fitness-----*/
| These measurements were made on men involved in a physical |
| fitness course at N.C.State Univ. The variables are age(years)|
| weight(kg), oxygen uptake rate(ml per kg body weight per |
| minute), time to run 1.5 miles(minutes), heart rate while |
| resting, heart rate while running (same time oxygen rate |
| measured), and maximum heart rate recorded while running. |
| Certain values of maxpulse were modified for consistency. |
| Data courtesy DR. A.C. Linnerud |
*-----*/
data =
{ 44 89.47 44.609 11.37 62 178 182 ,
  40 75.07 45.313 10.07 62 185 185 ,
  44 85.84 54.297 8.65 45 156 168 ,
  42 68.15 59.571 8.17 40 166 172 ,
  38 89.02 49.874 9.22 55 178 180 ,
  47 77.45 44.811 11.63 58 176 176 ,
  40 75.98 45.681 11.95 70 176 180 ,
  43 81.19 49.091 10.85 64 162 170 ,
  44 81.42 39.442 13.08 63 174 176 ,
  38 81.87 60.055 8.63 48 170 186 ,
  44 73.03 50.541 10.13 45 168 168 ,
  45 87.66 37.388 14.03 56 186 192 ,
  45 66.45 44.754 11.12 51 176 176 ,
  47 79.15 47.273 10.60 47 162 164 ,
  54 83.12 51.855 10.33 50 166 170 ,

```


Output 9.6.1 *continued*

bprint								
NPARM	MSE	RSQUARE	AGE	WEIGHT	RUNTIME	RSTPULS	RUNPULS	MAXPULS
1	7.5338	0.7434	0	0	-3.311	0	0	0
2	7.1684	0.7642	-0.15	0	-3.204	0	0	0
3	5.9567	0.8111	-0.256	0	-2.825	0	-0.131	0
4	5.3435	0.8368	-0.198	0	-2.768	0	-0.348	0.2705
5	5.1763	0.848	-0.22	-0.072	-2.683	0	-0.373	0.3049
6	5.3682	0.8487	-0.227	-0.074	-2.629	-0.022	-0.37	0.3032
FORWARD SELECTION METHOD								
bprint								
NPARM	MSE	RSQUARE	AGE	WEIGHT	RUNTIME	RSTPULS	RUNPULS	MAXPULS
1	7.5338	0.7434	0	0	-3.311	0	0	0
2	7.1684	0.7642	-0.15	0	-3.204	0	0	0
3	5.9567	0.8111	-0.256	0	-2.825	0	-0.131	0
4	5.3435	0.8368	-0.198	0	-2.768	0	-0.348	0.2705
BACKWARD ELIMINATION								
bprint								
NPARM	MSE	RSQUARE	AGE	WEIGHT	RUNTIME	RSTPULS	RUNPULS	MAXPULS
6	5.3682	0.8487	-0.227	-0.074	-2.629	-0.022	-0.37	0.3032
5	5.1763	0.848	-0.22	-0.072	-2.683	0	-0.373	0.3049
4	5.3435	0.8368	-0.198	0	-2.768	0	-0.348	0.2705
STEPWISE METHOD								
bprint								
NPARM	MSE	RSQUARE	AGE	WEIGHT	RUNTIME	RSTPULS	RUNPULS	MAXPULS
1	7.5338	0.7434	0	0	-3.311	0	0	0
2	7.1684	0.7642	-0.15	0	-3.204	0	0	0
3	5.9567	0.8111	-0.256	0	-2.825	0	-0.131	0
4	5.3435	0.8368	-0.198	0	-2.768	0	-0.348	0.2705

Example 9.7: Response Surface Methodology

A regression model with a complete quadratic set of regressions across several factors can be processed to yield the estimated critical values that can optimize a response. First, the regression is performed for two variables according to the model

$$y = c + b_1x_1 + b_2x_2 + a_{11}x_1^2 + a_{12}x_1x_2 + a_{22}x_2^2 + e$$

The estimates are then divided into a vector of linear coefficients (estimates) **b** and a matrix of quadratic coefficients **A**. The solution for critical values is

$$\mathbf{x} = -\frac{1}{2}\mathbf{A}^{-1}\mathbf{b}$$

The following program creates a module to perform quadratic response surface regression.

```

/*          Quadratic Response Surface Regression          */
/* This matrix routine reads in the factor variables and   */
/* the response, forms the quadratic regression model and */
/* estimates the parameters, and then solves for the optimal */
/* response, prints the optimal factors and response, and   */
/* displays the eigenvalues and eigenvectors of the         */
/* matrix of quadratic parameter estimates to determine if */
/* the solution is a maximum or minimum, or saddlepoint, and */
/* which direction has the steepest and gentlest slopes.    */
/*                                                         */
/* Given that d contains the factor variables,              */
/* and y contains the response.                             */
/*                                                         */

start rsm;
  n=nrow(d);
  k=ncol(d);
  x=j(n,1,1)||d;
  do i=1 to k;
    do j=1 to i;
      x=x||d[,i] #d[,j];
    end;
  end;
  beta=solve(x`*x,x`*y);
  print "Parameter Estimates" , beta;
  c=beta[1];
  b=beta[2:(k+1)];
  a=j(k,k,0);
  L=k+1;
  do i=1 to k;
    do j=1 to i;
      L=L+1;
      a[i,j]=beta [L,];
    end;
  end;
  a=(a+a`)*.5;
  xx=-.5*solve(a,b);
  print , "Critical Factor Values" , xx;
  /* Compute response at critical value */
  yopt=c + b`*xx + xx`*a*xx;
  print , "Response at Critical Value" yopt;
  call eigen(eval,vec,a);
  print , "Eigenvalues and Eigenvectors", eval, vec;
  if min(eval)>0 then print , "Solution Was a Minimum";
  if max(eval)<0 then print , "Solution Was a Maximum";
finish rsm;

```

```

/* Sample Problem with Two Factors */
d={-1 -1, -1  0, -1  1,
    0 -1,  0  0,  0  1,
    1 -1,  1  0,  1  1};
y={ 71.7, 75.2, 76.3, 79.2, 81.5, 80.2, 80.1, 79.1, 75.8};
run rsm;

```

Running the module with the sample data produces the results shown in [Output 9.7.1](#):

Output 9.7.1 Response Surface Regression: Results

```

Parameter Estimates

      beta

      81.222222
      1.966667
      0.216667
      -3.933333
      -2.225
      -1.383333

Critical Factor Values

      xx

      0.2949376
      -0.158881

                                yopt
Response at Critical Value 81.495032

Eigenvalues and Eigenvectors

      eval

      -0.96621
      -4.350457

      evec

      -0.351076 0.9363469
      0.9363469 0.3510761

Solution Was a Maximum

```

Example 9.8: Logistic and Probit Regression for Binary Response Models

A binary response Y is fit to a linear model according to

$$\begin{aligned}\Pr(Y = 1) &= F(\mathbf{X}\beta) \\ \Pr(Y = 0) &= 1 - F(\mathbf{X}\beta)\end{aligned}$$

where F is some smooth probability distribution function. The normal and logistic distribution functions are supported. The method is maximum likelihood via iteratively reweighted least squares (described by Charnes, Frome, and Yu (1976); Jennrich and Moore (1975); and Nelder and Wedderburn (1972)). The row scaling is done by the derivative of the distribution (density). The weighting is done by $w/p(1-p)$, where w has the counts or other weights. The following program calculates logistic and probit regression for binary response models.

```
/* routine for estimating binary response models */
/* y is the binary response, x are regressors, */
/* wgt are count weights, */
/* model is choice of logit probit, */
/* parm has the names of the parameters */

proc iml ;

start binest;
  b=repeat(0,ncol(x),1);
  oldb=b+1; /* starting values */
  do iter=1 to 20 while(max(abs(b-oldb))>1e-8);
    oldb=b;
    z=x*b;
    run f;
    loglik=sum(((y=1)#log(p) + (y=0)#log(1-p))#wgt);
    btransp=b`;
    print iter loglik btransp;
    w=wgt/(p#(1-p));
    xx=f#x;
    xpxi=inv(xx`*(w#xx));
    b=b + xpxi*(xx`*(w#(y-p)));
  end;
  p0=sum((y=1)#wgt)/sum(wgt); /* average response */
  loglik0=sum(((y=1)#log(p0) + (y=0)#log(1-p0))#wgt);
  chisq=(2#(loglik-loglik0));
  df=ncol(x)-1;
  prob=1-probchi(chisq,df);

  print ,
    'Likelihood Ratio, Intercept-only Model' chisq df prob;;

  stderr=sqrt(vecdiag(xpxi));
  tratio=b/stderr;
  print parm b stderr tratio,;
finish;
```

```

/*---routine to yield distribution function and density---*/
start f;
  if model='LOGIT' then
    do;
      p=1/(1+exp(-z));
      f=p#p#exp(-z);
    end;
  if model='PROBIT' then
    do;
      p=probnorm(z);
      f=exp(-z#z/2)/sqrt(8*atan(1));
    end;
finish;

/* Ingot data from COX (1970, pp. 67-68)*/
data={ 7 1.0 0 10, 14 1.0 0 31, 27 1.0 1 56, 51 1.0 3 13,
       7 1.7 0 17, 14 1.7 0 43, 27 1.7 4 44, 51 1.7 0 1,
       7 2.2 0 7, 14 2.2 2 33, 27 2.2 0 21, 51 2.2 0 1,
       7 2.8 0 12, 14 2.8 0 31, 27 2.8 1 22,
       7 4.0 0 9, 14 4.0 0 19, 27 4.0 1 16, 51 4.0 0 1};
nready=data[,3];
ntotal=data[,4];
n=nrow(data);
x=repeat(1,n,1)||(data[,{1 2}]); /* intercept, heat, soak */
x=x//x; /* regressors */
y=repeat(1,n,1)//repeat(0,n,1); /* binary response */
wgt=nready/(ntotal-nready); /* row weights */
parm={intercept, heat, soak}; /* names of regressors */

model={logit};
run binest; /* run logit model */

model={probit};
run binest; /* run probit model */

```

The results are shown in [Output 9.8.1](#).

Output 9.8.1 Logistic and Probit Regression: Results

iter	loglik	btransp		
1	-268.248	0	0	0
iter	loglik	btransp		
2	-76.29481	-2.159406	0.0138784	0.0037327
iter	loglik	btransp		
3	-53.38033	-3.53344	0.0363154	0.0119734

Output 9.8.1 *continued*

```

iter    loglik    btransp
      4 -48.34609 -4.748899 0.0640013 0.0299201

iter    loglik    btransp
      5 -47.69191 -5.413817 0.0790272 0.04982

iter    loglik    btransp
      6 -47.67283 -5.553931 0.0819276 0.0564395

iter    loglik    btransp
      7 -47.67281 -5.55916 0.0820307 0.0567708

iter    loglik    btransp
      8 -47.67281 -5.559166 0.0820308 0.0567713

                                chisq      df      prob
Likelihood Ratio, Intercept-only Model 11.64282      2 0.0029634

parm          b      stderr      tratio
INTERCEPT -5.559166 1.1196947 -4.964895
HEAT         0.0820308 0.0237345 3.4561866
SOAK         0.0567713 0.3312131 0.1714042

iter    loglik    btransp
      1 -268.248      0      0      0

iter    loglik    btransp
      2 -71.71043 -1.353207 0.008697 0.0023391

iter    loglik    btransp
      3 -51.64122 -2.053504 0.0202739 0.0073888

iter    loglik    btransp
      4 -47.88947 -2.581302 0.032626 0.018503

iter    loglik    btransp
      5 -47.48924 -2.838938 0.0387625 0.0309099

iter    loglik    btransp
      6 -47.47997 -2.890129 0.0398894 0.0356507

```

Output 9.8.1 *continued*

```

            iter    loglik    btransp
              7 -47.47995   -2.89327 0.0399529 0.0362166

            iter    loglik    btransp
              8 -47.47995   -2.893408 0.0399553 0.0362518

            iter    loglik    btransp
              9 -47.47995   -2.893415 0.0399554 0.0362537

            iter    loglik    btransp
             10 -47.47995   -2.893415 0.0399555 0.0362538

            iter    loglik    btransp
             11 -47.47995   -2.893415 0.0399555 0.0362538

                                     chisq      df      prob
Likelihood Ratio, Intercept-only Model 12.028543      2 0.0024436

      parm          b      stderr      tratio
INTERCEPT -2.893415 0.5006009 -5.779884
HEAT         0.0399555 0.0118466 3.3727357
SOAK         0.0362538 0.1467431 0.2470561

      parm          b      stderr      tratio
INTERCEPT -2.893415 0.5006009 -5.779884
HEAT         0.0399555 0.0118466 3.3727357
SOAK         0.0362538 0.1467431 0.2470561

```

Example 9.9: Linear Programming

The two-phase method for linear programming can be used to solve the problem

$$\begin{aligned}
 &\max \mathbf{c}'\mathbf{x} \\
 &\text{st. } \mathbf{Ax} \leq, =, \geq \mathbf{b} \\
 &\mathbf{x} \geq 0
 \end{aligned}$$

A SAS/IML routine that solves this problem follows. The approach appends slack, surplus, and artificial variables to the model where needed. It then solves phase 1 to find a primal feasible solution. If a primal

feasible solution exists and is found, the routine then goes on to phase 2 to find an optimal solution, if one exists. The routine is general enough to handle minimizations as well as maximizations.

```

/* Subroutine to solve Linear Programs */
/* names: names of the decision variables */
/* obj: coefficients of the objective function */
/* maxormin: the value 'MAX' or 'MIN', upper or lowercase */
/* coef: coefficients of the constraints */
/* rel: character array of values: '<=' or '>=' or '=' */
/* rhs: right-hand side of constraints */
/* activity: returns the optimal value of decision variables */
/*
*ods trace output;
proc iml;
start linprog( names, obj, maxormin, coef, rel, rhs, activity);

    bound=1.0e10;
    m=nrow(coef);
    n=ncol(coef);

    /* Convert to maximization */
    if upcase(maxormin)='MIN' then o=-1;
    else o=1;

    /* Build logical variables */
    rev=(rhs<0);
    adj=(-1*rev)+^ rev;
    ge=(( rel = '>=' ) & ^rev) | (( rel = '<=' ) & rev);
    eq=(rel='=');
    if max(ge)=1 then
    do;
        sr=I(m);
        logicals=-sr[,loc(ge)]||I(m);
        artobj=repeat(0,1,ncol(logicals)-m)|| (eq+ge)`;
    end;
    else do;
        logicals=I(m);
        artobj=eq`;
    end;
    nl=ncol(logicals);
    nv=n+nl+2;

    /* Build coef matrix */
    *ods trace output;
    proc iml;
    a=((o*obj)||repeat(0,1,nl)||{ -1 0 })//
      (repeat(0,1,n)||-artobj||{ 0 -1 })//
      ((adj#coef)||logicals||repeat(0,m,2));

    /* rhs, lower bounds, and basis */
    b={0,0}//(adj#rhs);
    L=repeat(0,1,nv-2)||-bound||-bound;
    basis=nv-(0:nv-1);

```

```

    /* Phase 1 - primal feasibility */
call lp(rc,x,y,a,b,nv,,l,basis);
print ( { ' ',
          '*****Primal infeasible problem*****',
          ' ',
          '*****Numerically unstable problem*****',
          '*****Singular basis encountered*****',
          '*****Solution is numerically unstable*****',
          '***Subroutine could not obtain enough memory***',
          '*****Number of iterations exceeded*****'
        }[rc+1]);
if x[nv] ^=0 then
do;
  print '*****Primal infeasible problem*****';
  stop;
end;
if rc>0 then stop;

    /* phase 2 - dual feasibility */
u=repeat(.,1,nv-2)||{ . 0 };
L=repeat(0,1,nv-2)||-bound||0;
call lp(rc,x,y,a,b,nv-1,u,l,basis);

    /* Report the solution */
print ( { '*****Solution is optimal*****',
          '*****Numerically unstable problem*****',
          '*****Unbounded problem*****',
          '*****Solution is numerically unstable*****',
          '*****Singular basis encountered*****',
          '*****Solution is numerically unstable*****',
          '***Subroutine could not obtain enough memory***',
          '*****Number of iterations exceeded*****'
        }[rc+1]);
value=o*x [nv-1];
print , 'Objective Value ' value;
activity= x [1:n] ;
print , 'Decision Variables ' activity[r=names];
lhs=coef*x[1:n];
dual=y[3:m+2];
print , 'Constraints ' lhs rel rhs dual,
          '*****';

finish;

```

Consider the following product mix example (Hadley 1962). A shop with three machines, A, B, and C, turns out products 1, 2, 3, and 4. Each product must be processed on each of the three machines (for example, lathes, drills, and milling machines). The following table shows the number of hours required by each product on each machine:

Machine	Product			
	1	2	3	4
A	1.5	1	2.4	1
B	1	5	1	3.5
C	1.5	3	3.5	1

The weekly time available on each of the machines is 2000, 8000, and 5000 hours, respectively. The products contribute 5.24, 7.30, 8.34, and 4.18 to profit, respectively. What mixture of products can be manufactured that maximizes profit? You can solve the problem as follows:

```
names={'product 1' 'product 2' 'product 3' 'product 4'};
profit={ 5.24 7.30 8.34 4.18};
tech={ 1.5 1 2.4 1 ,
      1 5 1 3.5 ,
      1.5 3 3.5 1 };
time={ 2000, 8000, 5000};
rel={ '<=', '<=', '<=' };
run linprog(names,profit,'max',tech,rel,time,products);
```

The results from this example are shown in [Output 9.9.1](#).

Output 9.9.1 Product Mix: Optimal Solution

```
*****Solution is optimal*****

                                value

Objective Value  12737.059

                                activity

Decision Variables  product 1 294.11765
                   product 2    1500
                   product 3      0
                   product 4 58.823529

                                lhs rel      rhs      dual
Constraints        2000 <=      2000 1.9535294
                   8000 <=      8000 0.2423529
                   5000 <=      5000 1.3782353

*****
```

The following example shows how to find the minimum cost flow through a network by using linear programming. The arcs are defined by an array of tuples; each tuple names a new arc. The elements in the arc tuples give the names of the tail and head nodes that define the arc. The following data are needed: arcs, cost for a unit of flow across the arcs, nodes, and supply and demand at each node.

The following program generates the node-arc incidence matrix and calls the linear program routine for solution:

```
arcs={ 'ab' 'bd' 'ad' 'bc' 'ce' 'de' 'ae' };
cost={ 1 2 4 3 3 2 9 };
nodes={ 'a', 'b', 'c', 'd', 'e' };
supdem={ 2, 0, 0, -1, -1 };
rel=repeat('=',nrow(nodes),1);
inode=substr(arcs,1,1);
onode=substr(arcs,2,1);
free n_a_i n_a_o;
do i=1 to ncol(arcs);
    n_a_i=n_a_i || (inode[i]=nodes);
    n_a_o=n_a_o || (onode[i]=nodes);
end;
n_a=n_a_i - n_a_o;
run linprog(arcs,cost,'min',n_a,rel,supdem,x);
```

The solution is shown in [Output 9.9.2](#).

Output 9.9.2 Minimum Cost Flow: Optimal Solution

*****Solution is optimal*****			
	value		
Objective Value	8		
	activity		
Decision Variables	ab	2	
	bd	2	
	ad	0	
	bc	0	
	ce	0	
	de	1	
	ae	0	
	lhs rel	rhs	dual
Constraints	2 =	2	-2.5
	0 =	0	-1.5
	0 =	0	-0.5
	-1 =	-1	-0.5
	-1 =	-1	-2.5

Example 9.10: Quadratic Programming

The quadratic program

$$\begin{aligned} &\min \mathbf{c}'\mathbf{x} + \mathbf{x}'\mathbf{H}\mathbf{x}/2 \\ &\text{st. } \mathbf{G}\mathbf{x} \leq, =, \geq \mathbf{b} \\ &\mathbf{x} \geq 0 \end{aligned}$$

can be solved by solving an equivalent linear complementarity problem when \mathbf{H} is positive semidefinite. The approach is outlined in the discussion of the [LCP subroutine](#).

The following routine solves the quadratic problem.

```

/*          Routine to solve quadratic programs          */
/* names: the names of the decision variables          */
/* c:  vector of linear coefficients of the objective function */
/* H:  matrix of quadratic terms in the objective function */
/* G:  matrix of constraint coefficients          */
/* rel: character array of values: '<=' or '>=' or '='          */
/* b:   right-hand side of constraints          */
/* activity: returns the optimal value of decision variables */

start qp( names, c, H, G, rel, b, activity);
  if min(eigval(h))<0 then
    do;
      print
        'ERROR: The minimum eigenvalue of the H matrix is negative. ';
      print '      Thus it is not positive semidefinite.          ';
      print '      QP is terminating with this error.            ';
      stop;
    end;
  nr=nrow(G);
  nc=ncol(G);

  /* Put in canonical form */
  rev=(rel='<=');
  adj=(-1 * rev) + ^rev;
  g=adj# G; b = adj # b;
  eq=( rel = '=' );
  if max(eq)=1 then
    do;
      g=g // -(diag(eq)*G)[loc(eq),];
      b=b // -(diag(eq)*b)[loc(eq)];
    end;
  m=(h || -g`) // (g || j(nrow(g),nrow(g),0));
  q=c // -b;

  /* Solve the problem */
  call lcp(rc,w,z,M,q);

```

```

/* Report the solution */
reset noname;
print ( { '*****Solution is optimal*****',
          '*****No solution possible*****',
          ' ',
          ' ',
          ' ',
          '*****Solution is numerically unstable*****',
          '*****Not enough memory*****',
          '*****Number of iterations exceeded*****'}[rc+1]);
reset name;
activity=z[1:nc];
objval=c`activity + activity`*H*activity/2;
print , 'Objective Value ' objval,
        'Decision Variables ' activity[r=names],
        '*****';
finish qp;

```

As an example, consider the following problem in portfolio selection. Models used in selecting investment portfolios include assessment of the proposed portfolio's expected gain and its associated risk. One such model seeks to minimize the variance of the portfolio subject to a minimum expected gain. This can be modeled as a quadratic program in which the decision variables are the proportions to invest in each of the possible securities. The quadratic component of the objective function is the covariance of gain between the securities; the first constraint is a proportionality constraint; and the second constraint gives the minimum acceptable expected gain.

The following data are used to illustrate the model and its solution:

```
c = { 0, 0, 0, 0 } ;
h = { 1003.1 4.3 6.3 5.9 ,
      4.3 2.2 2.1 3.9 ,
      6.3 2.1 3.5 4.8 ,
      5.9 3.9 4.8 10 } ;
g = { 1 1 1 1 ,
      .17 .11 .10 .18 } ;
b = { 1 , .10 } ;
rel = { '=', '>=' } ;
names = { 'ibm', 'dec', 'dg', 'prime' } ;
run qp(names,c,h,g,rel,b,activity);
```

The results in [Output 9.10.1](#) show that the minimum variance portfolio achieving the 0.10 expected gain is composed of DEC and DG stock in proportions of 0.933 and 0.067.

Output 9.10.1 Portfolio Selection: Optimal Solution

```
*****Solution is optimal*****  
  
objval  
  
Objective Value   1.096667
```

Output 9.10.1 continued

activity		
Decision Variables	ibm	0
	dec	0.9333333
	dg	0.0666667
	prime	0

Example 9.11: Regression Quantiles

The technique of estimating parameters in linear models by using the notion of regression quantiles is a generalization of the LAE or LAV least absolute value estimation technique. For a given quantile q , the estimate \mathbf{b}^* of β in the model

$$\mathbf{Y} = \mathbf{X}\beta + \epsilon$$

is the value of b that minimizes

$$\sum_{t \in T} q|y_t - x_t b| - \sum_{t \in S} (1 - q)|y_t - x_t b|$$

where $T = \{t | y_t \geq x_t b\}$ and $S = \{t | y_t \leq x_t b\}$. For $q = 0.5$, the solution \mathbf{b}^* is identical to the estimates produced by the LAE. The following routine finds this estimate by using linear programming.

```

/* Routine to find regression quantiles */
/* yname:   name of dependent variable */
/* y:       dependent variable */
/* xname:   names of independent variables */
/* X:       independent variables */
/* b:       estimates */
/* predict: predicted values */
/* error:   difference of y and predicted. */
/* q:       quantile */
/*
/* notes:   This subroutine finds the estimates b
/* that minimize
/*
/*          q * (y - Xb) * e + (1-q) * (y - Xb) * ^e
/*
/* where e = ( Xb <= y ).
/*
/* This subroutine follows the approach given in:
/*
/* Koenker, R. and G. Bassett (1978). Regression
/* quantiles. Econometrica. Vol. 46. No. 1. 33-50.
/*
/* Bassett, G. and R. Koenker (1982). An empirical

```

```

/* quantile function for linear models with iid errors.      */
/* JASA. Vol. 77. No. 378. 407-415.                        */
/*                                                          */
/* When q = .5 this is equivalent to minimizing the sum    */
/* of the absolute deviations, which is also known as      */
/* L1 regression. Note that for L1 regression, a faster     */
/* and more accurate algorithm is available in the SAS/IML  */
/* routine LAV, which is based on the approach given in:    */
/*                                                          */
/* Madsen, K. and Nielsen, H. B. (1993). A finite          */
/* smoothing algorithm for linear L1 estimation.           */
/* SIAM J. Optimization, Vol. 3. 223-235.                  */
/*-----*/
start rq( yname, y, xname, X, b, predict, error, q);
  bound=1.0e10;
  coef = X`;
  m = nrow(coef);
  n = ncol(coef);

/*-----build rhs and bounds-----*/
  e = repeat(1,1,n)`;
  r = {0 0} || ((1-q)*coef*e)`;
  sign = repeat(1,1,m);

  do i=1 to m;
    if r[2+i] < 0 then do;
      sign[i] = -1;
      r[2+i] = -r[2+i];
      coef[i,] = -coef[i,];
    end;
  end;

  l = repeat(0,1,n) || repeat(0,1,m) || -bound || -bound ;
  u = repeat(1,1,n) || repeat(.,1,m) || { . . } ;

/*-----build coefficient matrix and basis-----*/
  a = ( y` || repeat(0,1,m) || { -1 0 } ) //
      ( repeat(0,1,n) || repeat(-1,1,m) || { 0 -1 } ) //
      ( coef || I(m) || repeat(0,m,2) );
  basis = n+m+2 - (0:n+m+1);

/*-----find a feasible solution-----*/
call lp(rc,p,d,a,r,,u,l,basis);

/*-----find the optimal solution-----*/
  l = repeat(0,1,n) || repeat(0,1,m) || -bound || {0} ;
  u = repeat(1,1,n) || repeat(0,1,m) || { . 0 } ;
call lp(rc,p,d,a,r,n+m+1,u,l,basis);

/*----- report the solution-----*/
variable = xname`; b=d[3:m+2];
do i=1 to m;
  b[i] = b[i] * sign[i];

```

```

end;
predict = X*b;
error = y - predict;
wsum = sum ( choose(error<0 , (q-1)*error , q*error) );

print , 'Regression Quantile Estimation' ,
        'Dependent Variable: ' yname ,
        'Regression Quantile: ' q ,
        'Number of Observations: ' n ,
        'Sum of Weighted Absolute Errors: ' wsum ,
        variable b,
        X y predict error;
finish rq;

```

The following example uses data on the United States population from 1790 to 1970:

```

z = { 3.929 1790 ,
      5.308 1800 ,
      7.239 1810 ,
      9.638 1820 ,
      12.866 1830 ,
      17.069 1840 ,
      23.191 1850 ,
      31.443 1860 ,
      39.818 1870 ,
      50.155 1880 ,
      62.947 1890 ,
      75.994 1900 ,
      91.972 1910 ,
      105.710 1920 ,
      122.775 1930 ,
      131.669 1940 ,
      151.325 1950 ,
      179.323 1960 ,
      203.211 1970 };

y=z[,1];
x=repeat(1,19,1)||z[,2]||z[,2]##2;
run rq('pop',y,{ 'intercpt' 'year' 'yearsq' },x,b1,pred,resid,.5);

```

The results are shown in [Output 9.11.1](#).

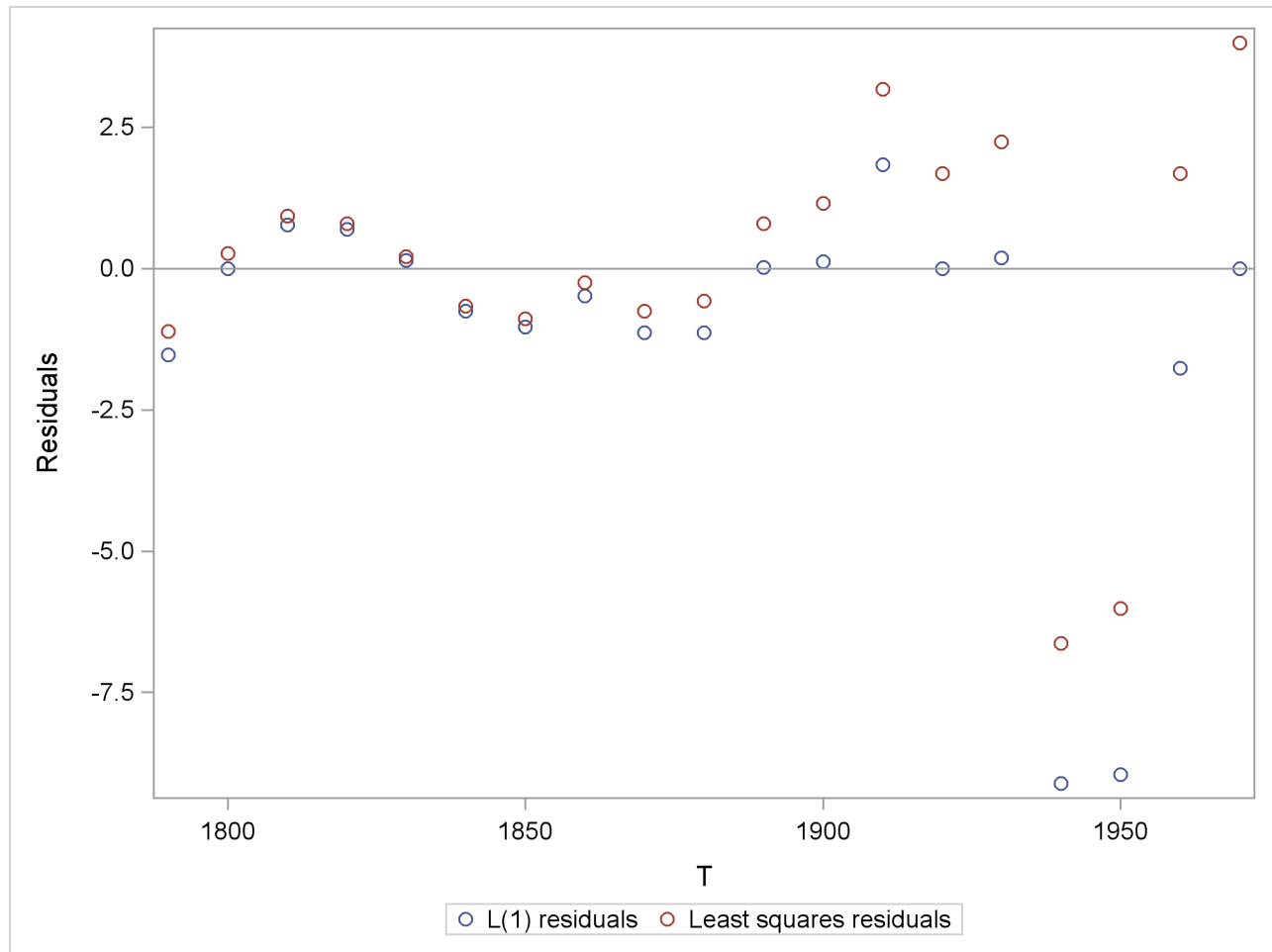
Output 9.11.1 Regression Quantiles: Results

Regression Quantile Estimation	
	yname
Dependent Variable:	pop
	q
Regression Quantile:	0.5

Output 9.11.1 *continued*

			n		
Number of Observations:			19		
			wsum		
Sum of Weighted Absolute Errors:			14.826429		
variable			b		
intercpt			21132.758		
year			-23.52574		
yearsq			0.006549		
X			y	predict	error
1	1790	3204100	3.929	5.4549176	-1.525918
1	1800	3240000	5.308	5.308	-4.54E-12
1	1810	3276100	7.239	6.4708902	0.7681098
1	1820	3312400	9.638	8.9435882	0.6944118
1	1830	3348900	12.866	12.726094	0.1399059
1	1840	3385600	17.069	17.818408	-0.749408
1	1850	3422500	23.191	24.220529	-1.029529
1	1860	3459600	31.443	31.932459	-0.489459
1	1870	3496900	39.818	40.954196	-1.136196
1	1880	3534400	50.155	51.285741	-1.130741
1	1890	3572100	62.947	62.927094	0.0199059
1	1900	3610000	75.994	75.878255	0.1157451
1	1910	3648100	91.972	90.139224	1.8327765
1	1920	3686400	105.71	105.71	8.669E-13
1	1930	3724900	122.775	122.59058	0.1844157
1	1940	3763600	131.669	140.78098	-9.111976
1	1950	3802500	151.325	160.28118	-8.956176
1	1960	3841600	179.323	181.09118	-1.768184
1	1970	3880900	203.211	203.211	-2.96E-12

The L1 norm (when $q = 0.5$) tends to cause the fit to be better at more points at the expense of causing some points to fit worse, as shown by the following plot, which compares the L1 residuals with the least squares residuals.

Output 9.11.2 L1 Residuals vs. Least Squares Residuals

When $q = 0.5$, the results of this module can be compared with the results of the LAV routine, as follows:

```

b0 = {1 1 1};          /* initial value          */
optn = j(4,1,.);        /* options vector        */

optn[1]= .;             /* gamma default         */
optn[2]= 5;             /* print all              */
optn[3]= 0;             /* McKean-Schrader variance */
optn[4]= 1;            /* convergence test       */

call LAV(rc, xr, x, y, b0, optn);

```

Example 9.12: Simulations of a Univariate ARMA Process

Simulations of time series with known ARMA structure are often needed as part of other simulations or as learning data sets for developing time series analysis skills. The following program generates a time

series by using the IML functions NORMAL, ARMACOV, HANKEL, PRODUCT, RATIO, TOEPLITZ, and ROOT.

```

proc iml;
reset noname;
start armasim(y,n,phi,theta,seed);
/*-----*/
/* IML Module: armasim */
/* Purpose: Simulate n data points from ARMA process */
/*          exact covariance method */
/* Arguments: */
/* */
/* Input: n      : series length */
/*        phi    : AR coefficients */
/*        theta  : MA coefficients */
/*        seed   : integer seed for normal deviate generator */
/* Output: y: realization of ARMA process */
/* -----*/

p=ncol(phi)-1;
q=ncol(theta)-1;
y=normal(j(1,n+q,seed));

/* Pure MA or white noise */
if p=0 then y=product(theta,y)[(q+1):(n+q)];
else do; /* Pure AR or ARMA */

/* Get the autocovariance function */
call armacov(gamma,cov,ma,phi,theta,p);
if gamma[1]<0 then
do;
print 'ARMA parameters not stable.';
print 'Execution terminating.';
stop;
end;

/* Form covariance matrix */
gamma=toeplitz(gamma);

/* Generate covariance between initial y and */
/* initial innovations */
if q>0 then
do;
psi=ratio(phi,theta,q);
psi=hankel(psi[-((-q):(-1))]);
m=max(1,(q-p+1));
psi=psi[-((-q):(-m)),];
if p>q then psi=j(p-q,q,0)//psi;
gamma=(gamma||psi)/(psi`||i(q));
end;

/* Use Cholesky root to get startup values */
gamma=root(gamma);
startup=y[,1:(p+q)]*gamma;

```

```

e=y[, (p+q+1):(n+q)];

/* Generate MA part */
if q>0 then
do;
e=startup[, (p+1):(p+q)]||e;
e=product(theta,e)[:, (q+1):(n+q-p)];
end;

y=startup[, 1:p];
phil=phi[, -(-(p+1):(-2))]`;

/* Use difference equation to generate */
/* remaining values */
do ii=1 to n-p;
y=y|| (e[, ii]-y[, ii:(ii+p-1)]*phil);
end;
end;
y=y`;
finish armasim; /* ARMASIM */

run armasim(y,10,{1 -0.8},{1 0.5},1234321);
print , 'Simulated Series:', y;

```

The results are shown in [Output 9.12.1](#).

Output 9.12.1 Simulated Series

Simulated Series:	
	3.0764594
	1.8931735
	0.9527984
	0.0892395
	-1.811471
	-2.8063
	-2.52739
	-2.865251
	-1.332334
	0.1049046

Example 9.13: Parameter Estimation for a Regression Model with ARMA Errors

Nonlinear estimation algorithms are required for obtaining estimates of the parameters of a regression model with innovations having an ARMA structure. The three estimation methods employed by the ARIMA procedure in SAS/ETS software are written in IML in the following program. The algorithms employed are slightly different from those used by PROC ARIMA, but the results obtained should be similar. This example combines the IML functions ARMALIK, PRODUCT, and RATIO to perform the estimation. Note

the interactive nature of this example, illustrating how you can adjust the estimates when they venture outside the stationary or invertible regions.

```

/*-----*/
/*----  Grunfeld's Investment Models Fit with ARMA Errors  ----*/
/*-----*/
data grunfeld;
  input year gei gef gec wi wf wc;
  label gei='gross investment ge'
        gec='capital stock lagged ge'
        gef='value of outstanding shares ge lagged'
        wi='gross investment w'
        wc='capital stock lagged w'
        wf='value of outstanding shares lagged w';
/*----  GE STANDS FOR GENERAL ELECTRIC AND W FOR WESTINGHOUSE  ----*/
datalines;
1935      33.1      1170.6      97.8      12.93      191.5      1.8
1936      45.0      2015.8      104.4      25.90      516.0      .8
1937      77.2      2803.3      118.0      35.05      729.0      7.4
1938      44.6      2039.7      156.2      22.89      560.4      18.1
1939      48.1      2256.2      172.6      18.84      519.9      23.5
1940      74.4      2132.2      186.6      28.57      628.5      26.5
1941     113.0      1834.1      220.9      48.51      537.1      36.2
1942      91.9      1588.0      287.8      43.34      561.2      60.8
1943      61.3      1749.4      319.9      37.02      617.2      84.4
1944      56.8      1687.2      321.3      37.81      626.7      91.2
1945      93.6      2007.7      319.6      39.27      737.2      92.4
1946     159.9      2208.3      346.0      53.46      760.5      86.0
1947     147.2      1656.7      456.4      55.56      581.4     111.1
1948     146.3      1604.4      543.4      49.56      662.3     130.6
1949      98.3      1431.8      618.3      32.04      583.8     141.8
1950      93.5      1610.5      647.4      32.24      635.2     136.7
1951     135.2      1819.4      671.3      54.38      723.8     129.7
1952     157.3      2079.7      726.1      71.78      864.1     145.5
1953     179.5      2371.6      800.3      90.08     1193.5     174.8
1954     189.6      2759.9      888.9      68.60     1188.9     213.5
;
run;

proc iml;
reset noname;
/*-----*/
/*  name: ARMAREG Modules                                     */
/*  purpose: Perform Estimation for regression model with    */
/*  ARMA errors                                              */
/*  usage: Before invoking the command                       */
/*  run armareg;                                             */
/*  define the global parameters                            */
/*  x      - matrix of predictors.                           */
/*  y      - response vector.                                */
/*  iphi   - defines indices of nonzero AR parameters,      */

```

```

/*      omit the index 0 which corresponds to the zero */
/*      order constant one. */
/*      itheta - defines indices of nonzero MA parameters, */
/*      omit the index 0 which corresponds to the zero */
/*      order constant one. */
/*      ml      - estimation option: -1 if Conditional Least */
/*      Squares, 1 if Maximum Likelihood, otherwise */
/*      Unconditional Least Squares. */
/*      delta   - step change in parameters (default 0.005). */
/*      par      - initial values of parms. First ncol(iphi) */
/*      values correspond to AR parms, next ncol(itheta) */
/*      values correspond to MA parms, and remaining */
/*      are regression coefficients. */
/*      init     - undefined or zero for first call to ARMAREG. */
/*      maxit    - maximum number of iterations. No other */
/*      convergence criterion is used. You can invoke */
/*      ARMAREG without changing parameter values to */
/*      continue iterations. */
/*      nopr     - undefined or zero implies no printing of */
/*      intermediate results. */
/*      notes: Optimization using Gauss-Newton iterations */
/*      No checking for invertibility or stationarity during */
/*      estimation process. The parameter array par can be */
/*      modified after running armareg to place estimates */
/*      in the stationary and invertible regions, and then */
/*      armareg can be run again. If a nonstationary AR operator */
/*      is employed, a PAUSE will occur after calling ARMALIK */
/*      because of a detected singularity. Using STOP will */
/*      permit termination of ARMAREG so that the AR */
/*      coefficients can be modified. */
/*      T-ratios are only approximate and can be undependable, */
/*      especially for small series. */
/*      The notation follows that of the IML function ARMALIK; */
/*      the autoregressive and moving average coefficients have */
/*      signs opposite those given by PROC ARIMA. */

/* Begin ARMA estimation modules */

/* Generate residuals */
start gres;
  noise=y-x*beta;
  previous=noise[:];
  if ml=-1 then do; /* Conditional LS */
    noise=j(nrow(y),1,previous)//noise;
    resid=product(phi,noise`)[,nrow(y)+1:nrow(noise)];
    resid=ratio(theta,resid,ncol(resid));
    resid=resid[,1:ncol(resid)]`;
  end;
  else do; /* Maximum likelihood */
    free l;

```

```

    call armalik(1,resid,std,noise,phi,theta);

    /* Nonstationary condition produces PAUSE */
    if nrow(1)=0 then do;
        print ,
        'In GRES: Parameter estimates outside stationary region.';
    end;
    else do;
        temp=l[3,]/(2#nrow(resid));
        if ml=1 then resid=resid#exp(temp);
    end;
end;
finish gres;                                /* finish module GRES */

start getpar;                                /* get parameters */
    if np=0 then phi=1;
    else do;
        temp=parm[,1:np];
        phi=1||j(1,p,0);
        phi[,iphi] =temp;
    end;
    if nq=0 then theta=1;
    else do;
        temp=parm[,np+1:np+nq];
        theta=1||j(1,q,0);
        theta[,itheta] =temp;
    end;
    beta=parm[(np+nq+1):ncol(parm)]`;
finish getpar;    /* finish module GETPAR */

/* Get SS Matrix - First Derivatives */
start getss;
    parm=par;
    run getpar;
    run gres;
    s=resid;
    oldsse=ssq(resid);
    do k=1 to ncol(par);
        parm=par;
        parm[,k]=parm[,k]+delta;
        run getpar;
        run gres;
        s=s||((resid-s[,1])/delta);    /* append derivatives */
    end;
    ss=s`s;
    if nopr^=0 then print , 'Gradient Matrix', ss;
    sssave=ss;
    do k=1 to 20;    /* Iterate if no reduction in SSE */
        do ii=2 to ncol(ss);
            ss[ii,ii]=(1+lambda)*ss[ii,ii];
        end;
        ss=sweep(ss,2:ncol(ss));    /* Gaussian elimination */
        delpar=ss[1,2:ncol(ss)];    /* update parm increments */
    end;
end;

```

```

parm=par+delpar;
run getpar;
run gres;
sse=ssq(resid);
ss=sssave;
if sse<oldsse then do;          /* reduction, no iteration */
    lambda=max(lambda/10,1e-12);
    k=21;
end;
else do;                        /* no reduction */
    /* increase lambda and iterate */
    if nopr^=0 then print ,
        'Lambda=' lambda 'SSE=' sse 'OLDSSE=' oldsse,
        'Gradient Matrix', ss ;
    lambda=min(10*lambda,1e12);
    if k=20 then do;
        print 'In module GETSS:'
            'No improvement in SSE after twenty iterations.';
        print ' Possible Ridge Problem. ';
        return;
    end;
end;
end;
if nopr^=0 then print , 'Gradient Matrix', ss;
finish getss;                  /* Finish module GETSS */

start armareg;                  /* ARMAREG main module */
/* Initialize options and parameters */
if nrow(delta)=0 then delta=0.005;
if nrow(maxiter)=0 then maxiter=5;
if nrow(nopr)=0 then nopr=0;
if nrow(ml)=0 then ml=1;
if nrow(init)=0 then init=0;
if init=0 then do;
    p=max(iphi);
    q=max(itheta);
    np=ncol(iphi);
    nq=ncol(itheta);

    /* Make indices one-based */
    do k=1 to np;
        iphi[,k]=iphi[,k]+1;
    end;
    do k=1 to nq;
        itheta[,k]=itheta[,k]+1;
    end;

    /* Create row labels for Parameter estimates */
    if p>0 then parmname = concat("AR",char(1:p,2));
    if q>0 then parmname = parmname||concat("MA",char(1:q,2));
    parmname = parmname||concat("B",char(1:ncol(x),2));

    /* Create column labels for Parameter estimates */
    pname = {"Estimate" "Std. Error" "T-Ratio"};

```

```

    init=1;
end;

/* Generate starting values */
if nrow(par)=0 then do;
    beta=inv(x`*x)*x`*y;
    if np+nq>0 then par=j(1,np+nq,0)||beta`;
    else par=beta`;
end;
print , 'Parameter Starting Values',;
print par [colname=parmname];          /* stderr tratio */
lambda=1e-6;                          /* Controls step size */
do iter=1 to maxiter;                  /* Do maxiter iterations */
    run getss;
    par=par+delpar;
    if nopr^=0 then do;
        print , 'Parameter Update',;
        print par [colname=parmname];    /* stderr tratio */
        print , 'Lambda=' lambda,;
    end;
end;

sighat=sqrt(sse/(nrow(y)-ncol(par)));
print , 'Innovation Standard Deviation:' sighat;
ss=sweep(ss,2:ncol(ss));              /* Gaussian elimination */
estm=par`||(sqrt(diag(ss[2:ncol(ss),2:ncol(ss)]))
    *j(ncol(par),1,sighat));
estm=estm||(estm[,1] /estm[,2]);
if ml=1 then print , 'Maximum Likelihood Estimation Results',;
else if ml=-1 then print ,
    'Conditional Least Squares Estimation Results',;
else print , 'Unconditional Least Squares Estimation Results',;
print estm [rowname=parmname colname=pname] ;
finish armareg;
/* End of ARMA Estimation modules */

/* Begin estimation for Grunfeld's investment models */
use grunfeld;
read all var {gei} into y;
read all var {gef gec} into x;
close grunfeld;

x=j(nrow(x),1,1)||x;
iphi=1;
itheta=1;
maxiter=10;
delta=0.0005;
ml=-1;
/*----- To prevent overflow, specify starting values -----*/
par={-0.5 0.5 -9.956306 0.0265512 0.1516939};
run armareg; /*----- Perform CLS estimation -----*/

```

The results are shown in [Output 9.13.1](#).

Output 9.13.1 Conditional Least Squares Results

Parameter Starting Values				
AR 1	MA 1	B 1	B 2	B 3
-0.5	0.5	-9.956306	0.0265512	0.1516939
In module GETSS: No improvement in SSE after twenty iterations.				
Possible Ridge Problem.				
In module GETSS: No improvement in SSE after twenty iterations.				
Possible Ridge Problem.				
In module GETSS: No improvement in SSE after twenty iterations.				
Possible Ridge Problem.				
Innovation Standard Deviation: 22.653769				
Conditional Least Squares Estimation Results				
	Estimate	Std. Error	T-Ratio	
AR 1	-0.230905	0.3429525	-0.673287	
MA 1	0.69639	0.2480617	2.8073252	
B 1	-20.87774	31.241368	-0.668272	
B 2	0.038706	0.0167503	2.3107588	
B 3	0.1216554	0.0441722	2.7541159	

```

/*---- With CLS estimates as starting values, ----*/
/*---- perform ML estimation. ----*/
ml=1;
maxiter=10;
run armareg;

```

The results are shown in [Output 9.13.2](#).

Output 9.13.2 Maximum Likelihood Results

	Estimate	Std. Error	T-Ratio
AR 1	-0.230905	0.3429525	-0.673287
MA 1	0.69639	0.2480617	2.8073252
B 1	-20.87774	31.241368	-0.668272
B 2	0.038706	0.0167503	2.3107588
B 3	0.1216554	0.0441722	2.7541159
Parameter Starting Values			

Output 9.13.2 *continued*

AR 1	MA 1	B 1	B 2	B 3
-0.230905	0.69639	-20.87774	0.038706	0.1216554
Innovation Standard Deviation: 23.039253				
Maximum Likelihood Estimation Results				
	Estimate	Std. Error	T-Ratio	
AR 1	-0.196224	0.3510868	-0.558904	
MA 1	0.6816033	0.2712043	2.5132468	
B 1	-26.47514	33.752826	-0.784383	
B 2	0.0392213	0.0165545	2.3692242	
B 3	0.1310306	0.0425996	3.0758622	

Example 9.14: Iterative Proportional Fitting

The classical use of iterative proportional fitting is to adjust frequencies to conform to new marginal totals. Use the IPF subroutine to perform this kind of analysis. You supply a table that contains new margins and a table that contains old frequencies. The IPF subroutine returns a table of adjusted frequencies that preserves any higher-order interactions appearing in the initial table.

The following example is a census study that estimates a population distribution according to age and marital status (Bishop, Fienberg, and Holland 1975). Estimates of the distribution are known for the previous year, but only estimates of marginal totals are known for the current year. You want to adjust the distribution of the previous year to fit the estimated marginal totals of the current year. Here is the program:

```
proc iml;

    /* Stopping criteria */
    mod={0.01 15};

    /* Marital status has 3 levels. age has 8 levels. */
    dim={3 8};

    /* New marginal totals for age by marital status */
    table={1412 0 0 ,
           1402 0 0 ,
           1174 276 0 ,
           0 1541 0 ,
           0 1681 0 ,
           0 1532 0 ,
           0 1662 0 ,
           0 5010 2634};

    /* Marginal totals are known for both */
    /* marital status and age */
```

```

config={1 2};

/* Use known distribution for start-up values */
initab={1306 83 0 ,
        619 765 3 ,
        263 1194 9 ,
        173 1372 28 ,
        171 1393 51 ,
        159 1372 81 ,
        208 1350 108 ,
        1116 4100 2329};

call ipf(fit,status,dim,table,config,initab,mod);

c={' SINGLE' ' MARRIED' 'WIDOWED/DIVORCED'};
r={'15 - 19' '20 - 24' '25 - 29' '30 - 34' '35 - 39' '40 - 44'
   '45 - 49' '50 OR OVER'};
print
'POPULATION DISTRIBUTION ACCORDING TO AGE AND MARITAL STATUS',,
'KNOWN DISTRIBUTION (PREVIOUS YEAR)',,
initab [colname=c rowname=r format=8.0] ,,
'ADJUSTED ESTIMATES OF DISTRIBUTION (CURRENT YEAR)',,
fit [colname=c rowname=r format=8.2] ;

```

The results are shown in [Output 9.14.1](#).

Output 9.14.1 Iterative Proportional Fitting: Results

POPULATION DISTRIBUTION ACCORDING TO AGE AND MARITAL STATUS			
KNOWN DISTRIBUTION (PREVIOUS YEAR)			
	initab		
	SINGLE	MARRIED	WIDOWED/DIVORCED
15 - 19	1306	83	0
20 - 24	619	765	3
25 - 29	263	1194	9
30 - 34	173	1372	28
35 - 39	171	1393	51
40 - 44	159	1372	81
45 - 49	208	1350	108
50 OR OVER	1116	4100	2329
ADJUSTED ESTIMATES OF DISTRIBUTION (CURRENT YEAR)			

Output 9.14.1 *continued*

	fit		
	SINGLE	MARRIED	WIDOWED/DIVORCED
15 - 19	1325.27	86.73	0.00
20 - 24	615.56	783.39	3.05
25 - 29	253.94	1187.18	8.88
30 - 34	165.13	1348.55	27.32
35 - 39	173.41	1454.71	52.87
40 - 44	147.21	1308.12	76.67
45 - 49	202.33	1352.28	107.40
50 OR OVER	1105.16	4181.04	2357.81

Example 9.15: Full-Screen Nonlinear Regression

This example shows how to build a menu system that enables you to perform nonlinear regression from a menu. Six modules are stored on an IML storage disk. After you have stored them, use this example to try out the system. First, invoke IML and set up some sample data in memory, in this case the population of the U.S. from 1790 to 1970. Then invoke the module NLIN, as follows:

```
reset storage='nlin';
load module=_all_;
uspop = {3929, 5308, 7239, 9638, 12866, 17069, 23191, 31443,
         39818, 50155, 62947, 75994, 91972, 105710, 122775, 131669,
         151325, 179323, 203211}/1000;
year=do(1790,1970,10)`;
time=year-1790;
print year time uspop;
run nlin;
```

A menu similar to the following menu appears. The entry fields are shown by underscores here, but the underscores become blanks in the real session.

```
Nonlinear Regression
Response function: _____
Predictor function: _____

Parameter Value Derivative
: _____
: _____
: _____
: _____
: _____
: _____
```

Enter an exponential model and fill in the response and predictor expression fields. For each parameter, enter the name, initial value, and derivative of the predictor with respect to the parameter. Here are the populated fields:

Nonlinear Regression

Response function: uspop_____

Predictor function: $a_0 \exp(a_1 \text{time})$ _____

Parameter Value Derivative

: a0	_____	3.9	exp(a1*time)	_____
: a1	_____	0	time*a0*exp(a1*time)	_____
:	_____			_____
:	_____			_____
:	_____			_____
:	_____			_____

Now press the SUBMIT key. The model compiles, the iterations start blinking on the screen, and when the model has converged, the estimates are displayed along with their standard errors, t test, and significance probability.

To modify and rerun the model, submit the following command:

```
run nlrn;
```

Here is the program that defines and stores the modules of the system.

```
/*          Full-Screen Nonlinear Regression          */
/* Six modules are defined, which constitute a system for */
/* nonlinear regression. The interesting feature of this */
/* system is that the problem is entered in a menu, and both */
/* iterations and final results are displayed on the same */
/* menu. */
/* */
/* Run this source to get the modules stored. Examples */
/* of use are separate. */
/* */
/* Caution: this is a demonstration system only. It does not */
/* have all the necessary safeguards in it yet to */
/* recover from user errors or rough models. */
/* Algorithm: */
/*   Gauss-Newton nonlinear regression with step-halving. */
/* Notes: program variables all start with nd or _ to */
/* minimize the problems that would occur if user variables */
/* interfered with the program variables. */

/* Gauss-Newton nonlinear regression with Hartley step-halving */

/*---Routine to set up display values for new problem---*/
start nlnit;
  window nlin rows=15 columns=80 color='green'
    msgline=_msg cmdndline=_cmdnd
    group=title +30 'Nonlinear Regression' color='white'
    group=model / @5 'Response function:' color='white'
    +1 nddep $55. color='blue'
    / @5 'Predictor function:' color='white'
```

```

+1 ndfun $55. color='blue'
group=parm0 // @5 'Parameter' color='white' @15 'Value'
@30 'Derivative'
group=parm1 // @5 'Parameter' color='white' @15 'Value'
group=parm2 // @5 'Parameter' color='white' @19 'Estimate'
@33 'Std Error'
@48 'T Ratio'
@62 'Prob>|T|'
group=parminit /@3 ':' color='white'
@5 ndparm $8. color='blue'
@15 ndbeta best12. @30 ndder $45.
group=parmiter / @5 _parm color='white'
@15 _beta best12. color='blue'
group=parmest / @5 _parm color='white'
@15 _beta best12. color='blue'
@30 _std best12.
@45 _t 10.4
@60 _prob 10.4
group=sse // @5 'Iteration =' color='white' _iter 5. color='blue'
' Stephalvings = ' color='white' _subit 3. color='blue'
/ @5 'Sum of Squares Error =' color='white' _sse best12.
color='blue';
nddep=cshape(' ',1,1,55,' ');
ndfun=nddep;
nd0=6;
ndparm=repeat(' ',nd0,1);
ndbeta=repeat(0,nd0,1);
ndder=cshape(' ',nd0,1,55,' ');
_msg='Enter New Nonlinear Problem';
finish nlininit; /* Finish module NLINIT */

/* Main routine */
start nlin;
run nlininit; /* initialization routine */
run nlrn; /* run routine */
finish nlin;

/* Routine to show each iteration */
start nliter;
display nlin.title noinput,
nlin.model noinput,
nlin.parm1 noinput,
nlin.parmiter repeat noinput,
nlin.sse noinput;
finish nliter;

/* Routine for one run */
start nlrn;
run nlgen; /* generate the model */
run nlest; /* estimate the model */
finish nlrn;

/* Routine to generate the model */

```

```

start nlgen;

/* Model definition menu */
display nlin.title, nlin.model, nlin.parm0, nlin.parminit repeat;

/* Get number of parameters */
t=loc(ndparm=' ');
if nrow(t)=0 then
do;
  print 'no parameters';
  stop;
end;
_k=t[1] -1;

/* Trim extra rows, and edit '*' to '#' */
_dep=nddep; call change(_dep, '*', '#', 0);
_fun=ndfun; call change(_fun, '*', '#', 0);
_parm=ndparm[1:_k,];
_beta=ndbeta[1:_k,];
_der=ndder [1:_k,];
call change(_der, '*', '#', 0);

/* Construct nlresid module to split up parameters and */
/* compute model */
call queue('start nlresid;');
do i=1 to _k;
  call queue(_parm[i] , "=_beta[" , char(i,2) , "]" );
end;
call queue("_y = " , _dep, ";",
          "_p = " , _fun, ";",
          "_r = _y-_p;",
          "_sse = ssq(_r);",
          "finish;" );

/* Construct nlderiv function */
call queue('start nlderiv; _x = ');
do i=1 to _k;
  call queue("(" , _der[i] , ")#repeat(1,nobs,1)||");
end;
call queue(" nlnothin; finish;");

/* Pause to compile the functions */
call queue("resume;");
pause *;
finish nlgen; /* Finish module NLGEN */

/* Routine to do estimation */
start nlest;

/* Modified Gauss-Newton Nonlinear Regression */
/* _parm has parm names */
/* _beta has initial values for parameters */
/* _k is the number of parameters */

```

```

/* after nlresid: */
/* _y has response, */
/* _p has predictor after call */
/* _r has residuals */
/* _sse has sse */
/* after nlderiv */
/* _x has jacobian */
/* */

eps=1;
_iter = 0;
_subit = 0;
_error = 0;
run nlresid;          /* f, r, and sse for initial beta */
run nliter;           /* print iteration zero */
nobs = nrow(_y);
_msg = 'Iterating';

/* Gauss-Newton iterations */
do _iter=1 to 30 while(eps>1e-8);
  run nlderiv;        /* subroutine for derivatives */
  _lastsse=_sse;
  _xpxi=sweep(_x`*_x);
  _delta=_xpxi*_x`*_r; /* correction vector */
  _old = _beta;        /* save previous parameters */
  _beta=_beta+_delta;  /* apply the correction */
  run nlresid;         /* compute residual */
  run nliter;          /* print iteration in window */
  eps=abs((_lastsse-_sse))/(_sse+1e-6);
                      /* convergence criterion */

  /* Hartley subiterations */
  do _subit=1 to 10 while(_sse>_lastsse);
    _delta=_delta*.5; /* halve the correction vector */
    _beta=_old+_delta; /* apply the halved correction */
    run nlresid;      /* find sse et al */
    run nliter;       /* print subiteration in window */
  end;
  if _subit>10 then
  do;
    _msg = "did not improve after 10 halvings";
    eps=0; /* make it fall through iter loop */
  end;
end;

/* print out results */
_msg = ' ';
if _iter>30 then
do;
  _error=1;
  _msg = 'convergence failed';
end;
_iter=_iter-1;

```



```

_dfe = nobs-_k;
_mse = _sse/_dfe;
_std = sqrt(vecdiag(_xpxi)#_mse);
_t = _beta/_std;
_prob= 1-probf(_t#_t,1,_dfe);
display nlin.title noinput,
nlin.model noinput,
nlin.parm2 noinput,
nlin.parmest repeat noinput,
nlin.sse noinput;
finish nlest;                                /* Finish module NLEST */

/* Store the modules to run later */
reset storage='nlin';
store module=_all_;

```

References

- Bishop, Y. M. M., Fienberg, S. E., and Holland, P. W. (1975), *Discrete Multivariate Analysis: Theory and Practice*, Cambridge, MA: MIT Press.
- Charnes, A., Frome, E. L., and Yu, P. L. (1976), “The Equivalence of Generalized Least Squares and Maximum Likelihood Estimation in the Exponential Family,” *Journal of the American Statistical Association*, 71, 169–172.
- Cox, D. R. (1970), *Analysis of Binary Data*, London: Methuen.
- Grizzle, J. E., Starmer, C. F., and Koch, G. G. (1969), “Analysis of Categorical Data by Linear Models,” *Biometrics*, 25, 489–504.
- Hadley, G. (1962), *Linear Programming*, Reading, MA: Addison-Wesley.
- Jennrich, R. I. and Moore, R. H. (1975), “Maximum Likelihood Estimation by Means of Nonlinear Least Squares,” *American Statistical Association*.
- Kaiser, H. F. and Caffrey, J. (1965), “Alpha Factor Analysis,” *Psychometrika*, 30, 1–14.
- Kastenbaum, M. A. and Lamphiear, D. E. (1959), “Calculation of Chi-Square to Test the No Three-Factor Interaction Hypothesis,” *Biometrics*, 15, 107–122.
- Nelder, J. A. and Wedderburn, R. W. M. (1972), “Generalized Linear Models,” *Journal of the Royal Statistical Society, Series A*, 135, 370–384.

Chapter 10

Submitting SAS Statements

Contents

Introduction to Submitting SAS Statements	179
Calling a Procedure	180
Passing Parameters from SAS/IML Matrices	182
Details of Parameter Substitution	183
Creating Graphics in a SUBMIT Block	185
Handling Errors in a SUBMIT Block	187
Differences between the SUBMIT Statement in PROC IML and in SAS/IML Studio	188

Introduction to Submitting SAS Statements

In 2002, the IML Workshop application (now known as SAS/IML Studio) introduced a mechanism for submitting SAS statements from programs written in the IMLPlus language. As of SAS/IML 9.22, this feature is also available in PROC IML. This chapter shows you how to submit SAS statements from PROC IML by using the **SUBMIT** and **ENDSUBMIT** statements. By using these statements, SAS/IML programmers can call any SAS procedure without losing the state of their PROC IML session.

The statements between the **SUBMIT** and the **ENDSUBMIT** statements are referred to as a *SUBMIT block*. The SUBMIT block is processed by the SAS language processor. You can use the SUBMIT statement to call DATA steps, macros, and SAS procedures.

This chapter covers the following topics:

- calling a SAS procedure from PROC IML
- passing parameters into the SUBMIT block
- creating ODS graphics in a SUBMIT block
- handling errors in the SUBMIT block
- differences between the SUBMIT statement in PROC IML and the IMLPlus statement of the same name as it is implemented in SAS/IML Studio

Calling a Procedure

This section describes how to call a procedure from PROC IML.

Suppose you have data in a SAS/IML matrix that you want to analyze by using a statistical procedure. In general, you can use the following steps to analyze the data:

1. Write the data to a SAS data set by using the [CREATE](#) and [APPEND](#) statements.
2. Use the SUBMIT statement to call a SAS procedure that analyzes the data.
3. Read the results of the analysis into SAS/IML matrices by using the [USE](#) and [READ](#) statements.
4. Use the results in further computations.

Of course, if the data are already in a SAS data set, you can skip the first step. Similarly, if you are solely interested in the printed output from a procedure, you can skip the third and fourth steps.

The following example calls the UNIVARIATE procedure in Base SAS software to compute a regression analysis. In order to tell the SAS/IML language interpreter that you want certain statements to be sent to the SAS System, you must enclose your SAS statements with SUBMIT and ENDSUBMIT statements. The ENDSUBMIT statement must appear on a line by itself.

- 1 The following statements create a SAS data set from data in a vector:

```
proc iml;  
  q = {3.7, 7.1, 2, 4.2, 5.3, 6.4, 8, 5.7, 3.1, 6.1, 4.4, 5.4, 9.5, 11.2};  
  
  create MyData var {q};  
  append;  
  close MyData;
```

The MyData data set is used in the rest of this chapter.

- 2 You can call the UNIVARIATE procedure to analyze these data. The following statements use the ODS SELECT statement to limit the output from the UNIVARIATE procedure. The output is shown in [Figure 10.1](#).

```
submit;  
  ods select Moments;  
  proc univariate data=MyData;  
    var q;  
    ods output Moments=Moments;  
  run;  
endsubmit;
```

Figure 10.1 Output from the UNIVARIATE Procedure

The UNIVARIATE Procedure			
Variable: Q			
Moments			
N	14	Sum Weights	14
Mean	5.86428571	Sum Observations	82.1
Std Deviation	2.49387161	Variance	6.2193956
Skewness	0.66401924	Kurtosis	0.34860956
Uncorrected SS	562.31	Corrected SS	80.8521429
Coeff Variation	42.5264343	Std Error Mean	0.66651522

- 3 The previous statements also used the ODS OUTPUT statement to create a data set named Moments that contains the statistics shown in Figure 10.1. In the data set, the first column of Figure 10.1 is contained in a variable named Label1 and the second column is contained in a variable named nValue1. The following statements read those variables into SAS/IML vectors of the same names and print the values:

```
use Moments;
read all var {"nValue1" "Label1"};
close Moments;

lab1 = "Statistics for " + name(q);
print nValue1[rowname=Label1 label=lab1];
```

Figure 10.2 Statistics Read into SAS/IML Vectors

Statistics for q	
N	14
Mean	5.8642857
Std Deviation	2.4938716
Skewness	0.6640192
Uncorrected SS	562.31
Coeff Variation	42.526434

- 4 By using this technique, you can read the value of any statistic that is created by any SAS procedure. You can then use these values in subsequent computations in PROC IML. For example, if you want to standardize the **y** vector, you can use the mean and standard deviation as computed by the UNIVARIATE procedure, as shown in the following statements:

```
mean = nValue1[2];
stddev = nValue1[3];
stdQ = (q - mean)/stddev;
```

Passing Parameters from SAS/IML Matrices

The SUBMIT statement enables you to substitute the values of a SAS/IML matrix into the statements that are submitted to the SAS System. For example, the following program calls the UNIVARIATE procedure to analyze data in the MyData data set that was created in the section “Calling a Procedure” on page 180. The program submits SAS statements that are identical to the SUBMIT block in that section:

```
table = "Moments";
varName = "q";

submit table varName;
ods select &table;
proc univariate data=MyData;
    var &varName;
    ods output &table=&table;
run;
endsubmit;
```

You can list the names of SAS/IML matrices in the SUBMIT statement and refer to the contents of those matrices inside the SUBMIT block. The syntax is reminiscent of the syntax for macro variables: an ampersand (&) preceding an expression means “substitute the value of the expression.” However, the substitution takes place before the SUBMIT block is sent to the SAS System; no macro variables are actually created.

You can substitute values from character or numeric matrices and vectors. If **x** is a vector, then **&x** lists the elements of **x** separated by spaces. For example, the following statements compute trimmed means for three separate values of the TRIM= option:

```
table = "TrimmedMeans";
varName = "q";
n = {1, 3, 5};           /* number of observations to trim */

submit table varName n;
ods select &table;
proc univariate data=MyData trim=&n;
    var &varName;
run;
endsubmit;
```

The output is shown in [Figure 10.3](#). The values in the column labeled “Number Trimmed in Tail” correspond to the values in the **n** matrix. These values were substituted into the TRIM= option in the PROC UNIVARIATE statement.

Figure 10.3 Statistics Read into SAS/IML Vectors

The UNIVARIATE Procedure						
Variable: Q						
Trimmed Means						
Percent Trimmed in Tail	Number Trimmed in Tail	Trimmed Mean	Std Error Trimmed Mean	95% Confidence Limits		DF
7.14	1	5.741667	0.664486	4.279142	7.204191	11
21.43	3	5.575000	0.587204	4.186483	6.963517	7
35.71	5	5.625000	0.408613	4.324612	6.925388	3
Trimmed Means						
Percent Trimmed in Tail	t for H0: Mu0=0.00			Pr > t		
7.14	8.64076			<.0001		
21.43	9.49414			<.0001		
35.71	13.76609			0.0008		

Details of Parameter Substitution

The SUBMIT statement supports two kinds of parameter substitution: full substitution and specific substitution.

Full Substitution

If you want to substitute many values into a SUBMIT block, it can be tedious to explicitly list the name of every SAS/IML matrix that you reference. You can use an asterisk (*) in the SUBMIT statement as a “wildcard character” to indicate that all SAS/IML matrices are available for parameter substitution. This is called *full substitution* and is shown in the following statements:

```
proc iml;
  DSName = "Sashelp.Class";
  NumObs = 1;

  submit *;
  proc print data=&DSName(obs=&NumObs);
  run;
  endsubmit;
```

Figure 10.4 Full Substitution

Obs	Name	Sex	Age	Height	Weight
1	Alfred	M	14	69	112.5

If the SUBMIT block contains a parameter reference (that is, a token that begins with an ampersand (&) for which there is no matching SAS/IML matrix, the parameter reference is not modified prior to being sent to the SAS language processor. In this way, you can reference SAS macro variables in a SUBMIT block.

Specific Substitution

A SUBMIT statement that contains an explicit list of parameters is easier to understand than a SUBMIT statement that contains only the asterisk wildcard character (*). Specifying an explicit list of parameters is called *specific substitution*. These—and only these—parameters are used to make substitutions into the SUBMIT block.

```
proc iml;
DSName = "Sashelp.Class";
NumObs = 2;

submit DSName NumObs;
proc print data=&DSName(obs=&NumObs);
run;
endsubmit;
```

Figure 10.5 Specific Substitution

Obs	Name	Sex	Age	Height	Weight
1	Alfred	M	14	69.0	112.5
2	Alice	F	13	56.5	84.0

If the SUBMIT block contains a parameter reference (that is, a token that begins with an ampersand (&) for which there is no matching parameter, the parameter reference is not modified prior to being sent to the SAS language processor. In this way, you can reference SAS macro variables in a SUBMIT block.

With specific substitution, you have additional options for specifying the value of a parameter. You can use any of the following ways to specify the value of a parameter:

- Specify the name of a SAS/IML matrix to use for the value of a parameter, as shown in the following statements:

```
s = "Sashelp.Class";    n = 2;

submit DSName=s NumObs=n;
proc print data=&DSName(obs=&NumObs);
run;
endsubmit;
```


- Specify a literal value to use for the value of a parameter, as shown in the following statements:

```
submit DSName="Sashelp.Class" NumObs=2;
proc print data=&DSName (obs=&NumObs);
run;
endsubmit;
```

- Specify a matrix expression that is enclosed in parentheses, as shown in the following statements:

```
libref = "Sashelp";
fname = "Class";
NumObs = 2;

submit DSName=(libref+"."+fname) NumObs;
proc print data=&DSName (obs=&NumObs);
run;
endsubmit;
```

Creating Graphics in a SUBMIT Block

If you use the SUBMIT statement to call a SAS procedure that creates a graph, that graph is sent to the current ODS destination. The following statements call the UNIVARIATE procedure, which creates a histogram as part of the analysis:

```
ods graphics on;

proc iml;
msg1 = "First PRINT Statement in PROC IML";
msg2 = "Second PRINT Statement in PROC IML";
print msg1;

submit;
ods select Moments Histogram;
proc univariate data=Sashelp.Class;
var Height;
histogram / kernel;
run;
endsubmit;

print msg2;
ods graphics off;
```

When you run the program, the PROC UNIVARIATE output is interleaved with the PROC IML output. The output from the program is shown in [Figure 10.6](#) through [Figure 10.8](#).

Figure 10.6 Output from PROC IML and from SUBMIT Block

msg1			
First PRINT Statement in PROC IML			
The UNIVARIATE Procedure			
Variable: Height			
Moments			
N	19	Sum Weights	19
Mean	62.3368421	Sum Observations	1184.4
Std Deviation	5.12707525	Variance	26.2869006
Skewness	-0.2596696	Kurtosis	-0.1389692
Uncorrected SS	74304.92	Corrected SS	473.164211
Coeff Variation	8.22479143	Std Error Mean	1.17623173

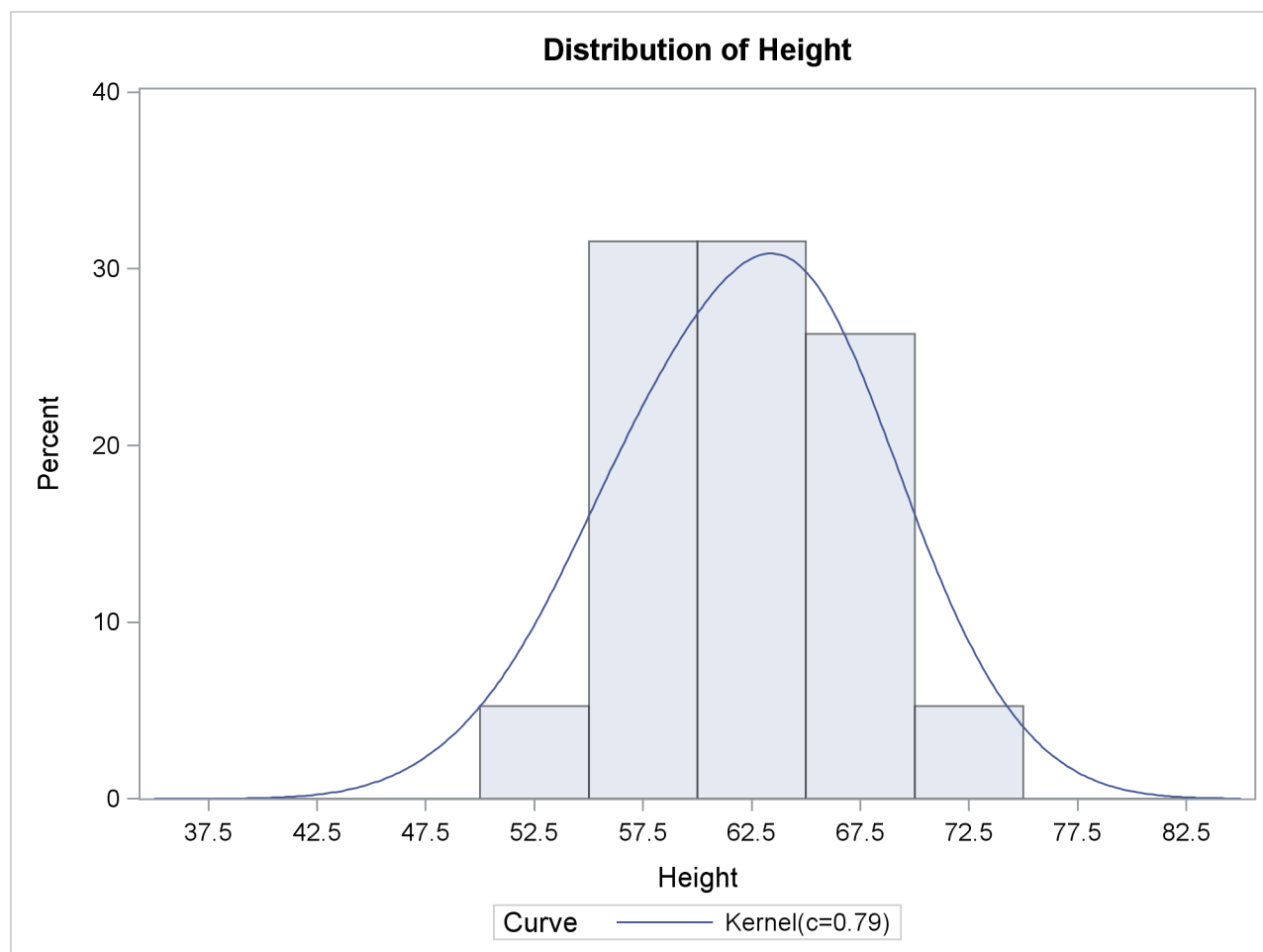
Figure 10.7 Graphic Created in a SUBMIT Block

Figure 10.8 Further PROC IML Output

<p style="text-align: center;">msg2</p> <p style="text-align: center;">Second PRINT Statement in PROC IML</p>

Handling Errors in a SUBMIT Block

After running a SUBMIT block, PROC IML continues to execute the remaining statements in the program. However, if there is an error in the SUBMIT block, it might make sense to abort the program or to handle the error in some other way.

The OK= option in the SUBMIT statement provides a limited form of error handling. If you specify the OK= option, then PROC IML sets a matrix to the value 1 if the SUBMIT block executes without error. Otherwise, the matrix is set to the value 0.

The following statements contain an error in a SUBMIT block: two letters are transposed when specifying the name of a data set. Consequently, the `isOK` matrix is set to 0, and the program handles the error.

```
DSName = "Sashelp.calss";    /* mistyped name; data set does not exist */

submit DSName / ok=isOK;
proc univariate data=&DSName;
  var Height;
  ods output Moments=Moments;
run;
endsubmit;

if isOK then do;              /* handle the no-error case */
  use Moments;
  read all var {"nValue1"} into m;
  close Moments;
  skewness = m[4];           /* get statistic from procedure output */
end;
else
  skewness = .;              /* handle an error */

print skewness;
```

Figure 10.9 The Result of Handling an Error in a SUBMIT Block

<p style="text-align: center;">skewness</p> <p style="text-align: center;">.</p>
--

Differences between the SUBMIT Statement in PROC IML and in SAS/IML Studio

This section lists differences between the SUBMIT statement as implemented in IMLPlus (the programming language used in SAS/IML Studio) and the SUBMIT statement in PROC IML:

- In PROC IML, macro variables that are created in a SUBMIT block are not accessible from outside the SUBMIT block. In IMLPlus, the macro variables are available.
- In PROC IML, global SAS statements such as the LIBNAME, FILEREF, and OPTIONS statements that are created in a SUBMIT block do not affect the environment outside the SUBMIT block. In IMLPlus, librefs, filerefs, and options that are created inside the SUBMIT block continue to be defined after the ENDSUBMIT statement.
- In PROC IML, ODS statements executed in a SUBMIT block do not affect the environment outside the SUBMIT block. In IMLPlus, ODS statements can affect subsequent output.
- In PROC IML, a SUBMIT block clears the ODS SELECT and ODS EXCLUDE lists, even if the SUBMIT block does not contain a DATA step or a procedure call. This does not occur in IMLPlus.
- In PROC IML, the SUBMIT statement causes a page break in some ODS destinations (such as the LISTING destination). In IMLPlus, there is no unnecessary page break.

Chapter 11

Calling Functions in the R Language

Contents

Overview of Calling Functions in the R Language	189
Installing the R Statistical Software	190
The RLANG System Option	190
Submit R Statements	191
Transferring Data between SAS and R Software	192
Transfer from a SAS Source to an R Destination	193
Transfer from an R Source to a SAS Destination	193
Call an R Analysis from PROC IML	194
Using R to Analyze Data in SAS/IML Matrices	194
Using R to Analyze Data in a SAS Data Set	196
Passing Parameters to R	196
Call R Packages from PROC IML	196
Call R Graphics from PROC IML	199
Handling Errors from R	200
Details of Data Transfer	200
Numeric Data Types	201
Logical Data Types	201
Unsupported Data Types	201
Special Numeric Values	201
Date, Time, and Datetime Values	202
Time Series Data	202
Data Structures	203
Differences from SAS/IML Studio	203

Overview of Calling Functions in the R Language

R is a freely available language and environment for statistical computing and graphics. Like the SAS/IML language, the R language has features suitable for developers of statistical algorithms: the ability to manipulate matrices and vectors, a large number of built-in functions for computing statistical quantities, and the capability to extend the basic function library by writing user-defined functions. There are also a large number of user-contributed packages in R that implement specialized computations.

In 2009, the SAS/IML Studio application introduced a mechanism for calling R functions from programs written in the IMLPlus language. As of SAS/IML 9.22, this feature is available in PROC IML. This chapter shows you how to call R functions from PROC IML by using the `SUBMIT` and `ENDSUBMIT` statements.

This chapter describes how to configure the SAS system so that you can call functions in the R language. The chapter also describes how to do the following:

- transfer data to R
- call R functions from PROC IML
- transfer the results from R to a number of SAS data structures

Installing the R Statistical Software

SAS does not distribute R software. In order to call R software, you must first install R on the same computer that runs SAS software. If you access a SAS workspace server through client software such as SAS[®] Enterprise Guide[®], then R must be installed on the SAS server.

You can download R from The Comprehensive R Archive Network Web site: <http://cran.r-project.org>. If you experience problems installing R, consult the R FAQ: <http://cran.r-project.org/doc/FAQ/R-FAQ.html>. SAS Technical Support does not provide support for installing or configuring third-party software.

In SAS/IML, the interface to R is supported on computers that run a 32-bit or 64-bit Windows operating system or Linux operating systems. If you are using SAS software in a 64-bit Linux environment, you must download a 64-bit binary distribution of R. Otherwise, download a 32-bit binary distribution.

The document “Installing R on Linux Operating Systems” is available on support.sas.com and includes pointers for installing R on Linux that it works with the SAS interface to R.

The RLANG System Option

The RLANG system option determines whether you have permission to call R from the SAS system. You can determine the value of the RLANG option by submitting the following SAS statements:

```
proc options option=RLANG;
run;
```

The result is one of the following statements in the SAS log:

NORLANG Do not support access to R language interfaces

If the SAS log contains this statement, you do not have permission to call R from the SAS system.

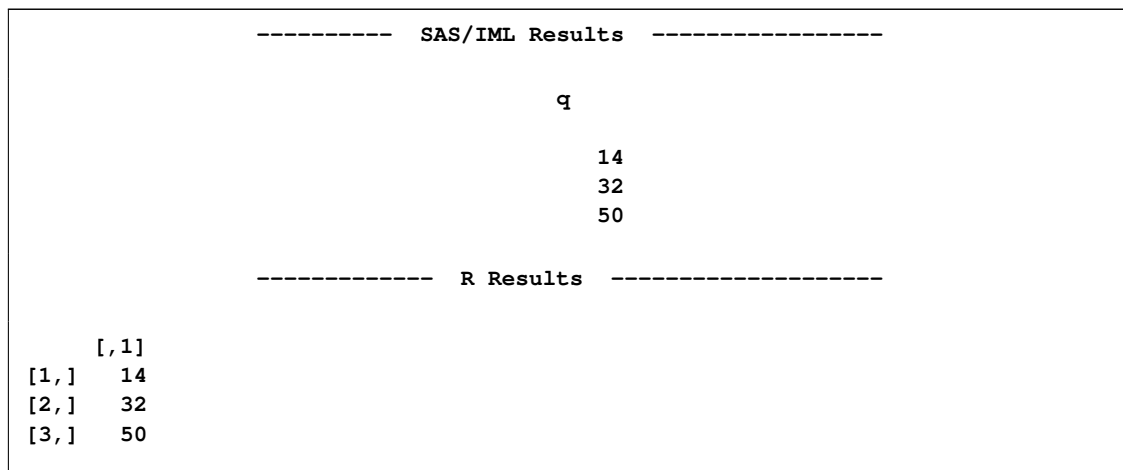

```

print "----- R Results -----";
submit / R;
  rx <- matrix( 1:3, nrow=1)           # vector of sequence 1,2,3
  rm <- matrix( 1:9, nrow=3, byrow=TRUE) # 3 x 3 matrix
  rq <- rm %*% t(rx)                   # matrix multiplication
  print(rq)
endsubmit;

```

The printed output from R is automatically routed to the SAS/IML Studio output window, as shown in Figure 11.1. As expected, the result of the computation is the same in R as in SAS/IML.

Figure 11.1 Output from SAS/IML and R



Transferring Data between SAS and R Software

Many research statisticians take advantage of special-purpose functions and packages written in the R language. When you call an R function, the data must be accessible to R, either in a data frame or in an R matrix. This section describes how you can transfer data and statistical results (for example, fitted values or parameter estimates) between SAS and R data structures.

You can transfer data to and from the following SAS data structures:

- a SAS data set in a libref
- a SAS/IML matrix

In addition, you can transfer data to and from the following R data structures:

- an R data frame
- an R matrix

Transfer from a SAS Source to an R Destination

Table 11.1 summarizes the subroutines that copy data from a SAS source to an R destination. For more information, see the section “Details of Data Transfer” on page 200.

Table 11.1 Transferring from a SAS Source to an R Destination

Subroutine	SAS Source	R Destination
<code>ExportDataSetToR</code>	SAS data set	R data frame
<code>ExportMatrixToR</code>	SAS/IML matrix	R matrix

As a simple example, the following program transfers a data set from the `Sashelp.class` libref into an R data frame named `df`. The program then submits an R statement that displays the names of the variables in the data frame.

```
proc iml;
call ExportDataSetToR("Sashelp.class", "df" );
submit / R;
    names(df)
endsubmit;
```

The R `names` function produces the output shown in Figure 11.2.

Figure 11.2 Result of Sending Data to R

```
[1] "Name"    "Sex"     "Age"     "Height"  "Weight"
```

Transfer from an R Source to a SAS Destination

You can transfer data and results from R data frames or matrices to a SAS data set or a SAS/IML matrix. Table 11.2 summarizes the frequently used methods that copy from an R source to a SAS destination.

Table 11.2 Transferring from an R Source to a SAS Destination

Subroutine	R Source	SAS Destination
<code>ImportDataSetFromR</code>	R expression	SAS data set
<code>ImportMatrixFromR</code>	R expression	SAS/IML matrix

The next section includes an example of calling an R analysis. Some of the results from the analysis are then transferred into SAS/IML matrices.

The result of an R analysis can be a complicated structure. In order to transfer an R object via the previously

mentioned methods and modules, the object must be coercible to a data frame. (The R object `m` can be coerced to a data frame provided that the function `as.data.frame(m)` succeeds.) There are many data structures that cannot be coerced into data frames. As the example in the next section shows, you can use R statements to extract and transfer simpler objects.

Call an R Analysis from PROC IML

You can use the techniques in Chapter 10, “Submitting SAS Statements,” to perform a linear regression by calling a regression procedure (such as REG, GLM, or MIXED) in SAS/STAT software. This section presents examples of submitting statements to R to perform a linear regression. The first example performs a linear regression on data that are transferred from SAS/IML vectors. The second example performs an identical analysis on data that are transferred from a SAS data set.

Using R to Analyze Data in SAS/IML Matrices

The program in this section consists of four parts:

1. Read the data into SAS/IML vectors.
 2. Transfer the data to R.
 3. Call R functions to analyze the data.
 4. Transfer the results of the analysis into SAS/IML vectors.
- 1** Read the data. The following statements read the `Weight` and `Height` variables from the `Sashelp.Class` data set into SAS/IML vectors with the same names:

```
proc iml;
  use Sashelp.Class;
  read all var {Weight Height};
  close Sashelp.Class;
```

- 2** Transfer the data to R. The following statements run the [ExportMatrixToR](#) subroutine in order to transfer data from a SAS/IML matrix into an R matrix. The names of the corresponding R vectors that contain the data are `w` and `h`.

```
/* send matrices to R */
call ExportMatrixToR(Weight, "w");
call ExportMatrixToR(Height, "h");
```

- 3** Call R functions to perform some analysis. The `SUBMIT` statement with the `R` option is used to send statements to R. Comments in R begin with a hash mark (`#`, also called a number sign or a pound sign).

```

submit / R;
  Model    <- lm(w ~ h, na.action="na.exclude")      # a
  ParamEst <- coef(Model)                            # b
  Pred     <- fitted(Model)
  Resid    <- residuals(Model)
endsubmit;

```

The R program consists of the following steps:

- a. The `lm` function computes a linear model of `w` as a function of `h`. The `na.action=` option specifies how the model handles missing values (which in R are represented by NA). In particular, the `na.exclude` option specifies that the `lm` function should not omit observations with missing values from residual and predicted values. This option makes it easier to merge the R results with the original data when the data contain missing values.
 - b. Various information is retrieved from the linear model and placed into R vectors named `ParamEst`, `Pred`, and `Resid`.
- 4 Transfer the data from R. The `ImportMatrixFromR` subroutine transfers the `ParamEst` vector from R into a SAS/IML vector named `pe`. This vector is printed by the SAS/IML PRINT statement. The predicted values (`Pred`) and residual values (`Resid`) can be transferred similarly. The parameter estimates are used to compute the predicted values for a series of hypothetical heights, as shown in [Figure 11.3](#).

```

call ImportMatrixFromR(pe, "ParamEst");
print pe[r={"Intercept" "Height"}];

ht = T( do(55, 70, 5) );
A = j(nrow(ht), 1, 1) || ht;
pred_wt = A * pe;
print ht pred_wt;

```

Figure 11.3 Results from an R Analysis

pe	
Intercept	-143.0269
Height	3.8990303
ht	pred_wt
55	71.419746
60	90.914898
65	110.41005
70	129.9052

You cannot directly transfer the contents of the `Model` object. Instead, various R functions are used to extract portions of the `Model` object, and those simpler pieces are transferred.

Using R to Analyze Data in a SAS Data Set

As an alternative to the data transfer statements in the previous section, you can call the `ExportDataSetToR` subroutine to transfer the entire SAS data set to an R data frame. For example, you could use the following statements to create an R data frame named `Class` and to model the `Weight` variable:

```
call ExportDataSetToR("Sashelp.Class", "Class");
submit / R;
  Model <- lm(Weight ~ Height, data=Class, na.action="na.exclude")
endsubmit;
```

The R language is case-sensitive so you must use the correct case to refer to variables in a data frame. You can use the `CONTENTS` function in the SAS/IML language to obtain the names and capitalization of variables in a SAS data set.

Passing Parameters to R

The `SUBMIT` statement supports parameter substitution from SAS/IML matrices as detailed in “[Passing Parameters from SAS/IML Matrices](#)” on page 182. For example, you can substitute the names of analysis variables into a `SUBMIT` block by using the following statements:

```
YVar = "Weight";
XVar = "Height";
submit XVar YVar / R;
  Model <- lm(&YVar ~ &XVar, data=Class, na.action="na.exclude")
  print (Model$call)
endsubmit;
```

Figure 11.4 shows the result of the `print (Model$call)` statement. The output shows that the values of the `YVar` and `XVar` matrices were substituted into the `SUBMIT` block.

Figure 11.4 Parameter Substitutions in a `SUBMIT` Block

```
lm(formula = Weight ~ Height, data = Class, na.action = "na.exclude")
```

Call R Packages from PROC IML

You do not need to do anything special to call an R package. Provided that an R package is installed, you can call `library(package)` from inside a `SUBMIT` block to load the package. You can then call the functions in the package.

The example in this section calls an R package and imports the results into a SAS data set. This example is similar to the example in “[Creating Graphics in a SUBMIT Block](#)” on page 185, which calls the UNIVARIATE procedure to create a kernel density estimate. The program in this section consists of the following steps:

1. Define the data and transfer the data to R.
 2. Call R functions to analyze the data.
 3. Transfer the results of the analysis into SAS/IML vectors.
- 1** Define the data in the SAS/IML vector **q** and then transfer the data to R by using the `ExportMatrixToR` subroutine. In R, the data are stored in a vector named **rq**.

```
proc iml;
q = {3.7, 7.1, 2, 4.2, 5.3, 6.4, 8, 5.7, 3.1, 6.1, 4.4, 5.4, 9.5, 11.2};
RVar = "rq";
call ExportMatrixToR( q, RVar );
```

- 2** Load the `KernSmooth` package. Because the functions in the `KernSmooth` package do not handle missing values, the nonmissing values in **q** must be copied to a matrix **p**. (There are no missing values in this example.) The Sheather-Jones plug-in bandwidth is computed by calling the `dpik` function in the `KernSmooth` package. This bandwidth is used in the `bkde` function (in the same package) to compute a kernel density estimate.

```
submit RVar / R;
  library(KernSmooth)
  idx <-which(!is.na(&RVar))      # must exclude missing values (NA)
  p <- &RVar[idx]                # from KernSmooth functions
  h = dpik(p)                    # Sheather-Jones plug-in bandwidth
  est <- bkde(p, bandwidth=h)    # est has 2 columns
endsubmit;
```

- 3** Copy the results into a SAS data set or a SAS/IML matrix, and perform additional computations. For example, the following statements use the trapezoidal rule to numerically estimate the density that is contained in the tail of the density estimate of the data:

```
call ImportMatrixFromR( m, "est" );
/* estimate the density for q >= 8 */
x = m[,1];                      /* x values for density */
idx = loc( x>=8 );              /* find values x >= 8 */
y = m[idx, 2];                 /* extract corresponding density values */

/* Use the trapezoidal rule to estimate the area under the density curve.
   The area of a trapezoid with base w and heights h1 and h2 is
   w*(h1+h2)/2. */
w = m[2,1] - m[1,1];
h1 = y[1:nrow(y)-1];
h2 = y[2:nrow(y)];
Area = w * sum(h1+h2) / 2;
```

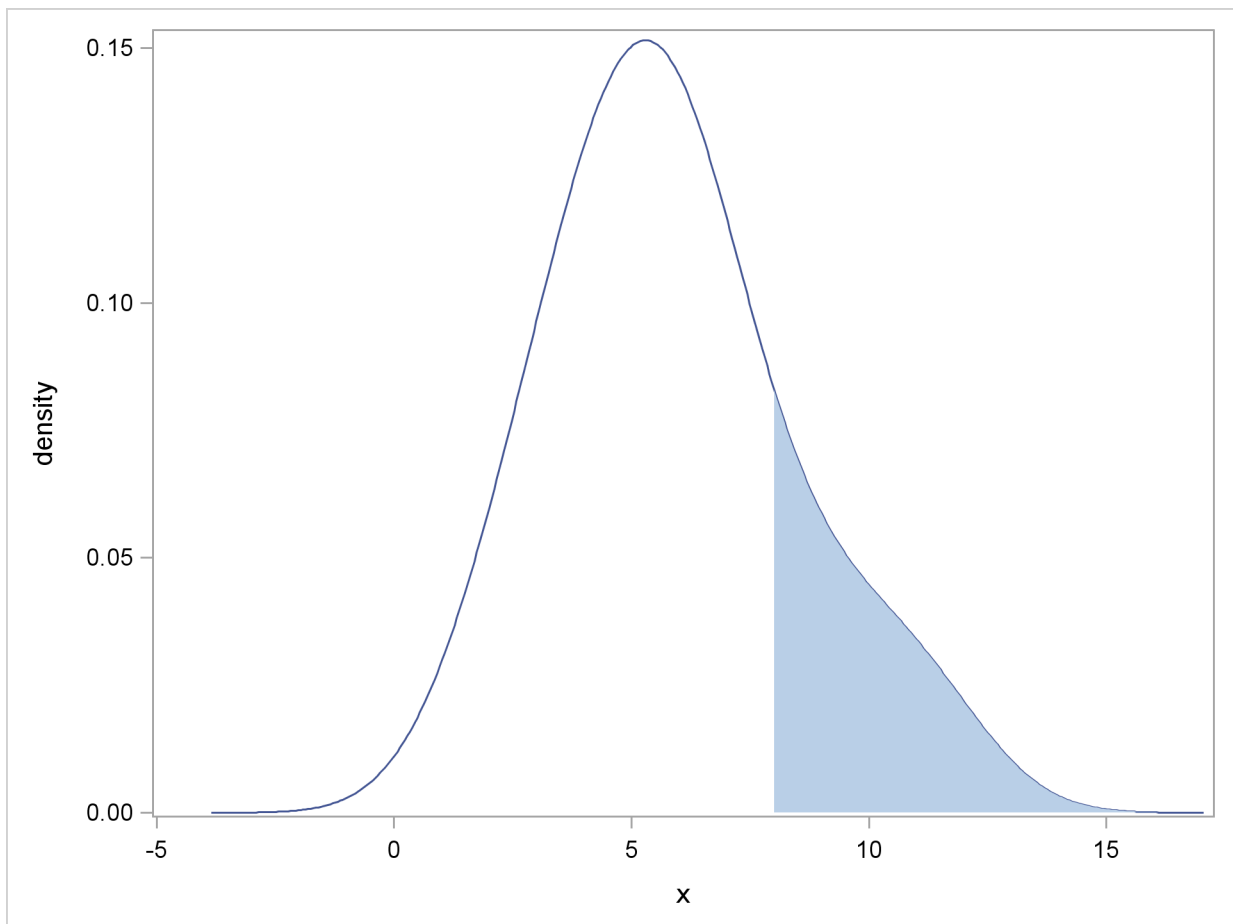
```
print Area;
```

The numerical estimate for the conditional density is shown in Figure 11.5. The estimate is shown graphically in Figure 11.6, where the conditional density corresponds to the shaded area in the figure. Figure 11.6 was created by using the SGPLOT procedure to display the density estimate computed by the R package.

Figure 11.5 Computation That Combines SAS/IML and R Computations

Area
0.2118117

Figure 11.6 Estimated Density for $x \geq 8$



Call R Graphics from PROC IML

R can create graphics in a separate window which, by default, appears on the same computer on which R is running. If you are running PROC IML and R locally on your desktop or laptop computer, you can display R graphics. However, if you are running client software that connects with a remote SAS server that is running PROC IML and R, then R graphics might be disabled.

The following statements describe some common scenarios for running a PROC IML program:

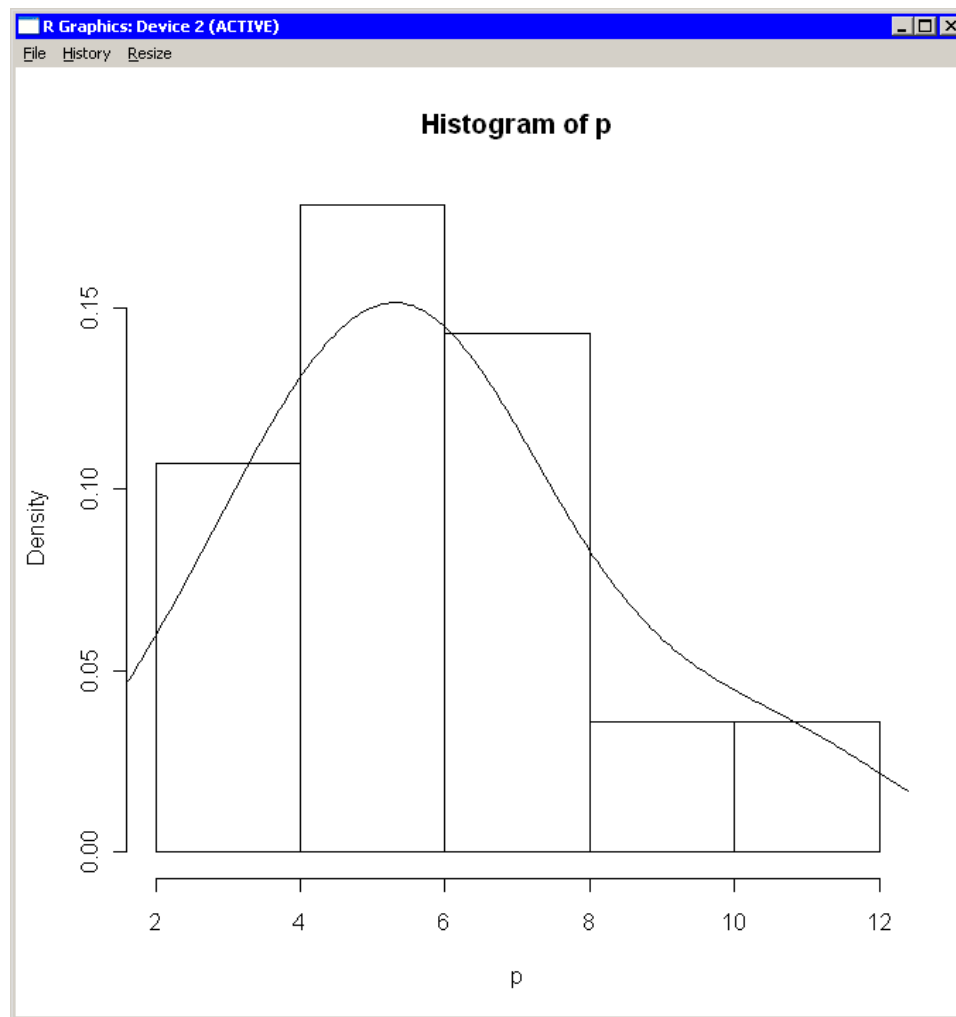
- If you run PROC IML through a SAS Display Manager Session (DMS), you can create R graphics from your PROC IML program. The graph appears in the standard R graphics window.
- If you run PROC IML through SAS Enterprise Guide, the display of R graphics is disabled because, in general, the SAS server (and therefore R) is running on a different computer than the SAS Enterprise Guide application.
- If you run PROC IML from interactive line mode or from batch mode, then R graphics are disabled.

You can determine whether R graphics are enabled by calling the **interactive** function in the R language.

For example, the previous section used R to compute a kernel density estimate for some data. If you are running PROC IML through SAS DMS, you can create a histogram and overlay the kernel density estimate by using the following statements:

```
submit / R;  
  hist(p, freq=FALSE) # histogram  
  lines(est)          # kde overlay  
endsubmit;
```

The **hist** function creates a histogram of the data in the **p** matrix, and the **lines** function adds the kernel density estimate contained in the **est** matrix. The R graphics window contains the histogram, which is shown in [Figure 11.7](#).

Figure 11.7 R Graphics

Handling Errors from R

If you submit R code that causes an error, you can attempt to handle the error by using the `OK=` option in the `SUBMIT` statement, as described in “[Handling Errors in a SUBMIT Block](#)” on page 187.

Details of Data Transfer

This section describes how data are transferred between SAS and R software. It includes a discussion of numerical data types, missing values, and data that represent dates and times.

Numeric Data Types

R can store numeric data in either an integer or a double-precision data type. When transferring R data to a SAS data type, integers types are converted to double precision.

Logical Data Types

R provides a logical data type for storing the values **TRUE** and **FALSE**. When logical data are transferred to a SAS data type, the value **TRUE** is converted to the number 1 and the value **FALSE** to the number 0.

Unsupported Data Types

R provides two data types that are not converted to a SAS data type: complex and raw. It is an error to attempt to transfer data stored in either of these data types to a SAS data type.

Special Numeric Values

The R language has four symbols that are used to represent special numerical values.

- The symbol **NA** represents a missing value.
- The symbol **Inf** represents positive infinity.
- The symbol **-Inf** represents negative infinity.
- The symbol **NaN** represents a “NaN,” which is a floating-point value that represents an undefined value such as the result of the division 0/0.

The SAS language has 28 symbols that are used to represent special numerical values.

- The symbol **.** represents a generic missing value.
- The symbols **.A-.Z** and **._** are also missing values. Some applications use **.I** to represent positive infinity and use **.M** to represent negative infinity.

The following table shows how special numeric values in R are converted to SAS missing values:

Value in R	SAS Missing Value
Inf	.I
-Inf	.M
NA	.
NaN	.

The following table shows how SAS missing values are converted when data are transferred to R:

SAS Missing Value	Value in R
.I	Inf
.M	-Inf
All others	NA

Date, Time, and Datetime Values

R supports date and time data differently than does SAS software. In SAS software, variables that represent dates or times are assigned a format such as DATE9. or TIME5. In R, classes are used to represent dates and times.

When a variable in a SAS data set is transferred to R software, the variable's format is examined and the following occurs:

- If the format is in the family of date formats (for example, DATE $w.d$), the variable in R is assigned the “Date” class.
- If the format is in the family of datetime formats (for example, DATETIME $w.d$) or time formats (for example, TIME $w.d$), the variable in R is assigned the “POSIXct” and “POSIXt” classes.
- In all other cases, the variable in R is assigned the “numeric” class.

When a variable in an R data frame is transferred to SAS software, the variable's class is examined and the following occurs:

- If the variable's class is “Date,” the corresponding SAS variable is assigned the DATE9. format.
- If the variable's class is “POSIXt,” the corresponding SAS variable is assigned the DATETIME19. format.
- In all other cases, the SAS variable is not assigned a format.

Time Series Data

In SAS, the sampling times for time series data are often stored in a separate variable. In R, the sampling times for a time series object are specified by the `ts$sp` attribute. When a time series object in R is transferred to SAS software, the following occurs:

- The R `time` function is used to generate a vector of the times at which the time series is sampled.
- A new variable named `VarName_ts` is created, where `VarName` is the name of the time series object in R. The variable contains sampling times for the time series.

No special processing of time series data is performed when data are transferred from SAS to R software.

Data Structures

R provides a wide range of built-in and user-defined data structures. When data are transferred from R to SAS software, the data are coerced to a data frame prior to the transfer. If the coercion fails, the data are not transferred.

The section “[Using R to Analyze Data in SAS/IML Matrices](#)” on page 194 presents an example of an R object that cannot be directly imported to SAS software and shows how to use R functions to extract simpler data structures from the R object.

Differences from SAS/IML Studio

This section lists differences between the R option in the SUBMIT statement as implemented in SAS/IML Studio and the same option in PROC IML:

- In PROC IML, R must be installed on the computer that runs the SAS server. In SAS/IML Studio, R must be installed on the computer that runs the SAS/IML Studio application.
- If R is installed on a SAS workspace server and is accessed through SAS Enterprise Guide, everyone that connects to that server uses the same version of R and the same set of installed packages. In SAS/IML Studio, R is installed locally on the client computer, so each user can potentially have a different version of R and different packages.

Chapter 12

Robust Regression Examples

Contents

Overview	205
Using LMS and LTS	207
Example 12.1: Substantial Leverage Points	208
Example 12.2: Comparison of LMS, V7 LTS, and FAST-LTS	211
Example 12.3: LMS and LTS Univariate (Location) Problem: Barnett and Lewis Data	218
Using MVE and MCD	221
Example 12.4: Brainlog Data	222
Example 12.5: Stackloss Data	229
Combining Robust Residual and Robust Distance	238
Example 12.6: Hawkins-Bradru-Kass Data	239
Example 12.7: Stackloss Data	244
References	246

Overview

SAS/IML has four subroutines that can be used for outlier detection and robust regression. The Least Median of Squares (LMS) and Least Trimmed Squares (LTS) subroutines perform *robust regression* (sometimes called *resistant regression*). These subroutines are able to detect outliers and perform a least-squares regression on the remaining observations. The Minimum Volume Ellipsoid Estimation (MVE) and Minimum Covariance Determinant Estimation (MCD) subroutines can be used to find a robust location and a robust covariance matrix that can be used for constructing confidence regions, detecting multivariate outliers and leverage points, and conducting robust canonical correlation and principal component analysis.

The LMS, LTS, MVE, and MCD methods were developed by Rousseeuw (1984) and Rousseeuw and Leroy (1987). All of these methods have the high breakdown value property. Roughly speaking, the breakdown value is a measure of the proportion of contamination that a procedure can withstand and still maintain its robustness.

The algorithm used in the LMS subroutine is based on the PROGRESS program of Rousseeuw and Hubert (1996), which is an updated version of Rousseeuw and Leroy (1987). In the special case of regression through the origin with a single regressor, Barreto and Maharry (2006) show that the PROGRESS algorithm does not, in general, find the slope that yields the least median of squares. Starting with release 9.2, the LMS subroutine uses the algorithm of Barreto and Maharry (2006) to obtain the correct LMS slope in the case of

regression through the origin with a single regressor. In this case, inputs to the LMS subroutine specific to the PROGRESS algorithm are ignored and output specific to the PROGRESS algorithm is suppressed.

The algorithm used in the LTS subroutine is based on the algorithm FAST-LTS of Rousseeuw and Van Driessen (2000). The MCD algorithm is based on the FAST-MCD algorithm given by Rousseeuw and Van Driessen (1999), which is similar to the FAST-LTS algorithm. The MVE algorithm is based on the algorithm used in the MINVOL program by Rousseeuw (1984). LTS estimation has higher statistical efficiency than LMS estimation. With the FAST-LTS algorithm, LTS is also faster than LMS for large data sets. Similarly, MCD is faster than MVE for large data sets.

Besides LTS estimation and LMS estimation, there are other methods for robust regression and outlier detection. You can refer to a comprehensive procedure, PROC ROBUSTREG, in SAS/STAT. A summary of these robust tools in SAS can be found in Chen (2002).

The four SAS/IML subroutines are designed for the following:

- LMS: minimizing the h th ordered squared residual
- LTS: minimizing the sum of the h smallest squared residuals
- MCD: minimizing the determinant of the covariance of h points
- MVE: minimizing the volume of an ellipsoid that contains h points

where h is defined in the range

$$\frac{N}{2} + 1 \leq h \leq \frac{3N}{4} + \frac{n+1}{4}$$

In the preceding equation, N is the number of observations and n is the number of regressors.¹ The value of h determines the *breakdown value*, which is “the smallest fraction of contamination that can cause the estimator T to take on values arbitrarily far from $T(Z)$ ” (Rousseeuw and Leroy 1987). Here, T denotes an estimator and $T(Z)$ applies T to a sample Z .

For each parameter vector $\mathbf{b} = (b_1, \dots, b_n)$, the residual of observation i is $r_i = y_i - \mathbf{x}_i \mathbf{b}$. You then denote the ordered, squared residuals as

$$(r^2)_{1:N} \leq \dots \leq (r^2)_{N:N}$$

The objective functions for the LMS, LTS, MCD, and MVE optimization problems are defined as follows:

- LMS, the objective function for the LMS optimization problem is the h th ordered squared residual,

$$F_{\text{LMS}} = (r^2)_{h:N} \longrightarrow \min$$

Note that, for $h = N/2 + 1$, the h th quantile is the median of the squared residuals. The default h in PROGRESS is $h = \left\lfloor \frac{N+n+1}{2} \right\rfloor$, which yields the breakdown value (where $[k]$ denotes the integer part of k).

¹The value of h can be specified, but in most applications the default value works just fine and the results seem to be quite stable with different choices of h .

- LTS, the objective function for the LTS optimization problem is the sum of the h smallest ordered squared residuals,

$$F_{\text{LTS}} = \sqrt{\frac{1}{h} \sum_{i=1}^h (r^2)_{i:N}} \longrightarrow \min$$

- MCD, the objective function for the MCD optimization problem is based on the determinant of the covariance of the selected h points,

$$F_{\text{MCD}} = \det(\mathbf{C}_h) \longrightarrow \min$$

where \mathbf{C}_h is the covariance matrix of the selected h points.

- MVE, the objective function for the MVE optimization problem is based on the h th quantile $d_{h:N}$ of the Mahalanobis-type distances $\mathbf{d} = (d_1, \dots, d_N)$,

$$F_{\text{MVE}} = \sqrt{d_{h:N} \det(\mathbf{C})} \longrightarrow \min$$

subject to $d_{h:N} = \sqrt{\chi_{n,0.5}^2}$, where \mathbf{C} is the scatter matrix estimate, and the Mahalanobis-type distances are computed as

$$\mathbf{d} = \text{diag}(\sqrt{(\mathbf{X} - \mathbf{T})^T \mathbf{C}^{-1} (\mathbf{X} - \mathbf{T})})$$

where \mathbf{T} is the location estimate.

Because of the nonsmooth form of these objective functions, the estimates cannot be obtained with traditional optimization algorithms. For LMS and LTS, the algorithm, as in the PROGRESS program, selects a number of subsets of n observations out of the N given observations, evaluates the objective function, and saves the subset with the lowest objective function. As long as the problem size enables you to evaluate all such subsets, the result is a global optimum. If computing time does not permit you to evaluate all the different subsets, a random collection of subsets is evaluated. In such a case, you might not obtain the global optimum.

Note that the LMS, LTS, MCD, and MVE subroutines are executed only when the number N of observations is more than twice the number n of explanatory variables x_j (including the intercept)—that is, if $N > 2n$.

Using LMS and LTS

Because of space considerations, the output of the tables that contains residuals and resistant diagnostics are not included in this document. The SCATLMTS and LMSDIAP are used in these examples for printing and plotting the results. The PRILMTS module can be used for printing the results. These routines are in the `robustmc.sas` file that is contained in the sample library.

Example 12.1: LMS and LTS with Substantial Leverage Points: Hertzprung-Russell Star Data

The following data are reported in Rousseeuw and Leroy (1987) and are based on Humphreys (1978) and Vansina and De Greve, J. P. (1982). The 47 observations correspond to the 47 stars of the CYG OB1 cluster in the direction of the constellation Cygnus. The regressor variable (column 2) x is the logarithm of the effective temperature at the surface of the star (T_e), and the response variable (column 3) y is the logarithm of its light intensity (L/L_0). The results for LS and LMS on page 28 of Rousseeuw and Leroy (1987) are based on a more precise (five decimal places) version of the data set. This data set is remarkable in that it contains four substantial leverage points (which represent giant stars) that greatly affect the results of L_2 and even L_1 regression. The high leverage points are observations 11, 20, 30, and 34.

```
ab = { 1  4.37  5.23,  2  4.56  5.74,  3  4.26  4.93,
       4  4.56  5.74,  5  4.30  5.19,  6  4.46  5.46,
       7  3.84  4.65,  8  4.57  5.27,  9  4.26  5.57,
      10  4.37  5.12, 11  3.49  5.73, 12  4.43  5.45,
      13  4.48  5.42, 14  4.01  4.05, 15  4.29  4.26,
      16  4.42  4.58, 17  4.23  3.94, 18  4.42  4.18,
      19  4.23  4.18, 20  3.49  5.89, 21  4.29  4.38,
      22  4.29  4.22, 23  4.42  4.42, 24  4.49  4.85,
      25  4.38  5.02, 26  4.42  4.66, 27  4.29  4.66,
      28  4.38  4.90, 29  4.22  4.39, 30  3.48  6.05,
      31  4.38  4.42, 32  4.56  5.10, 33  4.45  5.22,
      34  3.49  6.29, 35  4.23  4.34, 36  4.62  5.62,
      37  4.53  5.10, 38  4.45  5.22, 39  4.53  5.18,
      40  4.43  5.57, 41  4.38  4.62, 42  4.45  5.06,
      43  4.50  5.34, 44  4.45  5.34, 45  4.55  5.54,
      46  4.45  4.98, 47  4.42  4.50 } ;
```

```
a = ab[,2]; b = ab[,3];
```

The following statements specify that most of the output be printed:

```
print "*** Hertzprung-Russell Star Data: Do LMS ***";
optn = j(9,1,.);
optn[2]= 3;    /* ipri */
optn[3]= 3;    /* ilsq */
optn[8]= 3;    /* icov */

call lms(sc,coef,wgt,optn,b,a);
```

Some simple statistics for the independent and response variables are shown in [Output 12.1.1](#).

Output 12.1.1 Some Simple Statistics

Median and Mean		
	Median	Mean
VAR1	4.42	4.31
Intercep	1	1
Response	5.1	5.0121276596
Dispersion and Standard Deviation		
	Dispersion	StdDev
VAR1	0.163086244	0.2908234187
Intercep	0	0
Response	0.6671709983	0.5712493409

Partial output for LS regression is shown in [Output 12.1.2](#).

Output 12.1.2 Table of Unweighted LS Regression

LS Parameter Estimates						
Variable	Estimate	Approx Std Err	t Value	Pr > t	Lower WCI	Upper WCI
VAR1	-0.4133039	0.28625748	-1.44	0.1557	-0.9743582	0.14775048
Intercep	6.7934673	1.23651563	5.49	<.0001	4.3699412	9.21699339
Cov Matrix of Parameter Estimates						
	VAR1		Intercep			
VAR1	0.0819433428		-0.353175807			
Intercep	-0.353175807		1.5289708954			

[Output 12.1.3](#) displays the iteration history. Looking at the column Best Crit in the iteration history table, you see that, with complete enumeration, the optimal solution is quickly found.

Output 12.1.3 History of the Iteration Process

Subset	Singular	Best Criterion	Percent
271	5	0.392791	25
541	8	0.392791	50
811	27	0.392791	75
1081	45	0.392791	100

The results of the optimization for LMS estimation are displayed in [Output 12.1.4](#).

Output 12.1.4 Results of Optimization

Observations of Best Subset	
2	29
Estimated Coefficients	
VAR1	Intercep
3.9705882353	-12.62794118

Output 12.1.5 displays the results for WLS regression. Due to the size of the scaled residuals, six observations (with numbers 7, 9, 11, 20, 30, 34) were assigned zero weights in the following WLS analysis.

The LTS regression implements the FAST-LTS algorithm, which improves the algorithm (used in SAS/IML Version 7 and earlier versions, denoted as V7 LTS in this chapter) in Rousseeuw and Leroy (1987) by using techniques called “selective iteration” and “nested extensions.” These techniques are used in the C-steps of the algorithm. See Rousseeuw and Van Driessen (2000) for details. The FAST-LTS algorithm significantly improves the speed of computation.

Output 12.1.5 Table of Weighted LS Regression Based on LMS

RLS Parameter Estimates Based on LMS						
Variable	Estimate	Approx Std Err	t Value	Pr > t	Lower WCI	Upper WCI
VAR1	3.04615694	0.43733923	6.97	<.0001	2.18898779	3.90332608
Intercep	-8.5000549	1.92630783	-4.41	<.0001	-12.275549	-4.7245609
Cov Matrix of Parameter Estimates						
	VAR1		Intercep			
VAR1	0.1912656038		-0.842128459			
Intercep	-0.842128459		3.7106618752			

The following statements implement the LTS regression on the Hertzsprung-Russell star data:

```
print "*** Hertzsprung-Russell Star Data: Do LTS ***";
optn = j(9,1,.);
optn[2]= 3;    /* ipri */
optn[3]= 3;    /* ilsq */
optn[8]= 3;    /* icov */

call lts(sc,coef,wgt,optn,b,a);
```

Output 12.1.6 summarizes the information for the LTS optimization.

Output 12.1.6 Summary of Optimization

2	4	6	10	13	15	17	19	21	22	25	27	28
29	33	35	36	38	39	41	42	43	44	45	46	

Output 12.1.7 displays the optimization results and **Output 12.1.8** displays the weighted LS regression based on LTS estimates.

Output 12.1.7 Results of Optimization

Estimated Coefficients	
VAR1	Intercep
4.219182102	-13.6239903

Output 12.1.8 Table of Weighted LS Regression Based on LTS

RLS Parameter Estimates Based on LTS						
Variable	Estimate	Approx Std Err	t Value	Pr > t	Lower WCI	Upper WCI
VAR1	3.04615694	0.43733923	6.97	<.0001	2.18898779	3.90332608
Intercep	-8.5000549	1.92630783	-4.41	<.0001	-12.275549	-4.7245609
Cov Matrix of Parameter Estimates						
	VAR1	Intercep				
VAR1	0.1912656038	-0.842128459				
Intercep	-0.842128459	3.7106618752				

Example 12.2: Comparison of LMS, V7 LTS, and FAST-LTS

The following example presents comparisons of LMS, V7 LTS, and FAST-LTS. The data analyzed are the stackloss data of Brownlee (1965), which are also used for documenting the L1 regression module. The three explanatory variables correspond to measurements for a plant oxidizing ammonia to nitric acid on 21 consecutive days:

- x_1 air flow to the plant
- x_2 cooling water inlet temperature
- x_3 acid concentration

The response variable y_i gives the permillage of ammonia lost (stackloss). The following data are also given in Rousseeuw and Leroy (1987) and Osborne (1985):

```
print "Stackloss Data";
aa = { 1  80  27  89  42,
       1  80  27  88  37,
       1  75  25  90  37,
       1  62  24  87  28,
       1  62  22  87  18,
       1  62  23  87  18,
       1  62  24  93  19,
       1  62  24  93  20,
       1  58  23  87  15,
       1  58  18  80  14,
       1  58  18  89  14,
       1  58  17  88  13,
       1  58  18  82  11,
       1  58  19  93  12,
       1  50  18  89   8,
       1  50  18  86   7,
       1  50  19  72   8,
       1  50  19  79   8,
       1  50  20  80   9,
       1  56  20  82  15,
       1  70  20  91  15 };
```

Rousseeuw and Leroy (1987) cite a large number of papers in which the preceding data set was analyzed. They state that most researchers “concluded that observations 1, 3, 4, and 21 were outliers” and that some people also reported observation 2 as an outlier.

Consider 2,000 Random Subsets for LMS

For $N = 21$ and $n = 4$ (three explanatory variables including intercept), you obtain a total of 5,985 different subsets of 4 observations out of 21. If you do not specify OPTN[5], the LMS algorithms draw $N_{rep} = 2000$ random sample subsets. Since there is a large number of subsets with singular linear systems that you do not want to print, you can choose OPTN[2]=2 for reduced printed output, as in the following:

```
title2 "***Use 2000 Random Subsets for LMS***";
a = aa[,2:4]; b = aa[,5];
optn = j(9,1,.);
optn[2]= 2;    /* ipri */
optn[3]= 3;    /* ilsq */
optn[8]= 3;    /* icov */

call lms(sc,coef,wgt,optn,b,a);
```

Summary statistics are shown in [Output 12.2.1](#). [Output 12.2.2](#) displays the results of LS regression. [Output 12.2.3](#) displays the LMS results for the 2000 random subsets.

Output 12.2.1 Some Simple Statistics

Use 2000 Random Subsets for LMS		
Median and Mean		
	Median	Mean
VAR1	58	60.428571429
VAR2	20	21.095238095
VAR3	87	86.285714286
Intercep	1	1
Response	15	17.523809524
Dispersion and Standard Deviation		
	Dispersion	StdDev
VAR1	5.930408874	9.1682682584
VAR2	2.965204437	3.160771455
VAR3	4.4478066555	5.3585712381
Intercep	0	0
Response	5.930408874	10.171622524

Output 12.2.2 Table of Unweighted LS Regression

LS Parameter Estimates						
Variable	Estimate	Approx Std Err	t Value	Pr > t	Lower WCI	Upper WCI
VAR1	0.7156402	0.13485819	5.31	<.0001	0.45132301	0.97995739
VAR2	1.29528612	0.36802427	3.52	0.0026	0.57397182	2.01660043
VAR3	-0.1521225	0.15629404	-0.97	0.3440	-0.4584532	0.15420818
Intercep	-39.919674	11.8959969	-3.36	0.0038	-63.2354	-16.603949
Cov Matrix of Parameter Estimates						
	VAR1	VAR2	VAR3	Intercep		
VAR1	0.0181867302	-0.036510675	-0.007143521	0.2875871057		
VAR2	-0.036510675	0.1354418598	0.0000104768	-0.651794369		
VAR3	-0.007143521	0.0000104768	0.024427828	-1.676320797		
Intercep	0.2875871057	-0.651794369	-1.676320797	141.51474107		

Output 12.2.3 Iteration History and Optimization Results

Subset	Singular	Best Criterion	Percent
500	23	0.163262	25
1000	55	0.140519	50
1500	79	0.140519	75
2000	103	0.126467	100

Observations of Best Subset

15	11	19	10
----	----	----	----

Estimated Coefficients

VAR1	VAR2	VAR3	Intercep
0.75	0.5	0	-39.25

For LMS, observations 1, 3, 4, and 21 have scaled residuals larger than 2.5 (output not shown), and they are considered outliers. [Output 12.2.4](#) displays the corresponding WLS results.

Output 12.2.4 Table of Weighted LS Regression

RLS Parameter Estimates Based on LMS						
Variable	Estimate	Approx Std Err	t Value	Pr > t	Lower WCI	Upper WCI
VAR1	0.79768556	0.06743906	11.83	<.0001	0.66550742	0.9298637
VAR2	0.57734046	0.16596894	3.48	0.0041	0.25204731	0.9026336
VAR3	-0.0670602	0.06160314	-1.09	0.2961	-0.1878001	0.05367975
Intercep	-37.652459	4.73205086	-7.96	<.0001	-46.927108	-28.37781

Cov Matrix of Parameter Estimates

	VAR1	VAR2	VAR3	Intercep
VAR1	0.0045480273	-0.007921409	-0.001198689	0.0015681747
VAR2	-0.007921409	0.0275456893	-0.00046339	-0.065017508
VAR3	-0.001198689	-0.00046339	0.0037949466	-0.246102248
Intercep	0.0015681747	-0.065017508	-0.246102248	22.392305355

Consider 2,000 Random Subsets for V7 LTS

The V7 LTS algorithm is similar to the LMS algorithm. Here is the code:

```
title2 "***Use 2000 Random Subsets for LTS***";
a = aa[,2:4]; b = aa[,5];
optn = j(9,1,.);
optn[2]= 2; /* ipri */
```

```

optn[3]= 3;    /* ilsq */
optn[8]= 3;    /* icov */
optn[9]= 1;    /* V7 LTS */

call lts(sc,coef,wgt,optn,b,a);

```

Output 12.2.5 Iteration History and Optimization Results

Use 2000 Random Subsets for LTS			
Subset	Singular	Best Criterion	Percent
500	23	0.099507	25
1000	55	0.087814	50
1500	79	0.084061	75
2000	103	0.084061	100
Observations of Best Subset			
10	11	7	15
Estimated Coefficients			
VAR1	VAR2	VAR3	Intercep
0.75	0.3333333333	0	-35.70512821

In addition to observations 1, 3, 4, and 21, which were considered outliers in LMS, observations 2 and 13 for LTS have absolute scaled residuals that are larger (but not as significantly as observations 1, 3, 4, and 21) than 2.5 (output not shown). Therefore, the WLS results based on LTS are different from those based on LMS.

Output 12.2.6 displays the results for the weighted LS regression.

Output 12.2.6 Table of Weighted LS Regression

RLS Parameter Estimates Based on LTS						
Variable	Estimate	Approx Std Err	t Value	Pr > t	Lower WCI	Upper WCI
VAR1	0.75694055	0.07860766	9.63	<.0001	0.60287236	0.91100874
VAR2	0.45353029	0.13605033	3.33	0.0067	0.18687654	0.72018405
VAR3	-0.05211	0.05463722	-0.95	0.3607	-0.159197	0.054977
Intercep	-34.05751	3.82881873	-8.90	<.0001	-41.561857	-26.553163

Output 12.2.6 *continued*

Cov Matrix of Parameter Estimates				
	VAR1	VAR2	VAR3	Intercep
VAR1	0.0061791648	-0.005776855	-0.002300587	-0.034290068
VAR2	-0.005776855	0.0185096933	0.0002582502	-0.069740883
VAR3	-0.002300587	0.0002582502	0.0029852254	-0.131487406
Intercep	-0.034290068	-0.069740883	-0.131487406	14.659852903

Consider 500 Random Subsets for FAST-LTS

The FAST-LTS algorithm uses only 500 random subsets and gets better optimization results. Here is the code:

```
title2 "***Use 500 Random Subsets for FAST-LTS***";
a = aa[,2:4]; b = aa[,5];
optn = j(9,1,.);
optn[2]= 2;    /* ipri */
optn[3]= 3;    /* ilsq */
optn[8]= 3;    /* icov */
optn[9]= 0;    /* FAST-LTS */

call lts(sc,coef,wgt,optn,b,a);
```

For this example, the two LTS algorithms identify the same outliers; however, the FAST-LTS algorithm uses only 500 random subsets and gets a smaller objective function, as seen in [Output 12.2.7](#). For large data sets, the advantages of the FAST-LTS algorithm are more obvious.

Output 12.2.7 Optimization Results for FAST-LTS

Use 500 Random Subsets for FAST-LTS												
5	6	7	8	9	10	11	12	15	16	17	18	19
Estimated Coefficients												
VAR1			VAR2			VAR3			Intercep			
0.7409210642			0.3915267228			0.0111345398			-37.32332647			

Consider All 5,985 Subsets

You now report the results of LMS for all different subsets. Here is the code:

```
title2 "*** Use All 5985 Subsets***";
a = aa[,2:4]; b = aa[,5];
optn = j(9,1,.);
```



```

optn[2]= 2;    /* ipri */
optn[3]= 3;    /* ilsq */
optn[5]= -1;   /* nrep: all 5985 subsets */
optn[8]= 3;    /* icov */

```

```

ods select IterHist0 BestSubset EstCoeff;
call lms(sc,coef,wgt,optn,b,a);

```

Output 12.2.8 displays the results for LMS.

Output 12.2.8 Iteration History and Optimization Results for LMS

*** Use All 5985 Subsets***			
Subset	Singular	Best Criterion	Percent
1497	36	0.185899	25
2993	87	0.158268	50
4489	149	0.140519	75
5985	266	0.126467	100
Observations of Best Subset			
8	10	15	19
Estimated Coefficients			
VAR1	VAR2	VAR3	Intercep
0.75	0.5	1.29526E-16	-39.25

Next, report the results of LTS for all different subsets, as follows:

```

title2 "*** Use All 5985 Subsets***";
a = aa[,2:4]; b = aa[,5];
optn = j(9,1,.);
optn[2]= 2;    /* ipri */
optn[3]= 3;    /* ilsq */
optn[5]= -1;   /* nrep: all 5985 subsets */
optn[8]= 3;    /* icov */
optn[9]= 1;    /* V7 LTS */

ods select IterHist0 BestSubset EstCoeff;
call lts(sc,coef,wgt,optn,b,a);

```

Output 12.2.9 displays the results for LTS.

Output 12.2.9 Iteration History and Optimization Results for LTS

Subset	Singular	Best Criterion	Percent
1497	36	0.135449	25
2993	87	0.107084	50
4489	149	0.081536	75
5985	266	0.081536	100
Observations of Best Subset			
5	12	17	18
Estimated Coefficients			
VAR1	VAR2	VAR3	Intercep
0.7291666667	0.4166666667	-8.54713E-18	-36.22115385

Example 12.3: LMS and LTS Univariate (Location) Problem: Barnett and Lewis Data

If you do not specify matrix X of the last input argument, the regression problem is reduced to the estimation problem of the location parameter a . The following example is described in Rousseeuw and Leroy (1987):

```

title2 "*** Barnett and Lewis (1978) ***";
b = { 3, 4, 7, 8, 10, 949, 951 };

optn = j(9,1,.);
optn[2]= 3;    /* ipri */
optn[3]= 3;    /* ilsq */
optn[8]= 3;    /* icov */

call lms(sc,coef,wgt,optn,b);

```

Output 12.3.1 shows the results of the unweighted LS regression.

Output 12.3.1 Table of Unweighted LS Regression

*** Barnett and Lewis (1978) ***			
LS Residuals			
N	Observed	Residual	Res / S
1	3.000000	-273.000000	-0.592916
2	4.000000	-272.000000	-0.590744
3	7.000000	-269.000000	-0.584229
4	8.000000	-268.000000	-0.582057
5	10.000000	-266.000000	-0.577713
6	949.000000	673.000000	1.461658
7	951.000000	675.000000	1.466002
	MinRes	1st Qu.	Median
	-273	-272	-268
	Mean	3rd Qu.	MaxRes
	0	-266	675

Output 12.3.2 shows the results for LMS regression.

Output 12.3.2 Table of LMS Results

LMS Residuals			
N	Observed	Residual	Res / S
1	3.000000	-2.500000	-0.819232
2	4.000000	-1.500000	-0.491539
3	7.000000	1.500000	0.491539
4	8.000000	2.500000	0.819232
5	10.000000	4.500000	1.474617
6	949.000000	943.500000	309.178127
7	951.000000	945.500000	309.833512
	MinRes	1st Qu.	Median
	-2.5	-1.5	2.5
	Mean	3rd Qu.	MaxRes
	270.5	4.5	945.5

You obtain the LMS location estimate 6.5 compared with the mean 276 (which is the LS estimate of the location parameter) and the median 8. The scale estimate in the univariate problem is a resistant (high breakdown) estimator for the dispersion of the data (see Rousseeuw and Leroy (1987)).

For weighted LS regression, the last two observations are ignored (that is, given zero weights), as shown in [Output 12.3.3](#).

Output 12.3.3 Table of Weighted LS Regression

Weighted LS Residuals				
N	Observed	Residual	Res / S	Weight
1	3.000000	-3.400000	-1.180157	1.000000
2	4.000000	-2.400000	-0.833052	1.000000
3	7.000000	0.600000	0.208263	1.000000
4	8.000000	1.600000	0.555368	1.000000
5	10.000000	3.600000	1.249578	1.000000
6	949.000000	942.600000	327.181236	0
7	951.000000	944.600000	327.875447	0
	MinRes	1st Qu.	Median	
	-3.4	-2.4	1.6	
	Mean	3rd Qu.	MaxRes	
	269.6	3.6	944.6	

Use the following code to obtain results from LTS:

```

title2 "*** Barnett and Lewis (1978) ***";
b = { 3, 4, 7, 8, 10, 949, 951 };

optn = j(9,1,.);
optn[2]= 3;    /* ipri */
optn[3]= 3;    /* ilsq */
optn[8]= 3;    /* icov */

call lts(sc,coef,wgt,optn,b);

```

The results for LTS are similar to those reported for LMS in Rousseeuw and Leroy (1987), as shown in [Output 12.3.4](#).

Output 12.3.4 Table of LTS Results

*** Barnett and Lewis (1978) ***			
LTS Residuals			
N	Observed	Residual	Res / S
1	3.000000	-2.500000	-0.819232
2	4.000000	-1.500000	-0.491539
3	7.000000	1.500000	0.491539
4	8.000000	2.500000	0.819232
5	10.000000	4.500000	1.474617
6	949.000000	943.500000	309.178127
7	951.000000	945.500000	309.833512
	MinRes	1st Qu.	Median
	-2.5	-1.5	2.5
	Mean	3rd Qu.	MaxRes
	270.5	4.5	945.5

Since nonzero weights are chosen for the same observations as with LMS, the WLS results based on LTS agree with those based on LMS (shown previously in [Output 12.3.3](#)).

In summary, you obtain the following estimates for the location parameter:

- LS estimate (unweighted mean) = 276
- Median = 8
- LMS estimate = 5.5
- LTS estimate = 5.5
- WLS estimate (weighted mean based on LMS or LTS) = 6.4

Using MVE and MCD

The SCATMVE and SCATMCD modules are used in these examples for plotting the results. The PRIMVE module can be used for printing results. These routines are in the `robustmc.sas` file that is contained in the sample library.

Example 12.4: Brainlog Data

The following data are the body weights (in kilograms) and brain weights (in grams) of $N = 28$ animals as reported by Jerison (1973) and as analyzed in Rousseeuw and Leroy (1987). Instead of the original data, the following example uses the logarithms of the measurements of the two variables.

```
title "*** Brainlog Data: Do MCD, MVE ***";
aa={ 1.303338E-001  9.084851E-001 ,
      2.6674530      2.6263400 ,
      1.5602650      2.0773680 ,
      1.4418520      2.0606980 ,
      1.703332E-002  7.403627E-001 ,
      4.0681860      1.6989700 ,
      3.4060290      3.6630410 ,
      2.2720740      2.6222140 ,
      2.7168380      2.8162410 ,
      1.0000000      2.0606980 ,
      5.185139E-001  1.4082400 ,
      2.7234560      2.8325090 ,
      2.3159700      2.6085260 ,
      1.7923920      3.1205740 ,
      3.8230830      3.7567880 ,
      3.9731280      1.8450980 ,
      8.325089E-001  2.2528530 ,
      1.5440680      1.7481880 ,
      -9.208187E-001  .0000000 ,
      -1.6382720     -3.979400E-001 ,
      3.979400E-001  1.0827850 ,
      1.7442930      2.2430380 ,
      2.0000000      2.1959000 ,
      1.7173380      2.6434530 ,
      4.9395190      2.1889280 ,
      -5.528420E-001  2.787536E-001 ,
      -9.136401E-001  4.771213E-001 ,
      2.2833010      2.2552720 };
```

By default, the MVE subroutine uses only 1500 randomly selected subsets rather than all subsets. The following specification of the options vector requires that all 3276 subsets of 3 cases out of 28 cases are generated and evaluated:

```
title2 "***MVE for BrainLog Data***";
title3 "*** Use All Subsets***";
optn = j(9,1,.);
optn[1]= 3;          /* ipri */
optn[2]= 1;          /* pcov: print COV */
optn[3]= 1;          /* pcov: print CORR */
optn[5]= -1;         /* nrep: all subsets */

call mve(sc,xmve,dist,optn,aa);
```

Specifying OPTN[1]=3, OPTN[2]=1, and OPTN[3]=1 requests that all output be printed. [Output 12.4.1](#) shows the classical scatter and correlation matrix.

Output 12.4.1 Some Simple Statistics

```

*** Brainlog Data: Do MCD, MVE ***
***MVE for BrainLog Data***
*** Use All Subsets***

Classical Covariance Matrix

          VAR1          VAR2
VAR1      2.6816512357      1.3300846932
VAR2      1.3300846932      1.0857537552

Classical Correlation Matrix

          VAR1          VAR2
VAR1              1      0.7794934643
VAR2      0.7794934643      1

Classical Mean

VAR1      1.6378572186
VAR2      1.9219465964

```

Output 12.4.2 shows the results of the combinatoric optimization (complete subset sampling).

Output 12.4.2 Iteration History for MVE

```

          Subset      Singular      Best
          Criterion      Percent
819          0      0.439709      25
1638         0      0.439709      50
2457         0      0.439709      75
3276         0      0.439709     100

Observations of Best Subset

1          22          28

Initial MVE Location
Estimates

VAR1      1.3859759333
VAR2      1.8022650333

Initial MVE Scatter Matrix

          VAR1          VAR2
VAR1      4.9018525125      3.2937139101
VAR2      3.2937139101      2.3400650932

```

Output 12.4.3 shows the optimization results after local improvement.

Output 12.4.3 Table of MVE Results

Robust MVE Location Estimates		
VAR1	1.29528238	
VAR2	1.8733722792	
Robust MVE Scatter Matrix		
	VAR1	VAR2
VAR1	2.0566592937	1.5290250167
VAR2	1.5290250167	1.2041353589
Eigenvalues of Robust Scatter Matrix		
VAR1	3.2177274012	
VAR2	0.0430672514	
Robust Correlation Matrix		
	VAR1	VAR2
VAR1	1	0.9716184659
VAR2	0.9716184659	1

Output 12.4.4 presents a table that contains the classical Mahalanobis distances, the robust distances, and the weights identifying the outlier observations.

Output 12.4.4 Mahalanobis and Robust Distances

Classical Distances and Robust (Rousseeuw) Distances			
Unsquared Mahalanobis Distance and			
Unsquared Rousseeuw Distance of Each Observation			
N	Mahalanobis Distances	Robust Distances	Weight
1	1.006591	0.897076	1.000000
2	0.695261	1.405302	1.000000
3	0.300831	0.186726	1.000000
4	0.380817	0.318701	1.000000
5	1.146485	1.135697	1.000000
6	2.644176	8.828036	0
7	1.708334	1.699233	1.000000
8	0.706522	0.686680	1.000000
9	0.858404	1.084163	1.000000
10	0.798698	1.580835	1.000000
11	0.686485	0.693346	1.000000
12	0.874349	1.071492	1.000000
13	0.677791	0.717545	1.000000
14	1.721526	3.398698	0
15	1.761947	1.762703	1.000000
16	2.369473	7.999472	0
17	1.222253	2.805954	0
18	0.203178	1.207332	1.000000
19	1.855201	1.773317	1.000000
20	2.266268	2.074971	1.000000
21	0.831416	0.785954	1.000000
22	0.416158	0.342200	1.000000
23	0.264182	0.918383	1.000000
24	1.046120	1.782334	1.000000
25	2.911101	9.565443	0
26	1.586458	1.543748	1.000000
27	1.582124	1.808423	1.000000
28	0.394664	1.523235	1.000000

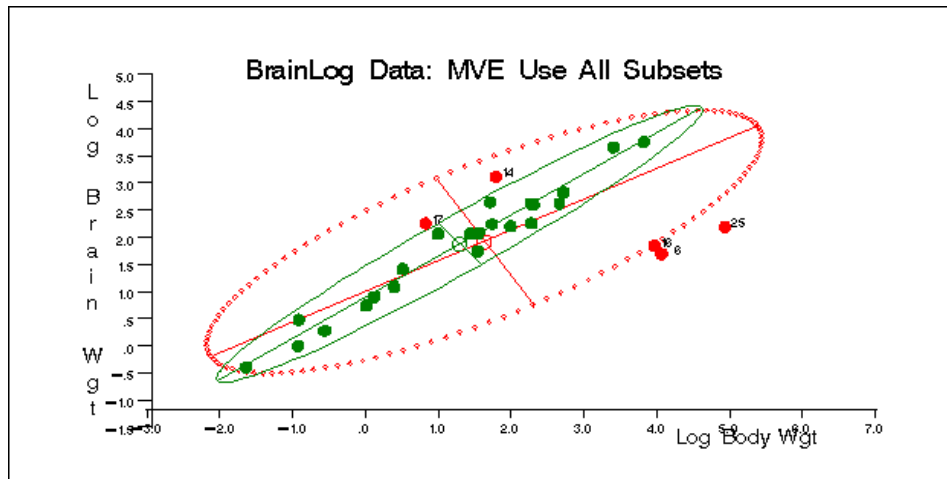
Again, you can call the subroutine SCATMVE(), which is included in the sample library in the file `robustmc.sas`, to plot the classical and robust confidence ellipsoids, as follows:

```

optn = j(9,1,.); optn[5]= -1;
vnam = { "Log Body Wgt", "Log Brain Wgt" };
filn = "brlmve";
titl = "BrainLog Data: MVE Use All Subsets";
%include 'robustmc.sas';
call scatmve(2,optn,.9,aa,vnam,titl,1,filn);

```

The plot is shown in [Figure 12.4.5](#).

Output 12.4.5 BrainLog Data: Classical and Robust Ellipsoid(MVE)

MCD is another subroutine that can be used to compute the robust location and the robust covariance of multivariate data sets. Here is the code:

```

title "*** Brainlog Data: Do MCD, MVE ***";
aa={ 1.303338E-001  9.084851E-001 ,
      2.6674530    2.6263400 ,
      1.5602650    2.0773680 ,
      1.4418520    2.0606980 ,
      1.703332E-002  7.403627E-001 ,
      4.0681860    1.6989700 ,
      3.4060290    3.6630410 ,
      2.2720740    2.6222140 ,
      2.7168380    2.8162410 ,
      1.0000000    2.0606980 ,
      5.185139E-001  1.4082400 ,
      2.7234560    2.8325090 ,
      2.3159700    2.6085260 ,
      1.7923920    3.1205740 ,
      3.8230830    3.7567880 ,
      3.9731280    1.8450980 ,
      8.325089E-001  2.2528530 ,
      1.5440680    1.7481880 ,
      -9.208187E-001  .0000000 ,
      -1.6382720    -3.979400E-001 ,
      3.979400E-001  1.0827850 ,
      1.7442930    2.2430380 ,
      2.0000000    2.1959000 ,
      1.7173380    2.6434530 ,
      4.9395190    2.1889280 ,
      -5.528420E-001  2.787536E-001 ,
      -9.136401E-001  4.771213E-001 ,
      2.2833010    2.2552720 };

title2 "****MCD for BrainLog Data****";
title3 "**** Use 500 Random Subsets****";

```

```

optn = j(9,1,.);
optn[1]= 3;          /* ipri */
optn[2]= 1;          /* pcov: print COV */
optn[3]= 1;          /* pcor: print CORR */

call mcd(sc,xmve,dist,optn,aa);

```

Similarly, specifying OPTN[1]=3, OPTN[2]=1, and OPTN[3]=1 requests that all output be printed.

Output 12.4.6 shows the results of the optimization.

Output 12.4.6 Results of the Optimization

```

*** Brainlog Data: Do MCD, MVE ***
***MCD for BrainLog Data***
*** Use 500 Random Subsets***

  1    2    3    4    5    8    9   11   12   13   18   21   22   23   28

      MCD Location Estimate

              VAR1              VAR2

      1.622226068      2.0150777867

      MCD Scatter Matrix Estimate

              VAR1              VAR2

      VAR1      0.8973945995      0.6424456706
      VAR2      0.6424456706      0.4793505736

```

Output 12.4.7 shows the reweighted results after removing outliers.

Output 12.4.7 Final Reweighted MCD Results

```

      Reweighted Location Estimate

              VAR1              VAR2

      1.3154029661      1.8568731174

      Reweighted Scatter Matrix

              VAR1              VAR2

      VAR1      2.139986054      1.6068556533
      VAR2      1.6068556533      1.2520384784

      Eigenvalues

              VAR1              VAR2

      3.363074897      0.0289496354

```

Output 12.4.7 *continued*

Reweighted Correlation Matrix			
	VAR1	VAR2	
VAR1	1	0.9816633012	
VAR2	0.9816633012	1	

Output 12.4.8 presents a table that contains the classical Mahalanobis distances, the robust distances, and the weights identifying the outlier observations.

Output 12.4.8 Mahalanobis and Robust Distances (MCD)

Classical Distances and Robust (Rousseeuw) Distances Unsquared Mahalanobis Distance and Unsquared Rousseeuw Distance of Each Observation			
N	Mahalanobis Distances	Robust Distances	Weight
1	1.006591	0.855347	1.000000
2	0.695261	1.477050	1.000000
3	0.300831	0.239828	1.000000
4	0.380817	0.517719	1.000000
5	1.146485	1.108362	1.000000
6	2.644176	10.599341	0
7	1.708334	1.808455	1.000000
8	0.706522	0.690099	1.000000
9	0.858404	1.052423	1.000000
10	0.798698	2.077131	1.000000
11	0.686485	0.888545	1.000000
12	0.874349	1.035824	1.000000
13	0.677791	0.683978	1.000000
14	1.721526	4.257963	0
15	1.761947	1.716065	1.000000
16	2.369473	9.584992	0
17	1.222253	3.571700	0
18	0.203178	1.323783	1.000000
19	1.855201	1.741064	1.000000
20	2.266268	2.026528	1.000000
21	0.831416	0.743545	1.000000
22	0.416158	0.419923	1.000000
23	0.264182	0.944610	1.000000
24	1.046120	2.289334	1.000000
25	2.911101	11.471953	0
26	1.586458	1.518721	1.000000
27	1.582124	2.054593	1.000000
28	0.394664	1.675651	1.000000

You can call the subroutine SCATMCD(), which is included in the sample library in file `robustmc.sas`, to plot the classical and robust confidence ellipsoids. Here is the code:

```
optn = j(9,1,.); optn[5]= -1;
```

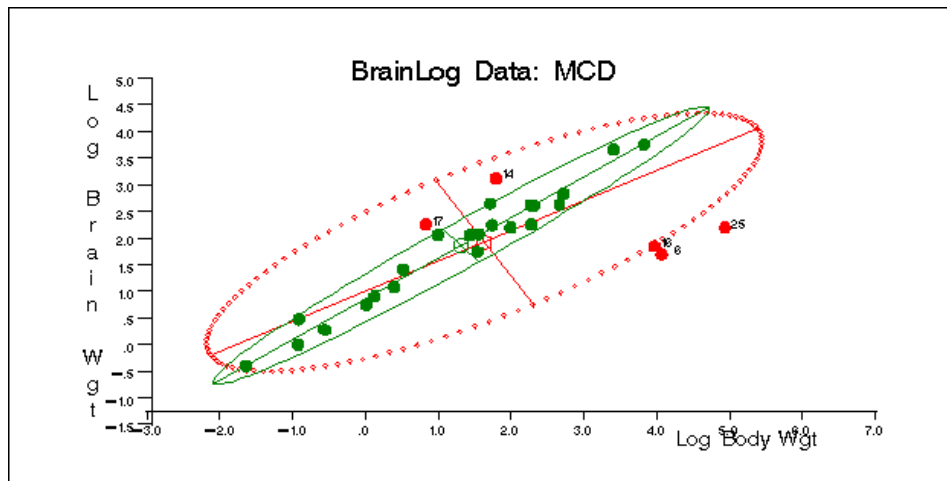
```

vnam = { "Log Body Wgt", "Log Brain Wgt" };
filn = "brlmcd";
titl = "BrainLog Data: MCD";
%include 'robustmc.sas';
call scatmcd(2,optn,.9,aa,vnam,titl,1,filn);

```

The plot is shown in Figure 12.4.9.

Output 12.4.9 BrainLog Data: Classical and Robust Ellipsoid (MCD)



Example 12.5: Stackloss Data

The following example analyzes the three regressors of Brownlee (1965) stackloss data. By default, the MVE subroutine tries only 2000 randomly selected subsets in its search. There are, in total, 5985 subsets of 4 cases out of 21 cases. Here is the code:

```

title2 "***MVE for Stackloss Data***";
title3 "*** Use All Subsets***";
aa = { 1 80 27 89 42,
       1 80 27 88 37,
       1 75 25 90 37,
       1 62 24 87 28,
       1 62 22 87 18,
       1 62 23 87 18,
       1 62 24 93 19,
       1 62 24 93 20,
       1 58 23 87 15,
       1 58 18 80 14,
       1 58 18 89 14,
       1 58 17 88 13,
       1 58 18 82 11,
       1 58 19 93 12,
       1 50 18 89 8,
       1 50 18 86 7,
       1 50 19 72 8,

```

```

      1  50  19  79   8,
      1  50  20  80   9,
      1  56  20  82  15,
      1  70  20  91  15 };
a = aa[,2:4];
optn = j(9,1,.);
optn[1]= 2;           /* ipri */
optn[2]= 1;           /* pcov: print COV */
optn[3]= 1;           /* pcov: print CORR */
optn[5]= -1;          /* nrep: use all subsets */

call mve(sc,xmve,dist,optn,a);

```

Output 12.5.1 of the output shows the classical scatter and correlation matrix.

Output 12.5.1 Some Simple Statistics

*** Brainlog Data: Do MCD, MVE ***			
MVE for Stackloss Data			
*** Use All Subsets***			
Classical Covariance Matrix			
	VAR1	VAR2	VAR3
VAR1	84.057142857	22.657142857	24.571428571
VAR2	22.657142857	9.9904761905	6.6214285714
VAR3	24.571428571	6.6214285714	28.714285714
Classical Correlation Matrix			
	VAR1	VAR2	VAR3
VAR1	1	0.781852333	0.5001428749
VAR2	0.781852333	1	0.3909395378
VAR3	0.5001428749	0.3909395378	1
Classical Mean			
	VAR1	60.428571429	
	VAR2	21.095238095	
	VAR3	86.285714286	

Output 12.5.2 shows the results of the optimization (complete subset sampling).

Output 12.5.2 Iteration History

	Subset	Singular	Best Criterion	Percent
	1497	22	253.312431	25
	2993	46	224.084073	50
	4489	77	165.830053	75
	5985	156	165.634363	100

Output 12.5.2 *continued*

Observations of Best Subset					
	7	10	14	20	
Initial MVE Location Estimates					
	VAR1		58.5		
	VAR2		20.25		
	VAR3		87		
Initial MVE Scatter Matrix					
	VAR1		VAR2		VAR3
VAR1	34.829014749		28.413143611		62.32560534
VAR2	28.413143611		38.036950318		58.659393261
VAR3	62.32560534		58.659393261		267.63348175

Output 12.5.3 shows the optimization results after local improvement.

Output 12.5.3 Table of MVE Results

Robust MVE Location Estimates			
VAR1	56.705882353		
VAR2	20.235294118		
VAR3	85.529411765		
Robust MVE Scatter Matrix			
	VAR1	VAR2	VAR3
VAR1	23.470588235	7.5735294118	16.102941176
VAR2	7.5735294118	6.3161764706	5.3676470588
VAR3	16.102941176	5.3676470588	32.389705882
Eigenvalues of Robust Scatter Matrix			
VAR1	46.597431018		
VAR2	12.155938483		
VAR3	3.423101087		
Robust Correlation Matrix			
	VAR1	VAR2	VAR3
VAR1	1	0.6220269501	0.5840361335
VAR2	0.6220269501	1	0.375278187
VAR3	0.5840361335	0.375278187	1

Output 12.5.4 presents a table that contains the classical Mahalanobis distances, the robust distances, and the weights identifying the outlying observations (that is, the leverage points when explaining y with these three regressor variables).

Output 12.5.4 Mahalanobis and Robust Distances

Classical Distances and Robust (Rousseeuw) Distances Unsquared Mahalanobis Distance and Unsquared Rousseeuw Distance of Each Observation			
N	Mahalanobis Distances	Robust Distances	Weight
1	2.253603	5.528395	0
2	2.324745	5.637357	0
3	1.593712	4.197235	0
4	1.271898	1.588734	1.000000
5	0.303357	1.189335	1.000000
6	0.772895	1.308038	1.000000
7	1.852661	1.715924	1.000000
8	1.852661	1.715924	1.000000
9	1.360622	1.226680	1.000000
10	1.745997	1.936256	1.000000
11	1.465702	1.493509	1.000000
12	1.841504	1.913079	1.000000
13	1.482649	1.659943	1.000000
14	1.778785	1.689210	1.000000
15	1.690241	2.230109	1.000000
16	1.291934	1.767582	1.000000
17	2.700016	2.431021	1.000000
18	1.503155	1.523316	1.000000
19	1.593221	1.710165	1.000000
20	0.807054	0.675124	1.000000
21	2.176761	3.657281	0

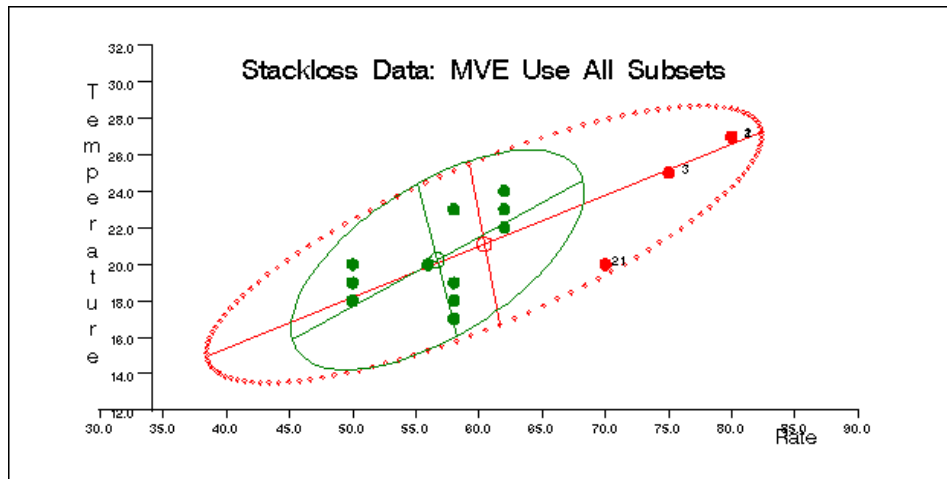
The following specification generates three bivariate plots of the classical and robust tolerance ellipsoids. They are shown in Figure 12.5.5, Figure 12.5.6, and Figure 12.5.7, one plot for each pair of variables.

```

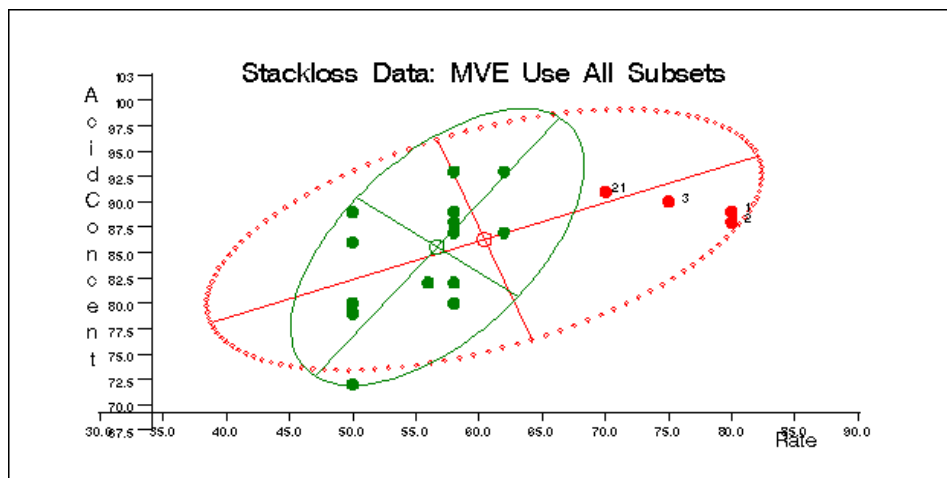
optn = j(9,1,.); optn[5]= -1;
vnam = { "Rate", "Temperature", "AcidConcent" };
filn = "stlmve";
titl = "Stackloss Data: Use All Subsets";
%include 'robustmc.sas';
call scatmve(2,optn,.9,a,vnam,titl,1,filn);

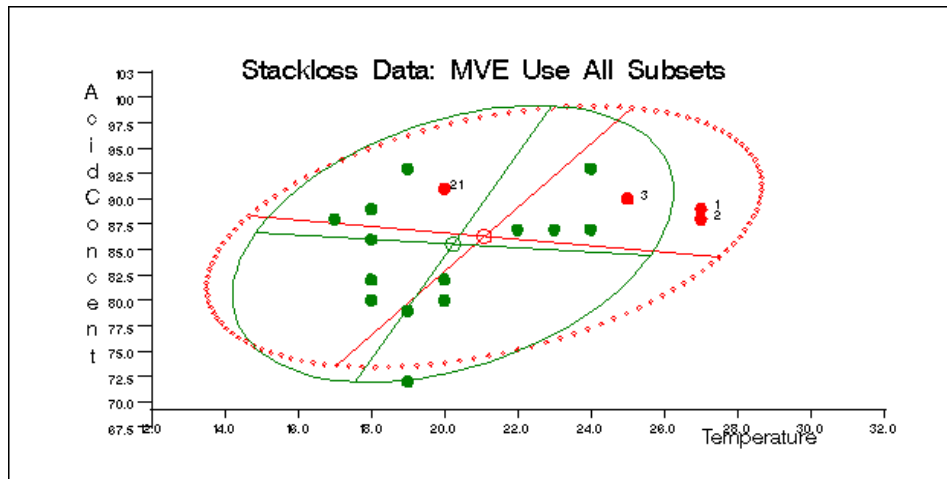
```


Output 12.5.5 Stackloss Data: Rate vs. Temperature (MVE)



Output 12.5.6 Stackloss Data: Rate vs. Acid Concentration (MVE)



Output 12.5.7 Stackloss Data: Temperature vs. Acid Concentration (MVE)

You can also use the MCD method for the stackloss data as follows:

```
title2 "****MCD for Stackloss Data****";
title3 "**** Use 500 Random Subsets****";
a = aa[,2:4];
optn = j(8,1,.);
optn[1]= 2;          /* ipri */
optn[2]= 1;          /* pcov: print COV */
optn[3]= 1;          /* pcov: print CORR */
optn[5]= -1 ;        /* nrep: use all subsets */

call mcd(sc,xmcd,dist,optn,a);
```

The optimization results are displayed in [Output 12.5.8](#). The reweighted results are displayed in [Output 12.5.9](#).

Output 12.5.8 MCD Results of Optimization

*** Brainlog Data: Do MCD, MVE *** ***MCD for Stackloss Data*** *** Use 500 Random Subsets***											
4	5	6	7	8	9	10	11	12	13	14	20
MCD Location Estimate											
VAR1			VAR2			VAR3					
59.5			20.833333333			87.333333333					

Output 12.5.8 *continued*

MCD Scatter Matrix Estimate			
	VAR1	VAR2	VAR3
VAR1	5.1818181818	4.8181818182	4.7272727273
VAR2	4.8181818182	7.6060606061	5.0606060606
VAR3	4.7272727273	5.0606060606	19.151515152
MCD Correlation Matrix			
	VAR1	VAR2	VAR3
VAR1	1	0.7674714142	0.4745347313
VAR2	0.7674714142	1	0.4192963398
VAR3	0.4745347313	0.4192963398	1
Consistent Scatter Matrix			
	VAR1	VAR2	VAR3
VAR1	8.6578437815	8.0502757968	7.8983838007
VAR2	8.0502757968	12.708297013	8.4553211199
VAR3	7.8983838007	8.4553211199	31.998580526

Output 12.5.9 Final Reweighted MCD Results

Reweighted Location Estimate			
	VAR1	VAR2	VAR3
	59.5	20.833333333	87.333333333
Reweighted Scatter Matrix			
	VAR1	VAR2	VAR3
VAR1	5.1818181818	4.8181818182	4.7272727273
VAR2	4.8181818182	7.6060606061	5.0606060606
VAR3	4.7272727273	5.0606060606	19.151515152
Eigenvalues			
	VAR1	VAR2	VAR3
	23.191069268	7.3520037086	1.3963209628
Reweighted Correlation Matrix			
	VAR1	VAR2	VAR3
VAR1	1	0.7674714142	0.4745347313
VAR2	0.7674714142	1	0.4192963398
VAR3	0.4745347313	0.4192963398	1

The MCD robust distances and outlying diagnostic are displayed in [Output 12.5.10](#). MCD identifies more leverage points than MVE.

Output 12.5.10 MCD Robust Distances

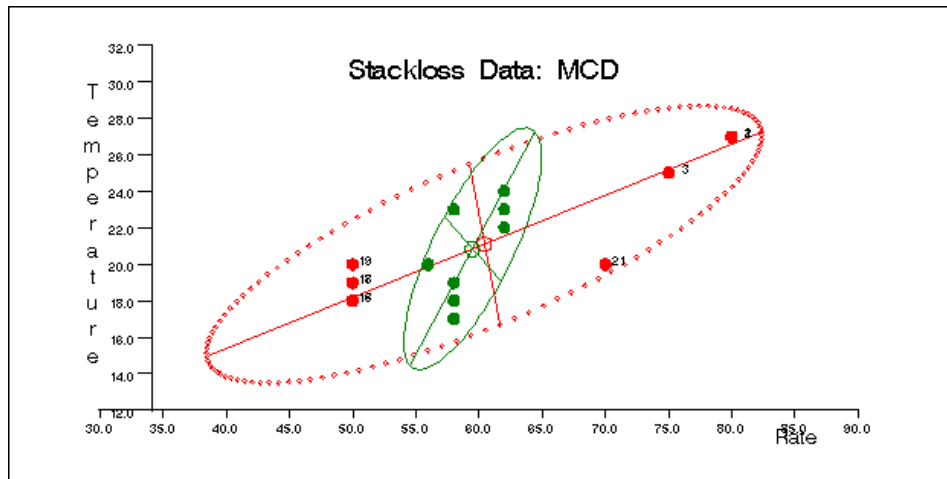
Classical Distances and Robust (Rousseeuw) Distances			
Unsquared Mahalanobis Distance and			
Unsquared Rousseeuw Distance of Each Observation			
N	Mahalanobis Distances	Robust Distances	Weight
1	2.253603	12.173282	0
2	2.324745	12.255677	0
3	1.593712	9.263990	0
4	1.271898	1.401368	1.000000
5	0.303357	1.420020	1.000000
6	0.772895	1.291188	1.000000
7	1.852661	1.460370	1.000000
8	1.852661	1.460370	1.000000
9	1.360622	2.120590	1.000000
10	1.745997	1.809708	1.000000
11	1.465702	1.362278	1.000000
12	1.841504	1.667437	1.000000
13	1.482649	1.416724	1.000000
14	1.778785	1.988240	1.000000
15	1.690241	5.874858	0
16	1.291934	5.606157	0
17	2.700016	6.133319	0
18	1.503155	5.760432	0
19	1.593221	6.156248	0
20	0.807054	2.172300	1.000000
21	2.176761	7.622769	0

Similarly, you can use the SCATMCD routine to generate three bivariate plots of the classical and robust tolerance ellipsoids, one plot for each pair of variables. Here is the code:

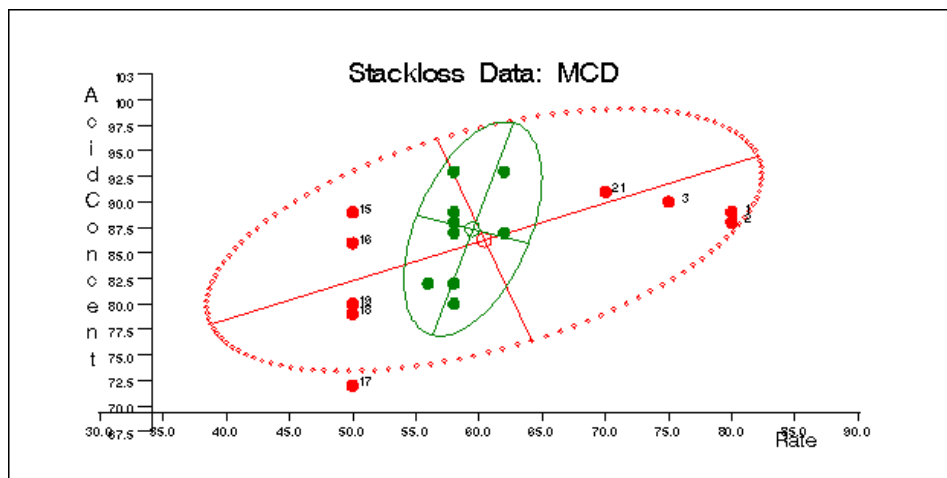
```
optn = j(9,1,.); optn[5]= -1;
vnam = { "Rate", "Temperature", "AcidConcent" };
filn = "stlmcd";
titl = "Stackloss Data: Use All Subsets";
%include 'robustmc.sas';
call scatmcd(2,optn,.9,a,vnam,titl,1,filn);
```

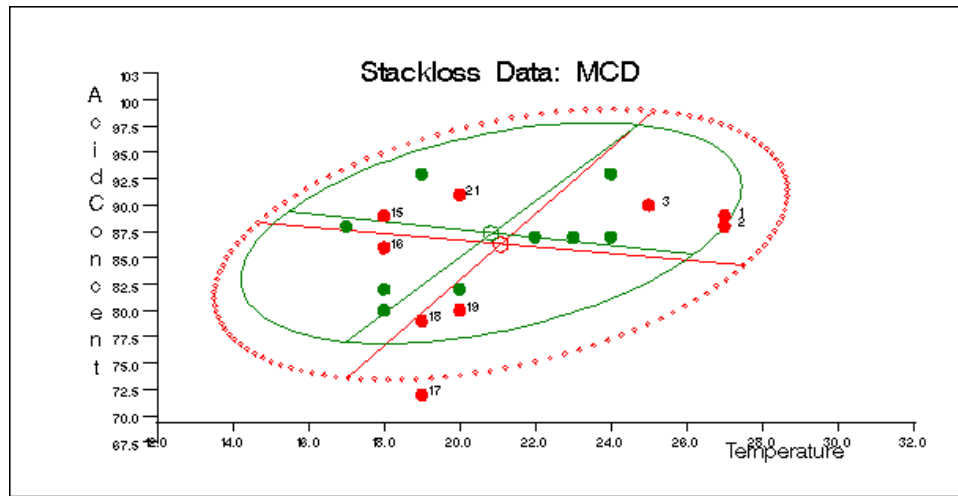
Figure 12.5.11, Figure 12.5.12, and Figure 12.5.13 display these plots.

Output 12.5.11 Stackloss Data: Rate vs. Temperature (MCD)



Output 12.5.12 Stackloss Data: Rate vs. Acid Concentration (MCD)



Output 12.5.13 Stackloss Data: Temperature vs. Acid Concentration (MCD)

Combining Robust Residual and Robust Distance

This section is based entirely on Rousseeuw and Van Zomeren (1990). Observations \mathbf{x}_i , which are far away from most of the other observations, are called *leverage points*. One classical method inspects the Mahalanobis distances MD_i to find outliers \mathbf{x}_i :

$$MD_i = \sqrt{(\mathbf{x}_i - \mu)\mathbf{C}^{-1}(\mathbf{x}_i - \mu)^T}$$

where \mathbf{C} is the classical sample covariance matrix.

Note that the MVE subroutine prints the classical Mahalanobis distances MD_i together with the robust distances RD_i . In classical linear regression, the diagonal elements h_{ii} of the *hat* matrix

$$\mathbf{H} = \mathbf{X}(\mathbf{X}^T\mathbf{X})^{-1}\mathbf{X}^T$$

are used to identify leverage points. Rousseeuw and Van Zomeren (1990) report the following monotone relationship between the h_{ii} and MD_i :

$$h_{ii} = \frac{(MD_i)^2}{N-1} + \frac{1}{n}$$

They point out that neither the MD_i nor the h_{ii} are entirely safe for detecting leverage points reliably. Multiple outliers do not necessarily have large MD_i values because of the masking effect.

The definition of a leverage point is, therefore, based entirely on the outlyingness of \mathbf{x}_i and is not related to the response value y_i . By including the y_i value in the definition, Rousseeuw and Van Zomeren (1990) distinguish between the following:

- *Good leverage points* are points (\mathbf{x}_i, y_i) that are close to the regression plane; that is, good leverage points improve the precision of the regression coefficients.

- *Bad leverage points* are points (\mathbf{x}_i, y_i) that are far from the regression plane; that is, bad leverage points reduce the precision of the regression coefficients.

Rousseeuw and Van Zomeren (1990) propose to plot the standardized residuals of robust regression (LMS or LTS) versus the robust distances RD_i obtained from MVE. Two horizontal lines that correspond to residual values of $+2.5$ and -2.5 are useful to distinguish between small and large residuals, and one vertical line that corresponds to the $\sqrt{\chi_{n,975}^2}$ is used to distinguish between small and large distances.

Example 12.6: Hawkins-Bradu-Kass Data

The first 14 observations of the following data set (see Hawkins, Bradu, and Kass (1984)) are leverage points; however, only observations 12, 13, and 14 have large h_{ii} , and only observations 12 and 14 have large MD_i values.

```

title "Hawkins, Bradu, Kass (1984) Data";
aa = { 1  10.1  19.6  28.3   9.7,
       2   9.5  20.5  28.9  10.1,
       3  10.7  20.2  31.0  10.3,
       4   9.9  21.5  31.7   9.5,
       5  10.3  21.1  31.1  10.0,
       6  10.8  20.4  29.2  10.0,
       7  10.5  20.9  29.1  10.8,
       8   9.9  19.6  28.8  10.3,
       9   9.7  20.7  31.0   9.6,
      10   9.3  19.7  30.3   9.9,
      11  11.0  24.0  35.0  -0.2,
      12  12.0  23.0  37.0  -0.4,
      13  12.0  26.0  34.0   0.7,
      14  11.0  34.0  34.0   0.1,
      15   3.4   2.9   2.1  -0.4,
      16   3.1   2.2   0.3   0.6,
      17   0.0   1.6   0.2  -0.2,
      18   2.3   1.6   2.0   0.0,
      19   0.8   2.9   1.6   0.1,
      20   3.1   3.4   2.2   0.4,
      21   2.6   2.2   1.9   0.9,
      22   0.4   3.2   1.9   0.3,
      23   2.0   2.3   0.8  -0.8,
      24   1.3   2.3   0.5   0.7,
      25   1.0   0.0   0.4  -0.3,
      26   0.9   3.3   2.5  -0.8,
      27   3.3   2.5   2.9  -0.7,
      28   1.8   0.8   2.0   0.3,
      29   1.2   0.9   0.8   0.3,
      30   1.2   0.7   3.4  -0.3,
      31   3.1   1.4   1.0   0.0,
      32   0.5   2.4   0.3  -0.4,
      33   1.5   3.1   1.5  -0.6,
      34   0.4   0.0   0.7  -0.7,

```

```

35  3.1  2.4  3.0  0.3,
36  1.1  2.2  2.7 -1.0,
37  0.1  3.0  2.6 -0.6,
38  1.5  1.2  0.2  0.9,
39  2.1  0.0  1.2 -0.7,
40  0.5  2.0  1.2 -0.5,
41  3.4  1.6  2.9 -0.1,
42  0.3  1.0  2.7 -0.7,
43  0.1  3.3  0.9  0.6,
44  1.8  0.5  3.2 -0.7,
45  1.9  0.1  0.6 -0.5,
46  1.8  0.5  3.0 -0.4,
47  3.0  0.1  0.8 -0.9,
48  3.1  1.6  3.0  0.1,
49  3.1  2.5  1.9  0.9,
50  2.1  2.8  2.9 -0.4,
51  2.3  1.5  0.4  0.7,
52  3.3  0.6  1.2 -0.5,
53  0.3  0.4  3.3  0.7,
54  1.1  3.0  0.3  0.7,
55  0.5  2.4  0.9  0.0,
56  1.8  3.2  0.9  0.1,
57  1.8  0.7  0.7  0.7,
58  2.4  3.4  1.5 -0.1,
59  1.6  2.1  3.0 -0.3,
60  0.3  1.5  3.3 -0.9,
61  0.4  3.4  3.0 -0.3,
62  0.9  0.1  0.3  0.6,
63  1.1  2.7  0.2 -0.3,
64  2.8  3.0  2.9 -0.5,
65  2.0  0.7  2.7  0.6,
66  0.2  1.8  0.8 -0.9,
67  1.6  2.0  1.2 -0.7,
68  0.1  0.0  1.1  0.6,
69  2.0  0.6  0.3  0.2,
70  1.0  2.2  2.9  0.7,
71  2.2  2.5  2.3  0.2,
72  0.6  2.0  1.5 -0.2,
73  0.3  1.7  2.2  0.4,
74  0.0  2.2  1.6 -0.9,
75  0.3  0.4  2.6  0.2 };

```

```
a = aa[,2:4]; b = aa[,5];
```

The data are also listed in Rousseeuw and Leroy (1987).

The complete enumeration must inspect 1,215,450 subsets.

Output 12.6.1 displays the iteration history for MVE.

```

optn = j(9,1,.);
optn[1]= 3;          /* ipri */
optn[2]= 1;          /* pcov: print COV */
optn[3]= 1;          /* pcor: print CORR */

```



```
optn[5]= -1;                /* nrep: all subsets */

call mve(sc,xmve,dist,optn,a);
```

Output 12.6.1 Iteration History for MVE

Hawkins, Bradu, Kass (1984) Data			
Subset	Singular	Best Criterion	Percent
121545	0	51.104276	10
243090	1	51.104276	20
364635	1	51.104276	30
486180	2	51.104276	40
607725	3	51.104276	50
729270	9	6.271725	60
850815	35	6.271725	70
972360	55	5.912308	80
1093905	76	5.912308	90
1215450	114	5.912308	100

Output 12.6.2 reports the robust parameter estimates for MVE.

Output 12.6.2 Robust Location Estimates

Robust MVE Location Estimates			
VAR1	1.5133333333		
VAR2	1.8083333333		
VAR3	1.7016666667		
Robust MVE Scatter Matrix			
	VAR1	VAR2	VAR3
VAR1	1.1143954802	0.0939548023	0.1416723164
VAR2	0.0939548023	1.1231497175	0.1174435028
VAR3	0.1416723164	0.1174435028	1.0747429379

Output 12.6.3 reports the eigenvalues of the robust scatter matrix and the robust correlation matrix.

Output 12.6.3 MVE Scatter Matrix

Eigenvalues of Robust Scatter Matrix	
VAR1	1.3396371545
VAR2	1.0281247572
VAR3	0.9445262239

Output 12.6.3 *continued*

Robust Correlation Matrix			
	VAR1	VAR2	VAR3
VAR1	1	0.0839808925	0.1294532696
VAR2	0.0839808925	1	0.1068951177
VAR3	0.1294532696	0.1068951177	1

Output 12.6.4 shows a portion of the classical Mahalanobis and robust distances obtained by complete enumeration. The first 14 observations are recognized as outliers (leverage points).

Output 12.6.4 Mahalanobis and Robust Distances

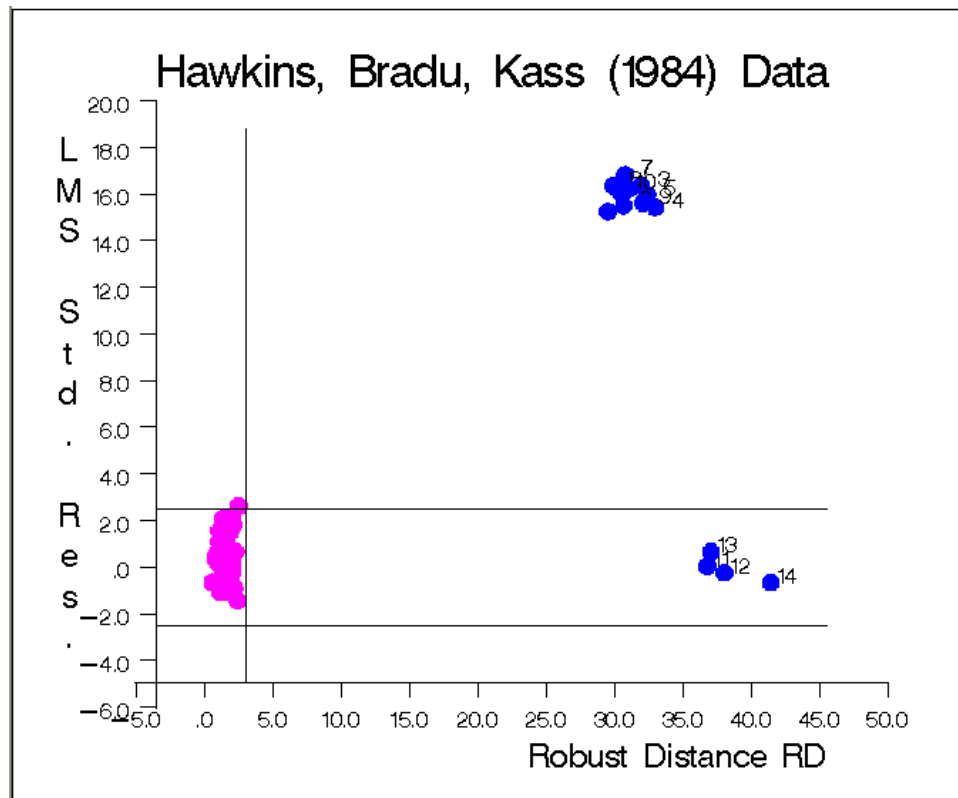
Classical Distances and Robust (Rousseeuw) Distances			
Unsquared Mahalanobis Distance and			
Unsquared Rousseeuw Distance of Each Observation			
N	Mahalanobis Distances	Robust Distances	Weight
1	1.916821	29.541649	0
2	1.855757	30.344481	0
3	2.313658	31.985694	0
4	2.229655	33.011768	0
5	2.100114	32.404938	0
6	2.146169	30.683153	0
7	2.010511	30.794838	0
8	1.919277	29.905756	0
9	2.221249	32.092048	0
10	2.333543	31.072200	0
11	2.446542	36.808021	0
12	3.108335	38.071382	0
13	2.662380	37.094539	0
14	6.381624	41.472255	0
15	1.815487	1.994672	1.000000
16	2.151357	2.202278	1.000000
17	1.384915	1.918208	1.000000
18	0.848155	0.819163	1.000000
19	1.148941	1.288387	1.000000
20	1.591431	2.046703	1.000000
21	1.089981	1.068327	1.000000
22	1.548776	1.768905	1.000000
23	1.085421	1.166951	1.000000
24	0.971195	1.304648	1.000000
25	0.799268	2.030417	1.000000
26	1.168373	1.727131	1.000000
27	1.449625	1.983831	1.000000
28	0.867789	1.073856	1.000000
29	0.576399	1.168060	1.000000
30	1.568868	2.091386	1.000000
...
75	1.899178	2.042560	1.000000

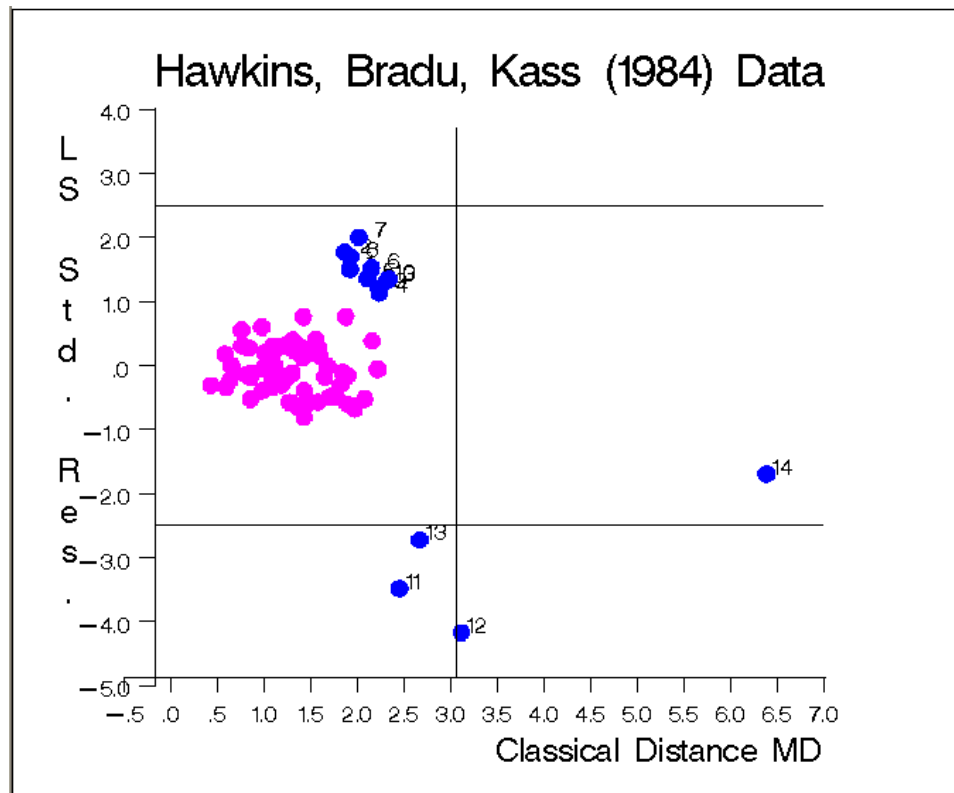
The graphs in Figure 12.6.5 and Figure 12.6.6 show the following:

- the plot of standardized LMS residuals vs. robust distances RD_i
- the plot of standardized LS residuals vs. Mahalanobis distances MD_i

The graph identifies the four good leverage points 11, 12, 13, and 14, which have small standardized LMS residuals but large robust distances, and the 10 bad leverage points 1, \dots , 10, which have large standardized LMS residuals and large robust distances.

Output 12.6.5 Hawkins-Bradu-Kass Data: LMS Residuals vs. Robust Distances



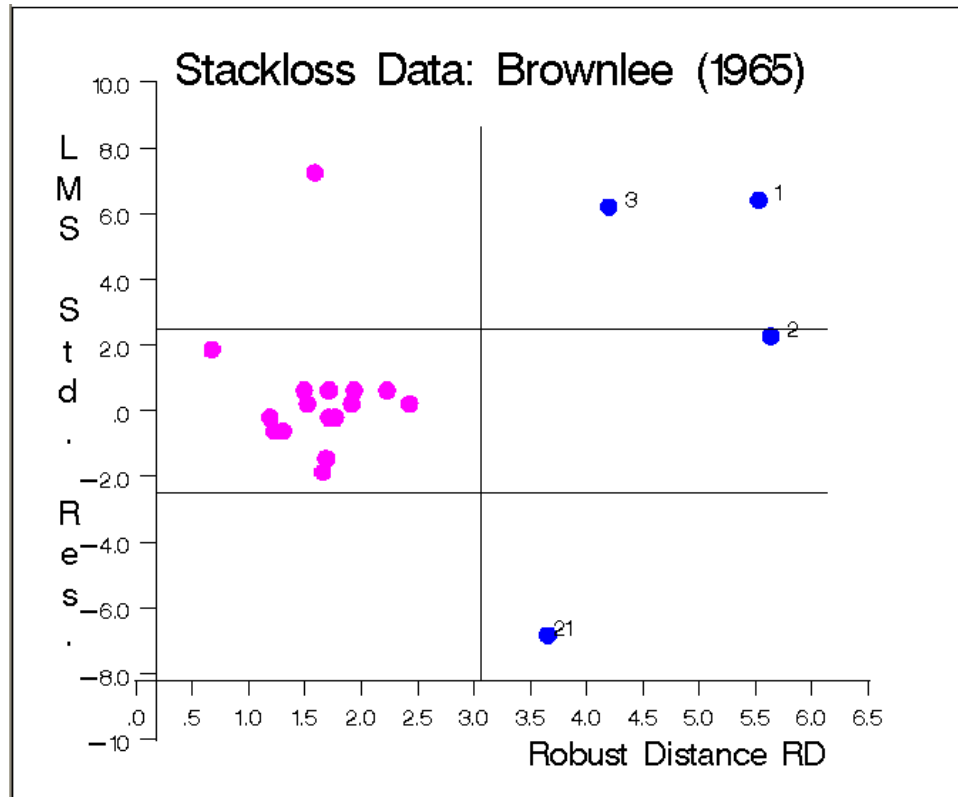
Output 12.6.6 Hawkins-Bradu-Kass Data: LS Residuals vs. Mahalanobis Distances

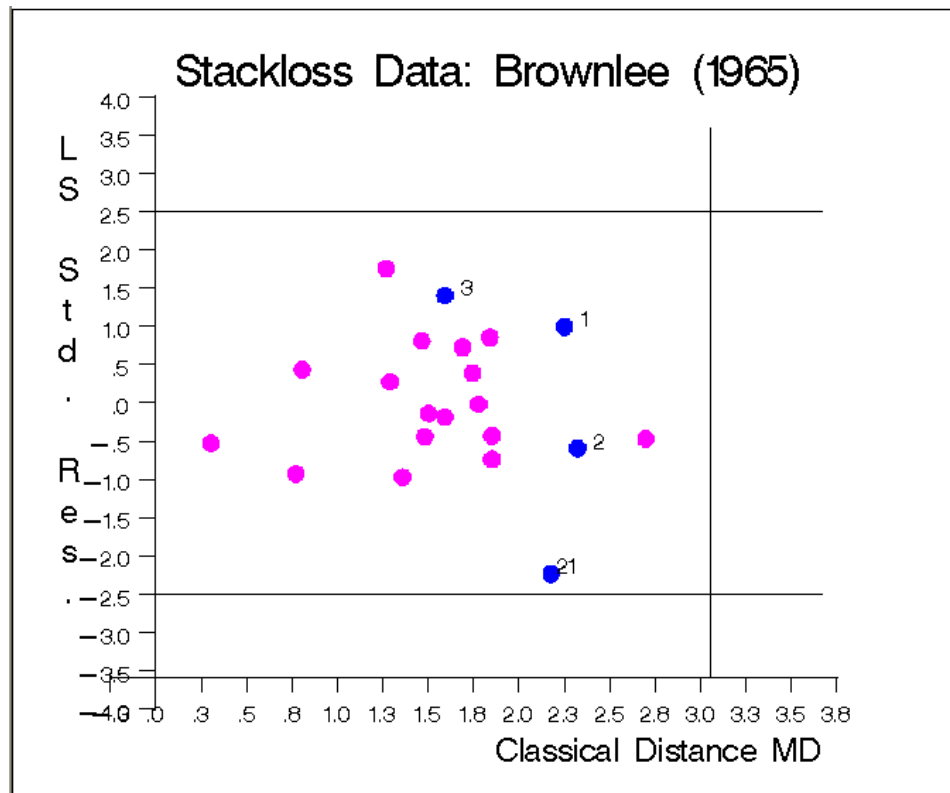
Example 12.7: Stackloss Data

The graphs in Figure 12.7.1 and Figure 12.7.2 show the following:

- the plot of standardized LMS residuals vs. robust distances RD_i
- the plot of standardized LS residuals vs. Mahalanobis distances MD_i

In the first plot, you see that case 4 is a regression outlier but not a leverage point, so it is a vertical outlier. Cases 1, 3, and 21 are bad leverage points, whereas case 2 is a good leverage point. Note that case 21 lies near the boundary line between vertical outliers and bad leverage points and that case 2 is very close to the boundary between good and bad leverage points.

Output 12.7.1 Stackloss Data: LMS Residuals vs. Robust Distances

Output 12.7.2 Stackloss Data: LS Residuals vs. Mahalanobis Distances

References

- Affi, A. A. and Azen, S. P. (1972), *Statistical Analysis: A Computer-Oriented Approach*, New York: Academic Press.
- Barnett, V. and Lewis, T. (1978), *Outliers in Statistical Data*, New York: John Wiley & Sons.
- Barreto, H. and Maharry, D. (2006), "Least Median of Squares and Regression Through the Origin," *Computational Statistics and Data Analysis*, 50, 1391–1397.
- Brownlee, K. A. (1965), *Statistical Theory and Methodology in Science and Engineering*, New York: John Wiley & Sons.
- Chen, C. (2002), *Developments in Robust Statistics: International Conference on Robust Statistics*, chapter Robust Tools in SAS, 125–133, Heidelberg: Springer-Verlag.
- Ezekiel, M. and Fox, K. A. (1959), *Methods of Correlation and Regression Analysis*, New York: John Wiley & Sons, Inc.
- Hawkins, D. M., Bradu, D., and Kass, G. V. (1984), "Location of Several Outliers in Multiple Regression Data Using Elemental Sets," *Technometrics*, 26, 197–208.
- Humphreys, R. M. (1978), "Studies of Luminous Stars in Nearby Galaxies. I. Supergiants and O Stars in the Milky Way," *The Astrophysical Journal Supplement Series*, 38, 309–350.

- Jerison, H. J. (1973), *Evolution of the Brain and Intelligence*, New York: Academic Press.
- Osborne, M. R. (1985), *Finite Algorithms in Optimization and Data Analysis*, New York: John Wiley & Sons, Inc.
- Prescott, P. (1975), “An Approximate Test for Outliers in Linear Models,” *Technometrics*, 17, 129–132.
- Rousseeuw, P. J. (1984), “Least Median of Squares Regression,” *Journal of the American Statistical Association*, 79, 871–880.
- Rousseeuw, P. J. (1985), “Multivariate Estimation with High Breakdown Point,” in W. Grossmann, G. Pflug, I. Vincze, and W. Wertz, eds., *Mathematical Statistics and Applications*, 283–297, Dordrecht: Reidel Publishing.
- Rousseeuw, P. J. and Hubert, M. (1996), “Recent Development in PROGRESS,” *Computational Statistics and Data Analysis*, 21, 67–85.
- Rousseeuw, P. J. and Leroy, A. M. (1987), *Robust Regression and Outlier Detection*, New York: John Wiley & Sons.
- Rousseeuw, P. J. and Van Driessen, K. (1999), “A Fast Algorithm for the Minimum Covariance Determinant Estimator,” *Technometrics*, 41, 212–223.
- Rousseeuw, P. J. and Van Driessen, K. (2000), *Data Analysis: Scientific Modeling and Practical Application*, chapter An Algorithm for Positive-Breakdown Regression Based on Concentration Steps, 335–346, New York: Springer Verlag.
- Rousseeuw, P. J. and Van Zomeren, B. C. (1990), “Unmasking Multivariate Outliers and Leverage Points,” *Journal of the American Statistical Association*, 85, 633–639.
- Vansina, F. and De Greve, J. P. (1982), “Close Binary Systems Before and After Mass Transfer,” *Astrophysics and Space Science*, 87, 377–401.

Chapter 13

Time Series Analysis and Examples

Contents

Overview	249
Basic Time Series Subroutines	250
Getting Started	251
Syntax	253
Time Series Analysis and Control Subroutines	253
Getting Started	255
Syntax	282
Details	282
Example 13.1: VAR Estimation and Variance Decomposition	303
Kalman Filter Subroutines	308
Getting Started	309
Syntax	310
Example 13.2: Kalman Filtering: Likelihood Function Evaluation	310
Example 13.3: Kalman Filtering: SSM Estimation With the EM Algorithm	314
Example 13.4: Diffuse Kalman Filtering	319
Vector Time Series Analysis Subroutines	322
Getting Started	322
Syntax	327
Fractionally Integrated Time Series Analysis	327
Getting Started	327
Syntax	331
References	331

Overview

This chapter describes SAS/IML subroutines related to univariate, multivariate, and fractional time series analysis, and subroutines for Kalman filtering and smoothing. These subroutines can be used in analyzing economic and financial time series. You can develop a model of univariate time series and a model of the relationships between vector time series. The Kalman filter subroutines provide analysis of various time series and are presented as a tool for dealing with state space models.

The subroutines offer the following functions:

- generating univariate, multivariate, and fractional time series
- computing likelihood function of ARMA, VARMA, and ARFIMA models
- computing an autocovariance function of ARMA, VARMA, and ARFIMA models
- checking the stationarity of ARMA and VARMA models
- filtering and smoothing of time series models by using Kalman method
- fitting AR, periodic AR, time-varying coefficient AR, VAR, and ARFIMA models
- handling Bayesian seasonal adjustment model

In addition, decomposition analysis, forecast of an ARMA model, and fractionally differencing of the series are provided.

This chapter consists of five sections. The first section includes the ARMACOV and ARMALIK subroutines and ARMASIM function. The second section includes the TSBAYSEA, TSDECOMP, TSMLOCAR, TSMLOMAR, TSMULMAR, TSPERARS, TSPRED, TSROOT, TSTVCAR, and TSUNIMAR subroutines. The third section includes the KALCVF, KALCVS, KALDFF, and KALDFS subroutines. The fourth section includes the VARMACOV, VARMALIK, VARMASIM, VNORMAL, and VTSROOT subroutines. The last section includes the FARMACOV, FARMAFIT, FARMALIK, FARMASIM, and FDIF subroutines.

Basic Time Series Subroutines

In classical linear regression analysis, the underlying process often can be represented simply by an intercept and slope parameters. A time series can be modeled by a type of regression analysis.

The ARMASIM function generates various time series from the underlying AR, MA, and ARMA models. Simulations of time series with known ARMA structure are often needed as part of other simulations or as learning data sets for developing time series analysis skills.

The ARMACOV subroutine provides the pattern of the autocovariance function of AR, MA, and ARMA models and helps to identify and fit a proper model.

The ARMALIK subroutine provides the log likelihood of an ARMA model and helps to obtain estimates of the parameters of a regression model with innovations having an ARMA structure.

The following subroutines and functions are supported:

ARMACOV	computes an autocovariance sequence for an ARMA model.
ARMALIK	computes the log likelihood and residuals for an ARMA model.
ARMASIM	simulates an ARMA series.

See the examples of the use of ARMACOV and ARMALIK subroutines in [Chapter 9](#).

Getting Started

Consider a time series of length 100 from the ARMA(2,1) model

$$y_t = 0.5y_{t-1} - 0.04y_{t-2} + e_t + 0.25e_{t-1}$$

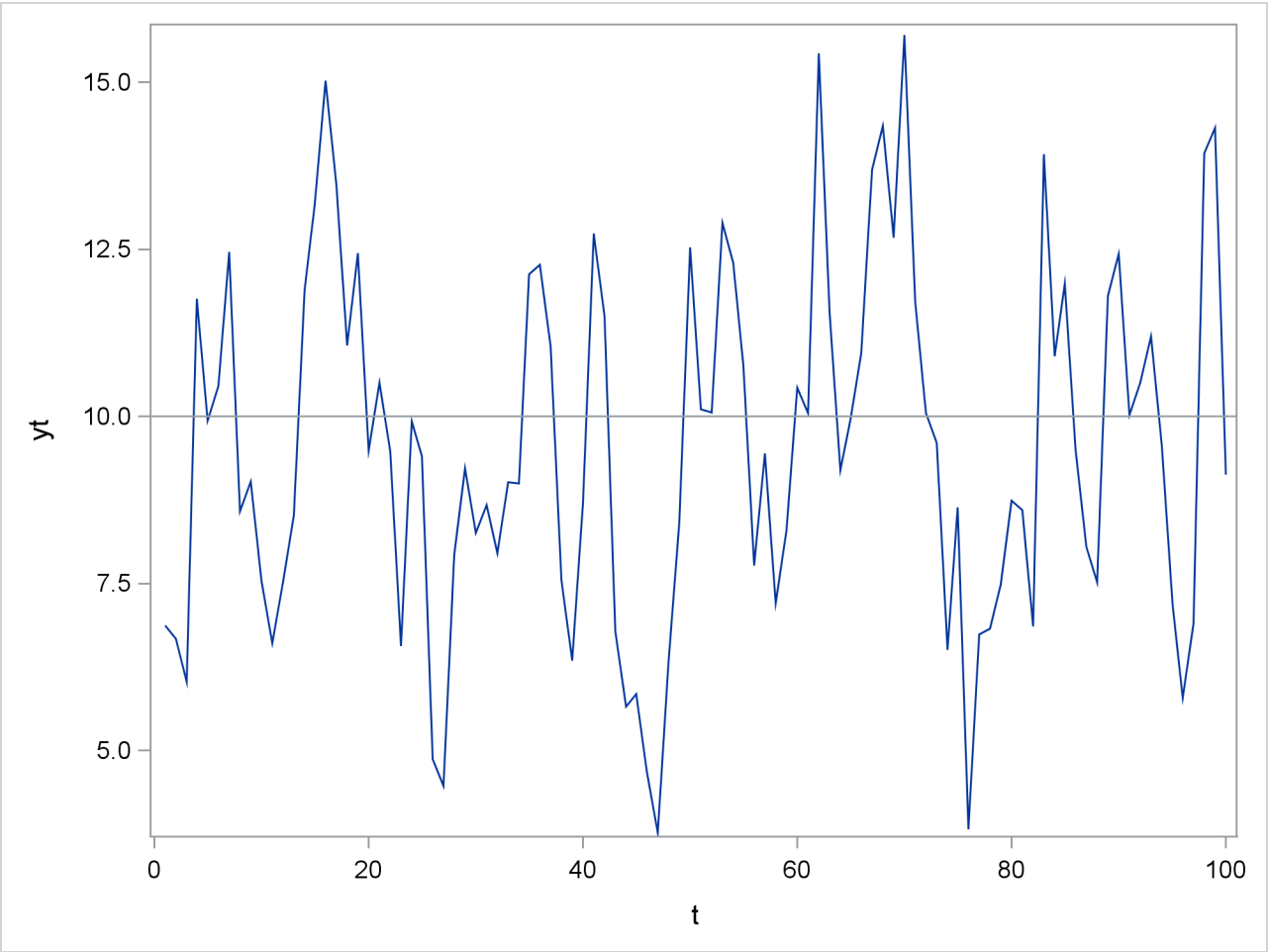
where the error series follows a normal distribution with mean 10 and standard deviation 2.

The following statements generate the ARMA(2,1) model, compute 10 lags of its autocovariance functions, and calculate its log-likelihood function and residuals:

```
proc iml;
  /* ARMA(2,1) model */
  phi = {1 -0.5 0.04};
  theta = {1 0.25};
  mu = 10;
  sigma = 2;
  nobs = 100;
  seed = 3456;
  lag = 10;
  yt = armasim(phi, theta, mu, sigma, nobs, seed);
  call armacov(autocov, cross, convol, phi, theta, lag);
  autocov = autocov`;
  cross = cross`;
  convol = convol`;
  lag = (0:lag-1)`;
  print autocov cross convol;
  call armalik(lnl, resid, std, yt, phi, theta);

  resid=resid[1:9];
  std=std[1:9];
  print lnl resid std;
```

Figure 13.1 Plot of Generated ARMA(2,1) Process (ARMASIM)



The ARMASIM function generates the data shown in Figure 13.1.

Figure 13.2 Autocovariance functions of ARMA(2,1) Model (ARMACOV)

autocov	cross	convol
1.6972803	1.1875	1.0625
1.0563848	0.25	0.25
0.4603012		
0.1878952		
0.0755356		
0.030252		
0.0121046		
0.0048422		
0.0019369		
0.0007748		

In Figure 13.2, the ARMACOV subroutine prints the autocovariance functions of the ARMA(2,1) model and the covariance functions of the moving-average term with lagged values of the process and the autocov-

variance functions of the moving-average term.

Figure 13.3 Log-Likelihood Function of ARMA(2,1) Model (ARMALIK)

lnl	resid	std
-154.9148	5.2779797	1.3027971
22.034073	2.3491607	1.0197
0.5705918	2.3893996	1.0011951
	8.4086892	1.0000746
	2.200401	1.0000047
	5.4127254	1.0000003
	6.2756004	1
	1.1944693	1
	4.9425372	1

The first column in [Figure 13.3](#) shows the log-likelihood function, the estimate of the innovation variance, and the log of the determinant of the variance matrix. The next two columns are part of the results in the standardized residuals and the scale factors used to standardize the residuals.

Syntax

CALL ARMACOV (*auto, cross, convol, phi, theta, num*) ;

CALL ARMALIK (*lnl, resid, std, x, phi, theta*) ;

ARMASIM (*phi, theta, mu, sigma, n, <seed>*) ;

Time Series Analysis and Control Subroutines

This section describes an adaptation of parts of the **Time Series Analysis and Control** (TIMSAC) package developed by the Institute of Statistical Mathematics (ISM) in Japan.

Selected routines from the TIMSAC package from ISM were converted by SAS Institute staff into SAS/IML routines under an agreement between SAS Institute and ISM. Credit for authorship of these TIMSAC SAS/IML routines goes to ISM, which has agreed to make them available to SAS users without charge.

There are four packages of TIMSAC programs. See the section “[ISM TIMSAC Packages](#)” on page 301 for more information about the TIMSAC package produced by ISM. Since these SAS/IML time series analysis subroutines are adapted from the corresponding FORTRAN subroutines in the TIMSAC package produced by ISM, they are collectively referred to as “the TIMSAC subroutines” in this chapter.

The subroutines analyze and forecast univariate and multivariate time series data. The nonstationary time series and seasonal adjustment models can also be analyzed by using the Interactive Matrix Language TIM-

SAC subroutines. These subroutines contain the Bayesian modeling of seasonal adjustment and changing spectrum estimation.

Discrete time series modeling has been widely used to analyze dynamic systems in economics, engineering, and statistics. The Box-Jenkins and Box-Tiao approaches are classical examples of unified time series analysis through identification, estimation, and forecasting (or control). The ARIMA procedure in the SAS/ETS product uses these approaches. Bayesian methods are being increasingly applied despite the controversial issues involved in choosing a prior distribution.

The fundamental idea of the Bayesian method is that uncertainties can be explained by probabilities. If there is a class model (Ω) that consists of sets of member models (ω), you can describe the uncertainty of Ω by using a prior distribution of ω . The member model ω is directly related to model parameters. Let the prior probability density function be $p(\omega)$. When you observe the data y that is generated from the model Ω , the data distribution is described as $p(Y|\omega)$ given the unknown ω with a prior probability density $p(\omega)$, where the function $p(Y|\omega)$ is the usual likelihood function. Then the posterior distribution is the updated prior distribution given the sample information. The posterior probability density function is proportional to *observed likelihood function* \times *prior density function*.

The TIMSAC subroutines contain various time series analysis and Bayesian models. Most of the subroutines are based on the minimum Akaike information criterion (AIC) or on the minimum Akaike Bayesian information criterion (ABIC) method to determine the best model among alternative models. The TSBAYSEA subroutine is a typical example of Bayesian modeling. The following subroutines are supported:

TSBAYSEA	Bayesian seasonal adjustment modeling
TSDECOMP	time series decomposition analysis
TSMLOCAR	locally stationary univariate AR model fitting
TSMLOMAR	locally stationary multivariate AR model fitting
TSMULMAR	multivariate AR model fitting
TSPERARS	periodic AR model fitting
TSPRED	ARMA model forecasting and forecast error variance
TSROOT	polynomial roots or ARMA coefficients computation
TSTVCAR	time-varying coefficient AR model estimation
TSUNIMAR	univariate AR model fitting

For univariate and multivariate autoregressive model estimation, the least squares method is used. The least squares estimate is an approximate maximum likelihood estimate if error disturbances are assumed to be Gaussian. The least squares method is performed by using the Householder transformation method. See the section “[Least Squares and Householder Transformation](#)” on page 295 for details.

The TSUNIMAR and TSMULMAR subroutines estimate the autoregressive models and select the appropriate AR order automatically by using the minimum AIC method. The TSMLOCAR and TSMLOMAR subroutines analyze the nonstationary time series data. The Bayesian time-varying AR coefficient model (TSTVCAR) offers another nonstationary time series analysis method. The state space and Kalman filter method is systematically applied to the smoothness priors models (TSDECOMP and TSTVCAR), which have stochastically perturbed difference equation constraints. The TSBAYSEA subroutine provides a way of handling Bayesian seasonal adjustment, and it can be an alternative to the SAS/ETS X-11 procedure. The

TSBAYSEA subroutine employs the smoothness priors idea through constrained least squares estimation, while the TSDECOMP and TSTVCAR subroutines estimate the smoothness tradeoff parameters by using the state space model and Kalman filter recursive computation. The TSPRED subroutine computes the one-step or multistep predicted values of the ARMA time series model. In addition, the TSPRED subroutine computes forecast error variances and impulse response functions. The TSROOT subroutine computes the AR and MA coefficients given the characteristic roots of the polynomial equation and the characteristic roots for the AR or MA model.

Getting Started

Minimum AIC Model Selection

The time series model is automatically selected by using the AIC. The TSUNIMAR call estimates the univariate autoregressive model and computes the AIC. You need to specify the maximum lag or order of the AR process with the MAXLAG= option or put the maximum lag as the sixth argument of the TSUNIMAR call. Here is an example:

```
proc iml;
y = { 2.430 2.506 2.767 2.940 3.169 3.450 3.594 3.774 3.695 3.411
      2.718 1.991 2.265 2.446 2.612 3.359 3.429 3.533 3.261 2.612
      2.179 1.653 1.832 2.328 2.737 3.014 3.328 3.404 2.981 2.557
      2.576 2.352 2.556 2.864 3.214 3.435 3.458 3.326 2.835 2.476
      2.373 2.389 2.742 3.210 3.520 3.828 3.628 2.837 2.406 2.675
      2.554 2.894 3.202 3.224 3.352 3.154 2.878 2.476 2.303 2.360
      2.671 2.867 3.310 3.449 3.646 3.400 2.590 1.863 1.581 1.690
      1.771 2.274 2.576 3.111 3.605 3.543 2.769 2.021 2.185 2.588
      2.880 3.115 3.540 3.845 3.800 3.579 3.264 2.538 2.582 2.907
      3.142 3.433 3.580 3.490 3.475 3.579 2.829 1.909 1.903 2.033
      2.360 2.601 3.054 3.386 3.553 3.468 3.187 2.723 2.686 2.821
      3.000 3.201 3.424 3.531 };
call tsunimar(arcoef,ev,nar,aic) data=y opt={-1 1}
              print=1 maxlag=20;
```

You can also invoke the TSUNIMAR subroutine as follows:

```
call tsunimar(arcoef,ev,nar,aic,y,20,{-1 1},,1);
```

The optional arguments can be omitted. In this example, the argument MISSING is omitted, and thus the default option (MISSING=0) is used. The summary table of the minimum AIC method is displayed in Figure 13.4 and Figure 13.5. The final estimates are given in Figure 13.6.

Figure 13.4 Minimum AIC Table - I

ORDER	INNOVATION	VARIANCE	
M	V (M)	AIC (M)	
0	0.31607294	-108.26753229	
1	0.11481982	-201.45277331	
2	0.04847420	-280.51201122	
3	0.04828185	-278.88576251	
4	0.04656506	-280.28905616	
5	0.04615922	-279.11190502	
6	0.04511943	-279.25356641	
7	0.04312403	-281.50543541	
8	0.04201118	-281.96304075	
9	0.04128036	-281.61262868	
10	0.03829179	-286.67686828	
11	0.03318558	-298.13013264	
12	0.03255171	-297.94298716	
13	0.03247784	-296.15655602	
14	0.03237083	-294.46677874	
15	0.03234790	-292.53337704	
16	0.03187416	-291.92021487	
17	0.03183282	-290.04220196	
18	0.03126946	-289.72064823	
19	0.03087893	-288.90203735	
20	0.02998019	-289.67854830	

Figure 13.5 Minimum AIC Table - II

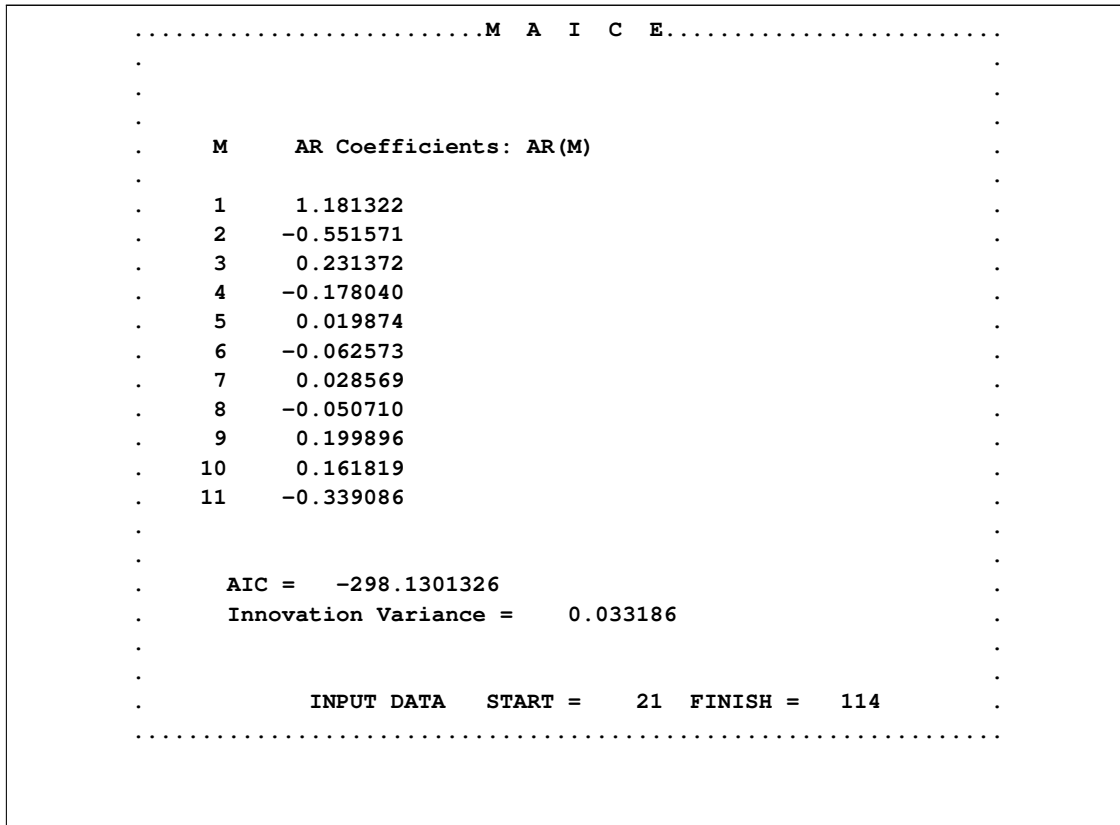
```

                                AIC(M)-AICMIN (truncated at 40.0)
                                0          10          20          30          40
M  AIC(M)-AICMIN  +-----+-----+-----+-----+
0   189.862600    |                                     .
1    96.677359    |                                     .
2    17.618121    |                                     *
3    19.244370    |                                     *
4    17.841076    |                                     *
5    19.018228    |                                     *
6    18.876566    |                                     *
7    16.624697    |                                     *
8    16.167092    |                                     *
9    16.517504    |                                     *
10   11.453264    |                                     *
11      0         *
12   0.187145    *
13   1.973577    | *
14   3.663354    |  *
15   5.596756    |  *
16   6.209918    |  *
17   8.087931    |  *
18   8.409484    |  *
19   9.228095    |  *
20   8.451584    |  *
                                +-----+-----+-----+-----+
***** MINIMUM AIC = -298.130133  ATTAINED AT M = 11 *****

```

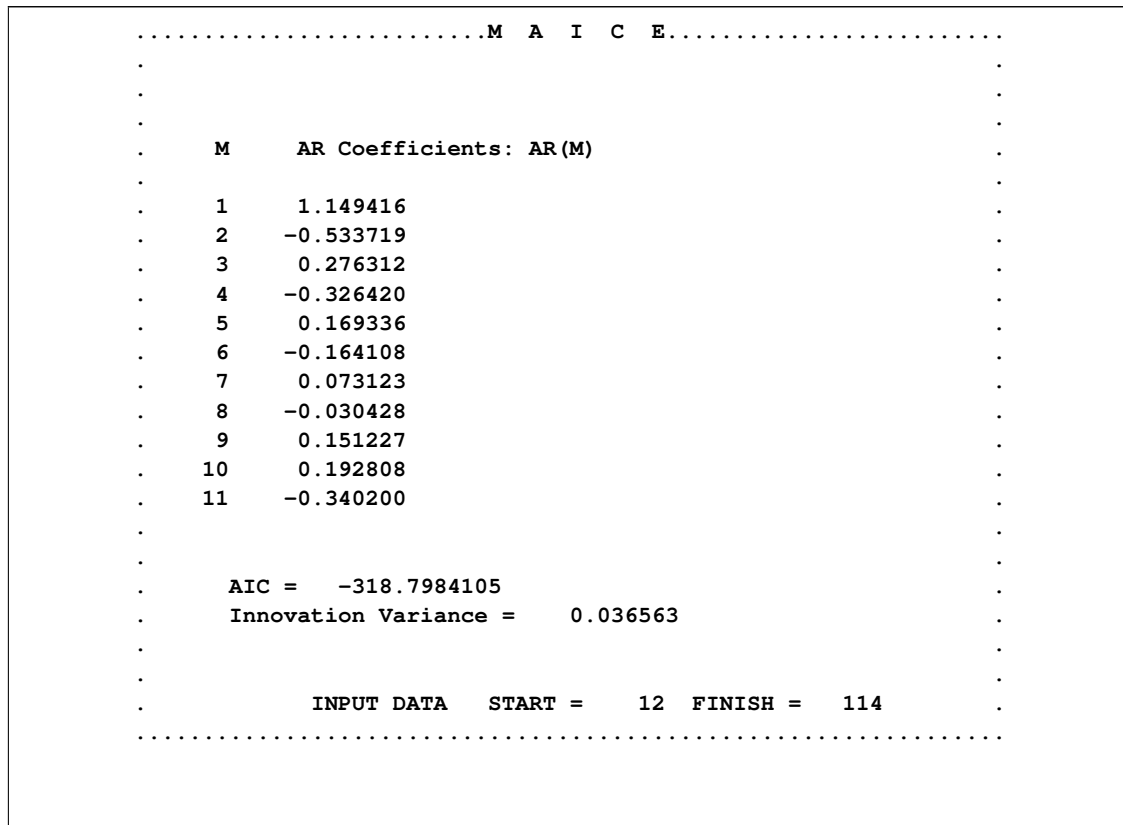

The minimum AIC order is selected as 11. Then the coefficients are estimated as in [Figure 13.6](#). Note that the first 20 observations are used as presample values.

Figure 13.6 Minimum AIC Estimation



You can estimate the AR(11) model directly by specifying `OPT={-1 0}` and using the first 11 observations as presample values. The AR(11) estimates shown in [Figure 13.7](#) are different from the minimum AIC estimates in [Figure 13.6](#) because the samples are slightly different. Here is the code:

```
call tsunimar(arcoef,ev,nar,aic,y,11,{-1 0},,1);
```

Figure 13.7 AR(11) Estimation

The minimum AIC procedure can also be applied to the vector autoregressive (VAR) model by using the TSMULMAR subroutine. See the section “[Multivariate Time Series Analysis](#)” on page 291 for details. Three variables are used as input. The maximum lag is specified as 10. Here is the code:

```

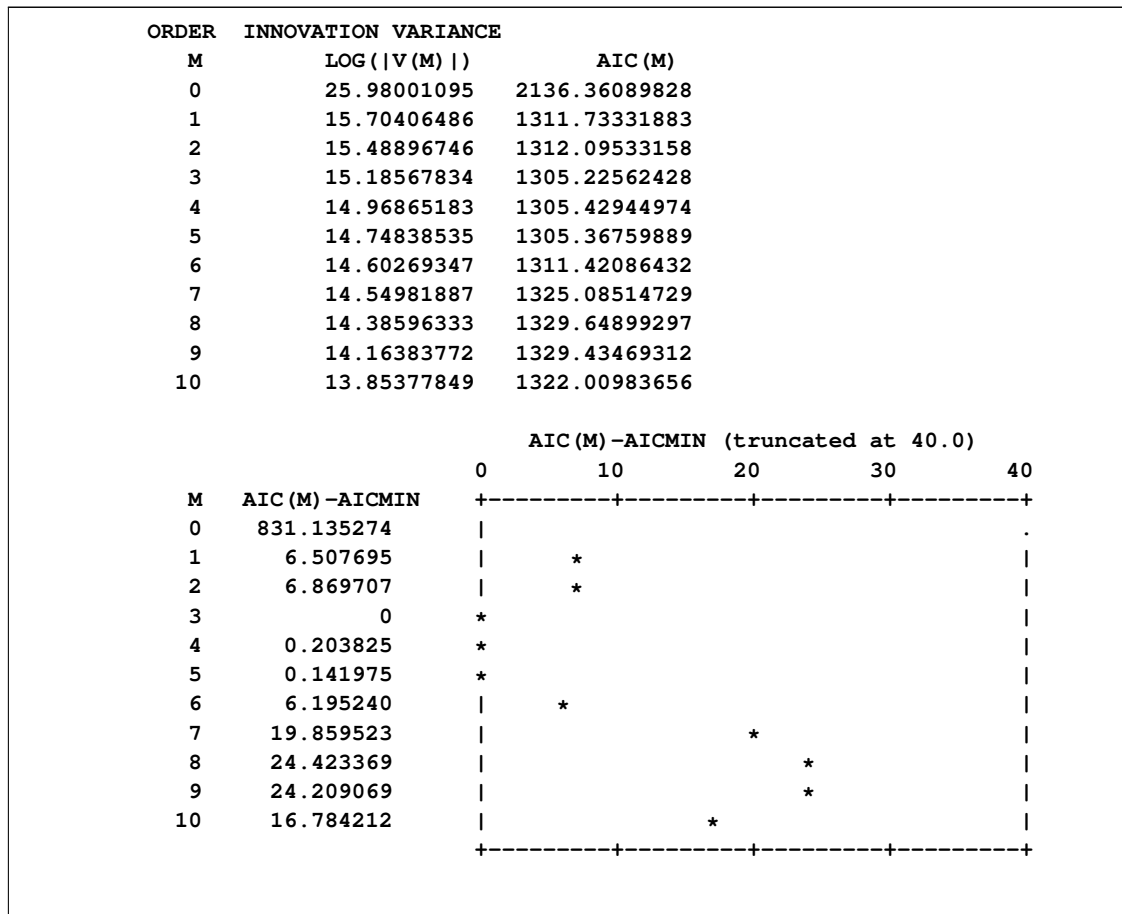
data one;
    input invest income consum @@;
datalines;
    . . . data lines omitted . . .
;
proc iml;
    use one;
    read all into y var{invest income consum};
    mdel = 1;
    maice = 2;
    misw = 0; /* instantaneous modeling ? */
    opt = mdel || maice || misw;
    maxlag = 10;
    miss = 0;
    print = 1;
    call tsmulmar(arcoef,ev,nar,aic,y,maxlag,opt,miss,print);

```

The VAR(3) model minimizes the AIC and was selected as an appropriate model (see [Figure 13.8](#)). However, AICs of the VAR(4) and VAR(5) models show little difference from VAR(3). You can also choose

VAR(4) or VAR(5) as an appropriate model in the context of minimum AIC since this AIC difference is much less than 1.

Figure 13.8 VAR Model Selection



The TSMULMAR subroutine estimates the instantaneous response model with diagonal error variance. See the section “[Multivariate Time Series Analysis](#)” on page 291 for details on the instantaneous response model. Therefore, it is possible to select the minimum AIC model independently for each equation. The best model is selected by specifying MAXLAG=5, as in the following code:

```
call tsmulmar(arcoef,ev,nar,aic) data=y maxlag=5
      opt={1 1 0} print=1;
```

Figure 13.9 Model Selection via Instantaneous Response Model

variance		
256.64375	29.803549	76.846777
29.803549	228.97341	119.60387
76.846777	119.60387	134.21764

Figure 13.9 continued

arcoef		
13.312109	1.5459098	15.963897
0.8257397	0.2514803	0
0.0958916	1.0057088	0
0.0320985	0.3544346	0.4698934
0.044719	-0.201035	0
0.0051931	-0.023346	0
0.1169858	-0.060196	0.0483318
0.1867829	0	0
0.0216907	0	0
-0.117786	0	0.3500366
0.1541108	0	0
0.0178966	0	0
0.0461454	0	-0.191437
-0.389644	0	0
-0.045249	0	0
-0.116671	0	0
aic		
1347.6198		

You can print the intermediate results of the minimum AIC procedure by using the PRINT=2 option.

Note that the AIC value depends on the MAXLAG=*lag* option and the number of parameters estimated. The minimum AIC VAR estimation procedure (MAICE=2) uses the following AIC formula:

$$(T - \text{lag}) \log(|\hat{\Sigma}|) + 2(p \times n^2 + n \times \text{intercept})$$

In this formula, p is the order of the n -variate VAR process, and *intercept*=1 if the intercept is specified; otherwise, *intercept*=0. When you use the MAICE=1 or MAICE=0 option, AIC is computed as the sum of AIC for each response equation. Therefore, there is an AIC difference of $n(n - 1)$ since the instantaneous response model contains the additional $n(n - 1)/2$ response variables as regressors.

The following code estimates the instantaneous response model. The results are shown in Figure 13.10.

```
call tsmulmar(arcoef,ev,nar,aic) data=y
                                maxlag=3 opt={1 0 0};
print aic nar;
print arcoef;
```

Figure 13.10 AIC from Instantaneous Response Model

aic	nar
1403.0762	3

Figure 13.10 *continued*

arcoef		
4.8245814	5.3559216	17.066894
0.8855926	0.3401741	-0.014398
0.1684523	1.0502619	0.107064
0.0891034	0.4591573	0.4473672
-0.059195	-0.298777	0.1629818
0.1128625	-0.044039	-0.088186
0.1684932	-0.025847	-0.025671
0.0637227	-0.196504	0.0695746
-0.226559	0.0532467	-0.099808
-0.303697	-0.139022	0.2576405

The following code estimates the VAR model. The results are shown in [Figure 13.11](#).

```
call tsmulmar(arcoef,ev,nar,aic) data=y maxlag=3
      opt={1 2 0};
print aic nar;
print arcoef;
```

Figure 13.11 AIC from VAR Model

aic	nar	
1397.0762	3	
arcoef		
4.8245814	5.3559216	17.066894
0.8855926	0.3401741	-0.014398
0.1684523	1.0502619	0.107064
0.0891034	0.4591573	0.4473672
-0.059195	-0.298777	0.1629818
0.1128625	-0.044039	-0.088186
0.1684932	-0.025847	-0.025671
0.0637227	-0.196504	0.0695746
-0.226559	0.0532467	-0.099808
-0.303697	-0.139022	0.2576405

The AIC computed from the instantaneous response model is greater than that obtained from the VAR model estimation by 6. There is a discrepancy between [Figure 13.11](#) and [Figure 13.8](#) because different observations are used for estimation.

Nonstationary Data Analysis

The following example shows how to manage nonstationary data by using TIMSAC calls. In practice, time series are considered to be stationary when the expected values of first and second moments of the series

do not change over time. This weak or covariance stationarity can be modeled by using the TSMLOCAR, TSMLOMAR, TSDECOMP, and TSTVCAR subroutines.

First, the locally stationary model is estimated. The whole series (1000 observations) is divided into three blocks of size 300 and one block of size 90, and the minimum AIC procedure is applied to each block of the data set. See the section “[Nonstationary Time Series](#)” on page 287 for more details. Here is the code:

```
data one;
  input y @@;
datalines;
  . . . data lines omitted . . .
;

proc iml;
  use one;
  read all var{y};

  mdel = -1;
  lspan = 300; /* local span of data */
  maice = 1;
  opt = mdel || lspan || maice;
  call tsmlocar(arcoef,ev,nar,aic,first,last)
              data=y maxlag=10 opt=opt print=2;
```

Estimation results are displayed with the graphs of power spectrum ($\log 10(f_{YY}(g))$), where $f_{YY}(g)$ is a rational spectral density function. See the section “[Spectral Analysis](#)” on page 292. The estimates for the first block and third block are shown in [Figure 13.12](#) and [Figure 13.15](#), respectively. As the first block and the second block do not have any sizable difference, the pooled model (AIC=45.892) is selected instead of the moving model (AIC=46.957) in [Figure 13.13](#). However, you can notice a slight change in the shape of the spectrum of the third block of the data (observations 611 through 910). See [Figure 13.14](#) and [Figure 13.16](#) for comparison. The moving model is selected since the AIC (106.830) of the moving model is smaller than that of the pooled model (108.867).

Figure 13.12 Locally Stationary Model for First Block

```

INITIAL LOCAL MODEL: N_CURR =   300
                     NAR_CURR =   8  AIC =   37.583203

.....CURRENT MODEL.....
.
.
.
.      M      AR Coefficients: AR(M)
.
.      1      1.605717
.      2      -1.245350
.      3      1.014847
.      4      -0.931554
.      5      0.394230
.      6      -0.004344
.      7      0.111608
.      8      -0.124992
.
.
.
.      AIC =      37.5832030
.      Innovation Variance =      1.067455
.
.
.      INPUT DATA  START =      11  FINISH =      310
.
.....

```

Figure 13.13 Locally Stationary Model Comparison

```

--- THE FOLLOWING TWO MODELS ARE COMPARED ---

MOVING MODEL: (N_PREV = 300, N_CURR = 300)
               NAR_CURR  = 7  AIC = 46.957398
CONSTANT MODEL: N_POOLED = 600
               NAR_POOLED = 8  AIC = 45.892350

*****  CONSTANT MODEL ADOPTED  *****

.....CURRENT MODEL.....
.
.
.
.      M      AR Coefficients: AR(M)
.
.      1      1.593890
.      2      -1.262379
.      3      1.013733
.      4      -0.926052
.      5      0.314480
.      6      0.193973
.      7      -0.058043
.      8      -0.078508
.
.
.
.      AIC =      45.8923501
.      Innovation Variance =      1.047585
.
.
.      INPUT DATA  START =      11  FINISH =      610
.
.....

```

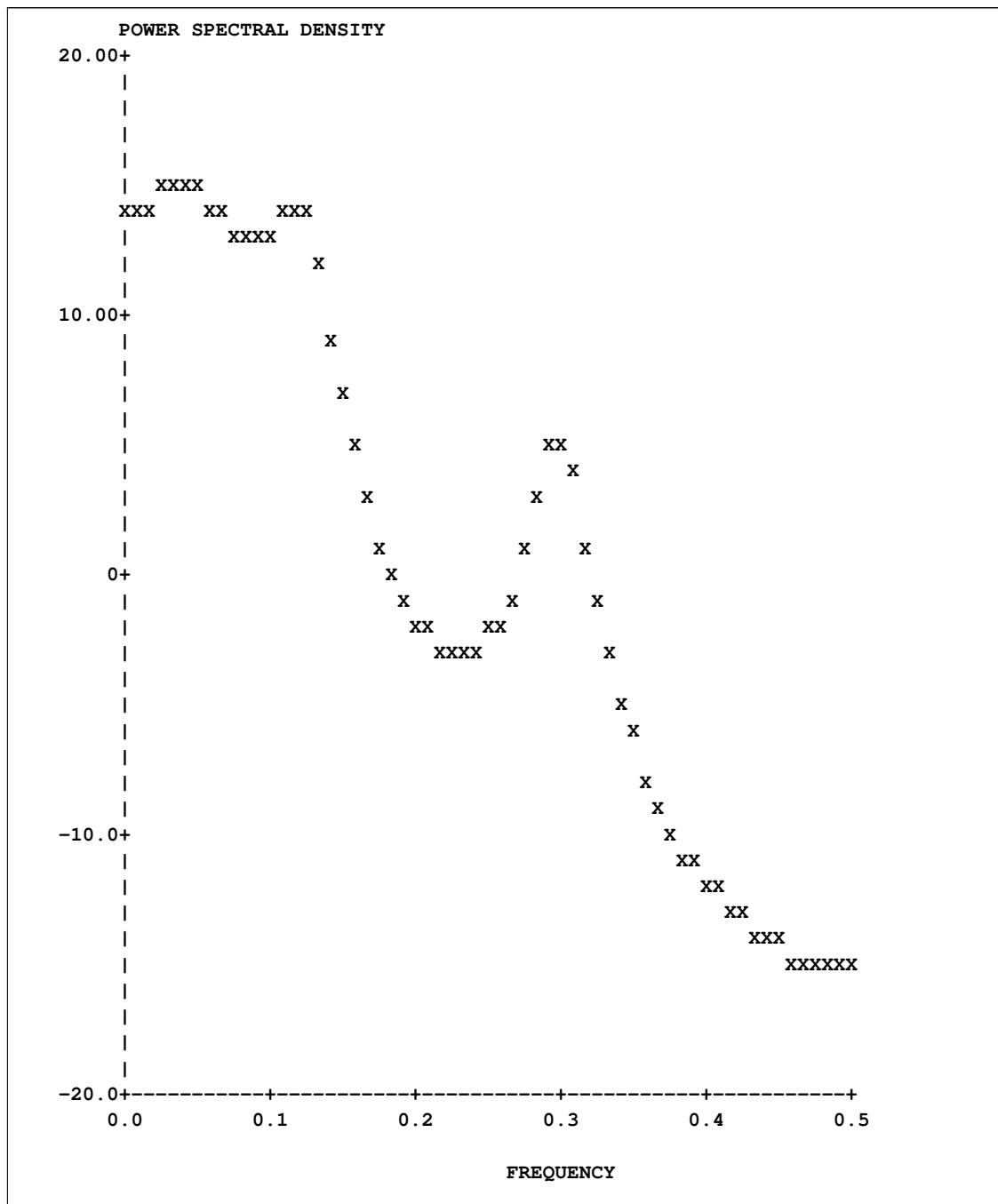

Figure 13.14 Power Spectrum for First and Second Blocks

Figure 13.15 Locally Stationary Model for Third Block

```

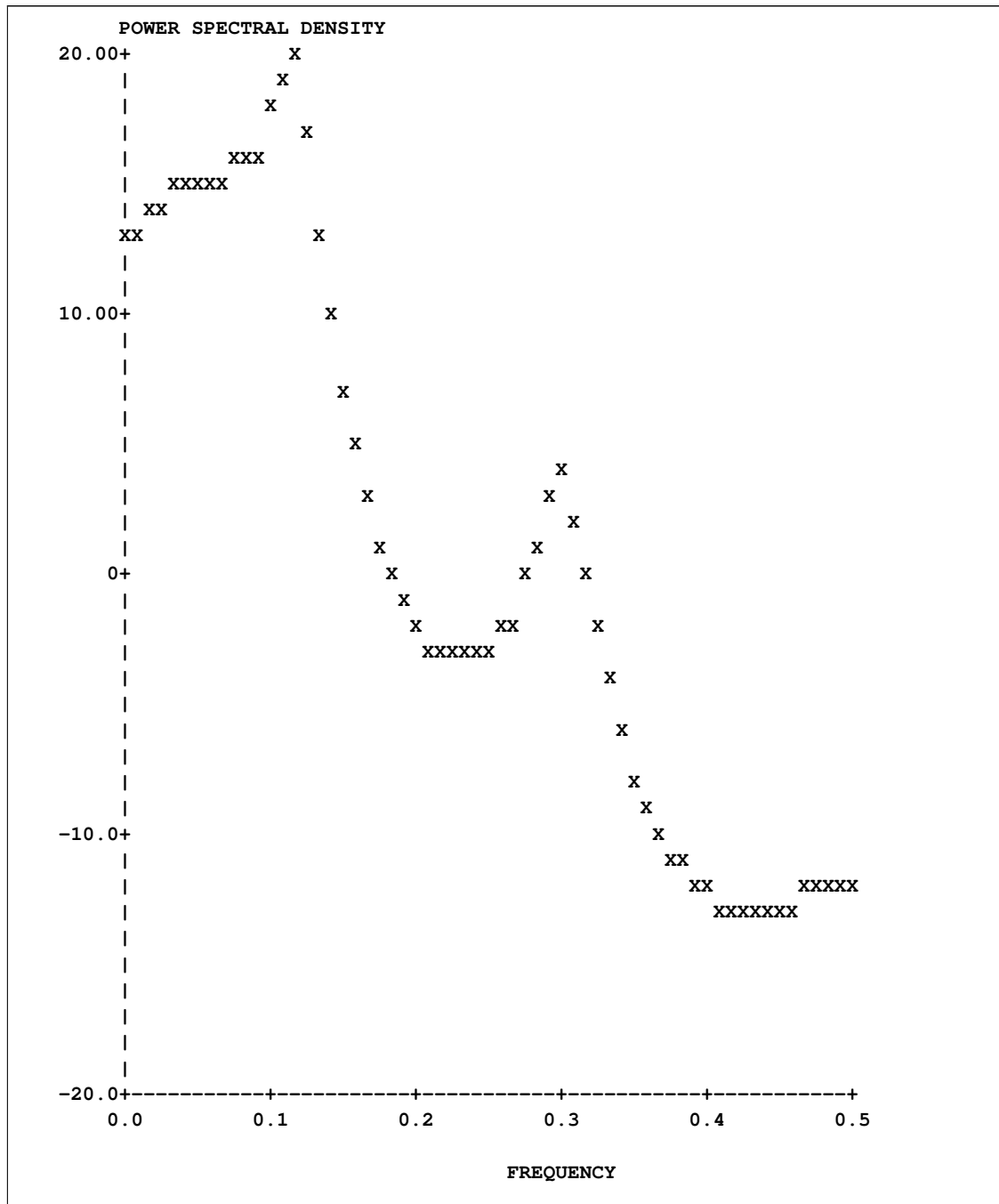
--- THE FOLLOWING TWO MODELS ARE COMPARED ---

MOVING MODEL: (N_PREV = 600, N_CURR = 300)
               NAR_CURR  = 7  AIC = 106.829869
CONSTANT MODEL: N_POOLED = 900
               NAR_POOLED = 8  AIC = 108.867091

*****
*****                                *****
*****      NEW MODEL ADOPTED          *****
*****                                *****
*****

.....CURRENT MODEL.....
.
.
.
.
.      M      AR Coefficients: AR(M)
.
.      1      1.648544
.      2      -1.201812
.      3      0.674933
.      4      -0.567576
.      5      -0.018924
.      6      0.516627
.      7      -0.283410
.
.
.
.      AIC =      60.9375188
.      Innovation Variance =      1.161592
.
.
.      INPUT DATA  START =      611  FINISH =      910
.
.....

```

Figure 13.16 Power Spectrum for Third Block

Finally, the moving model is selected since there is a structural change in the last block of data (observations 911 through 1000). The final estimates are stored in variables ARCOEF, EV, NAR, AIC, FIRST, and LAST. The final estimates and spectrum are given in [Figure 13.17](#) and [Figure 13.18](#), respectively. The power spectrum of the final model ([Figure 13.18](#)) is significantly different from that of the first and second blocks (see [Figure 13.14](#)).

Figure 13.17 Locally Stationary Model for Last Block

```

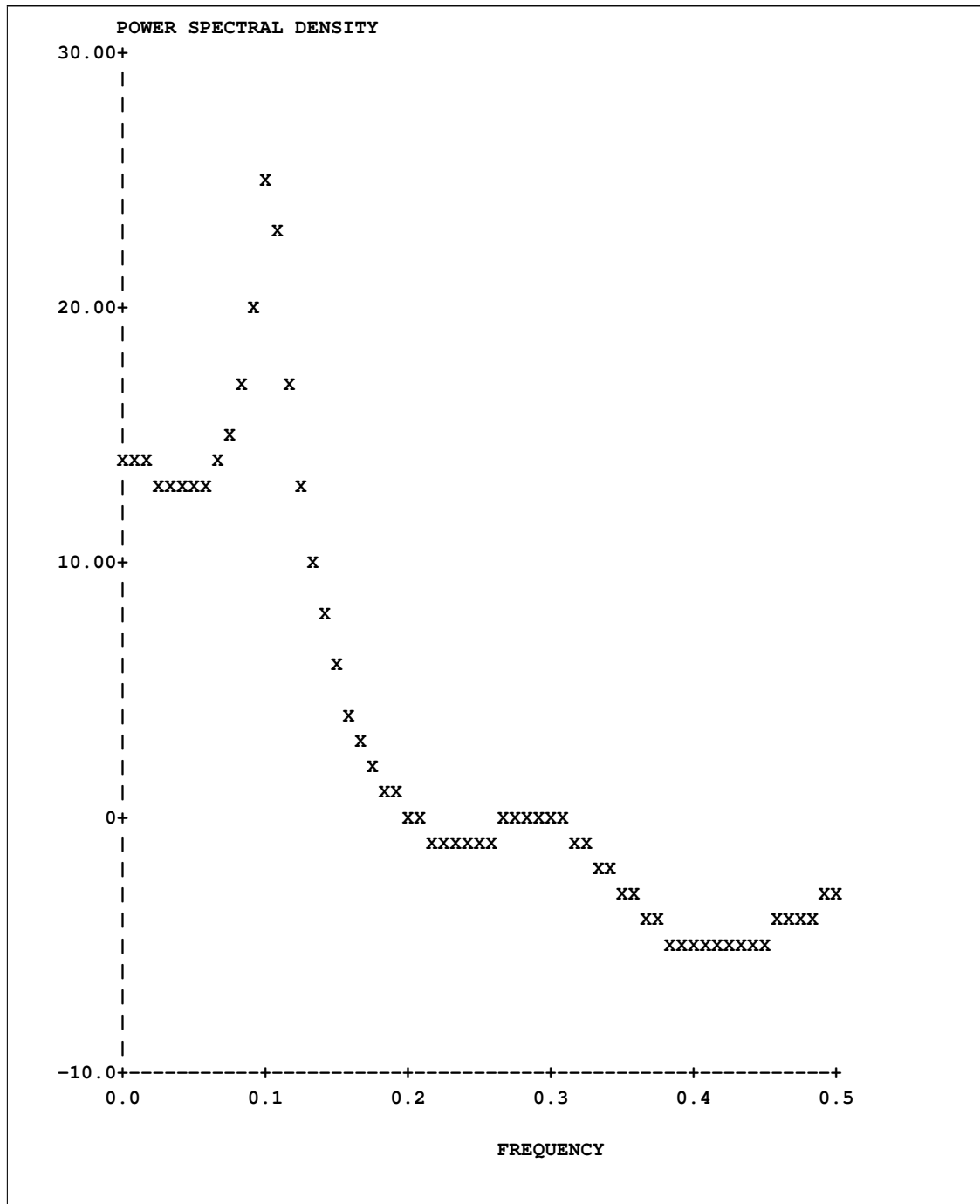
--- THE FOLLOWING TWO MODELS ARE COMPARED ---

MOVING MODEL: (N_PREV = 300, N_CURR = 90)
               NAR_CURR  = 6  AIC = 139.579012
CONSTANT MODEL: N_POOLED = 390
               NAR_POOLED = 9  AIC = 167.783711

*****
*****                                *****
*****      NEW MODEL ADOPTED          *****
*****                                *****
*****

.....CURRENT MODEL.....
.
.
.
.
.      M      AR Coefficients: AR(M)
.
.      1      1.181022
.      2      -0.321178
.      3      -0.113001
.      4      -0.137846
.      5      -0.141799
.      6      0.260728
.
.
.
.      AIC =      78.6414932
.      Innovation Variance =      2.050818
.
.
.      INPUT DATA  START = 911  FINISH = 1000
.
.....

```

Figure 13.18 Power Spectrum for Last Block

The multivariate analysis for locally stationary data is a straightforward extension of the univariate analysis. The bivariate locally stationary VAR models are estimated. The selected model is the VAR(7) process with some zero coefficients over the last block of data. There seems to be a structural difference between observations from 11 to 610 and those from 611 to 896. Here is the code:

```
proc iml;
```

```

rudder = {. . . data lines omitted . . .};
yawing = {. . . data lines omitted . . .};

y = rudder` || yawing`;
c = {0.01795 0.02419};
*-- calibration of data --*/
y = y # (c @ j(n,1,1));
mdel = -1;
lspan = 300; /* local span of data */
maice = 1;
call tsmmlomar(arcoef,ev,nar,aic,first,last) data=y maxlag=10
           opt=(mdel || lspans || maice) print=1;

```

The results of the analysis are shown in [Figure 13.19](#).

and the stationary AR(2) process.

$$\begin{aligned}T_t &= 2T_{t-1} - T_{t-2} + w_{1t} \\ u_t &= \alpha_1 u_{t-1} + \alpha_2 u_{t-2} + w_{2t}\end{aligned}$$

The seasonal component is ignored if you specify SORDER=0. Therefore, the following state space model is estimated:

$$\begin{aligned}y_t &= \mathbf{H}\mathbf{z}_t + \epsilon_t \\ \mathbf{z}_t &= \mathbf{F}\mathbf{z}_{t-1} + \mathbf{w}_t\end{aligned}$$

where

$$\begin{aligned}\mathbf{H} &= \begin{bmatrix} 1 & 0 & 1 & 0 \end{bmatrix} \\ \mathbf{F} &= \begin{bmatrix} 2 & -1 & 0 & 0 \\ 1 & 0 & 0 & 0 \\ 0 & 0 & \alpha_1 & \alpha_2 \\ 0 & 0 & 1 & 0 \end{bmatrix} \\ \mathbf{z}_t &= (T_t, T_{t-1}, u_t, u_{t-1})' \\ \mathbf{w}_t &= (w_{1t}, 0, w_{2t}, 0)' \sim \left(0, \begin{bmatrix} \sigma_1^2 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & \sigma_2^2 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix} \right)\end{aligned}$$

The parameters of this state space model are σ_1^2 , σ_2^2 , α_1 , and α_2 . Here is the code:

```
proc iml;
y = { 116.8 120.1 123.2 130.2 131.4 125.6 124.5 134.3
      135.2 151.8 146.4 139.0 127.8 147.0 165.9 165.5
      179.4 190.0 189.8 190.9 203.6 183.5 169.3 144.2
      141.5 154.3 169.5 193.0 203.2 192.9 209.4 227.2
      263.7 297.8 337.1 361.3 355.2 312.6 309.9 323.7
      324.1 355.3 383.4 395.1 412.8 406.0 438.0 446.1
      452.5 447.3 475.9 487.7 497.2 529.8 551.0 581.1
      617.8 658.1 675.2 706.6 724.7 };
y = y` ; /*-- convert to column vector --*/
mdel = 0;
trade = 0;
tvreg = 0;
year = 0;
period= 0;
log = 0;
maxit = 100;
update = .; /* use default update method */
line = .; /* use default line search method */
sigmax = 0; /* no upper bound for variances */
```



```

back = 100;
opt = mdel || trade || year || period || log || maxit ||
      update || line || sigmax || back;
call tsdecomp(cmp,coef,aic) data=y order=2 sorder=0 nar=2
      npred=5 opt=opt icmp={1 3} print=1;
y = y[52:61];
cmp = cmp[52:66,];
print y cmp;

```

The estimated parameters are printed when you specify the PRINT= option. In Figure 13.20, the estimated variances are printed under the title of TAU2(I), showing that $\hat{\sigma}_1^2 = 2.915$ and $\hat{\sigma}_2^2 = 113.9577$. The AR coefficient estimates are $\hat{\alpha}_1 = 1.397$ and $\hat{\alpha}_2 = -0.595$. These estimates are also stored in the output matrix COEF.

Figure 13.20 Nonstationary Time Series and State Space Modeling

```

<<<  Final Estimates  >>>

---  PARAMETER VECTOR  ---

1.607423E-01 6.283820E+00 8.761627E-01 -5.94879E-01

---  GRADIENT  ---

3.352158E-04 5.237221E-06 2.907539E-04 -1.24376E-04

LIKELIHOOD = -249.937193      SIG2 =      18.135085
AIC         =  509.874385

I   TAU2 (I)      AR (I)      PARCOR (I)
1   2.915075      1.397374      0.876163
2   113.957607    -0.594879     -0.594879

```

The trend and stationary AR components are estimated by using the smoothing method, and out-of-sample forecasts are computed by using a Kalman filter prediction algorithm. The trend and AR components are stored in the matrix CMP since the ICMP={1 3} option is specified. The last 10 observations of the original series Y and the last 15 observations of two components are shown in Figure 13.21. Note that the first column of CMP is the trend component and the second column is the AR component. The last 5 observations of the CMP matrix are out-of-sample forecasts.

Figure 13.21 Smoothed and Predicted Values of Two Components

	y	cmp	
	487.7	514.01141	-26.94342
	497.2	532.62744	-32.48672
	529.8	552.02402	-24.46593
	551	571.90121	-20.15112
	581.1	592.31944	-10.58646
	617.8	613.21855	5.2504401
	658.1	634.43665	20.799207
	675.2	655.70431	22.161604
	706.6	677.2125	27.927978
	724.7	698.72364	25.957962
		720.23478	19.6592
		741.74593	12.029396
		763.25707	5.1147111
		784.76821	-0.008876
		806.27935	-3.05504

Seasonal Adjustment

Consider the simple time series decomposition

$$y_t = T_t + S_t + \epsilon_t$$

The TSBAYSEA subroutine computes seasonally adjusted series by estimating the seasonal component. The seasonally adjusted series is computed as $y_t^* = y_t - \hat{S}_t$. The details of the adjustment procedure are given in the section “[Bayesian Seasonal Adjustment](#)” on page 285.

The monthly labor force series (1972–1978) are analyzed. You do not need to specify the options vector if you want to use the default options. However, you should change OPT[2] when the data frequency is not monthly (OPT[2]=12). The NPRED= option produces the multistep forecasts for the trend and seasonal components. The stochastic constraints are specified as ORDER=2 and SORDER=1.

$$\begin{aligned} T_t &= 2T_{t-1} - T_{t-2} + w_{1t} \\ S_t &= -S_{t-1} - \cdots - S_{t-11} + w_{2t} \end{aligned}$$

In [Figure 13.22](#), the first column shows the trend components; the second column shows the seasonal components; the third column shows the forecasts; the fourth column shows the seasonally adjusted series; the last column shows the value of ABIC. The last 12 rows are the forecasts. The figure is generated by using the following statements:

```
proc iml;
y = { 5447 5412 5215 4697 4344 5426
      5173 4857 4658 4470 4268 4116
      4675 4845 4512 4174 3799 4847
      4550 4208 4165 3763 4056 4058
      5008 5140 4755 4301 4144 5380
```

```

5260 4885 5202 5044 5685 6106
8180 8309 8359 7820 7623 8569
8209 7696 7522 7244 7231 7195
8174 8033 7525 6890 6304 7655
7577 7322 7026 6833 7095 7022
7848 8109 7556 6568 6151 7453
6941 6757 6437 6221 6346 5880 };
y = y`;

call tsbaysea(trend,season,series,adj,abic)
      data=y order=2 sorder=1 npred=12 print=2;
print trend season series adj abic;

```

Figure 13.22 Trend and Seasonal Component Estimates and Forecasts

	obs	trend	season	series	adj	abic
1	4843.2502	576.86675	5420.1169	4870.1332	874.04585	
2	4848.6664	612.79607	5461.4624	4799.2039		
3	4871.2876	324.02004	5195.3077	4890.98		
4	4896.6633	-198.7601	4697.9032	4895.7601		
5	4922.9458	-572.5562	4350.3896	4916.5562		
.
71	6551.6017	-266.2162	6285.3855	6612.2162		
72	6388.9012	-440.3472	5948.5539	6320.3472		
73	6226.2006	650.7707	6876.9713			
74	6063.5001	800.93733	6864.4374			
75	5900.7995	396.19866	6296.9982			
76	5738.099	-340.2852	5397.8137			
77	5575.3984	-719.1146	4856.2838			
78	5412.6979	553.19764	5965.8955			
79	5249.9973	202.06582	5452.0631			
80	5087.2968	-54.44768	5032.8491			
81	4924.5962	-295.2747	4629.3215			
82	4761.8957	-487.6621	4274.2336			
83	4599.1951	-266.1917	4333.0034			
84	4436.4946	-440.3354	3996.1591			

The estimated spectral density function of the irregular series $\hat{\epsilon}_t$ is shown in [Figure 13.23](#) and [Figure 13.24](#).

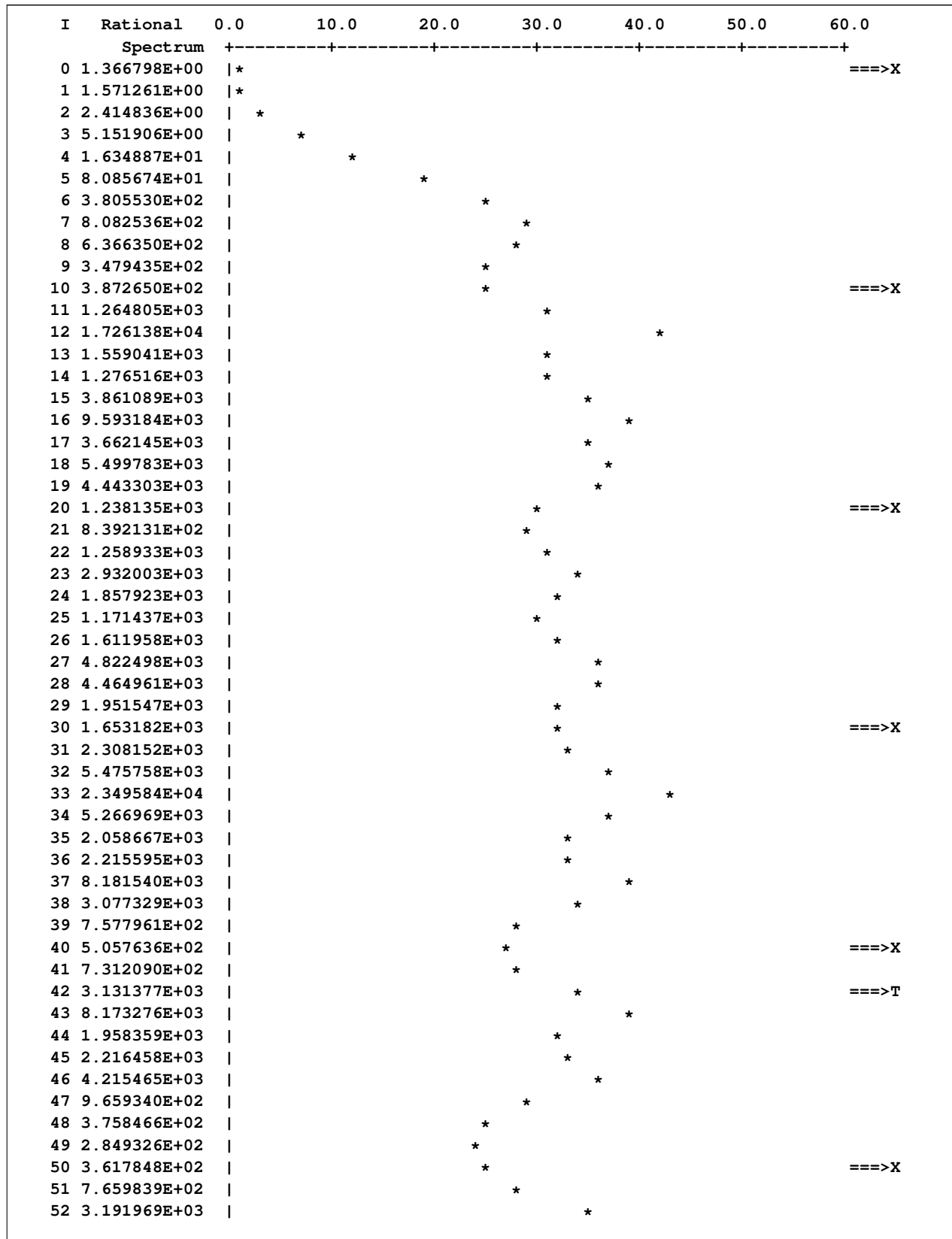
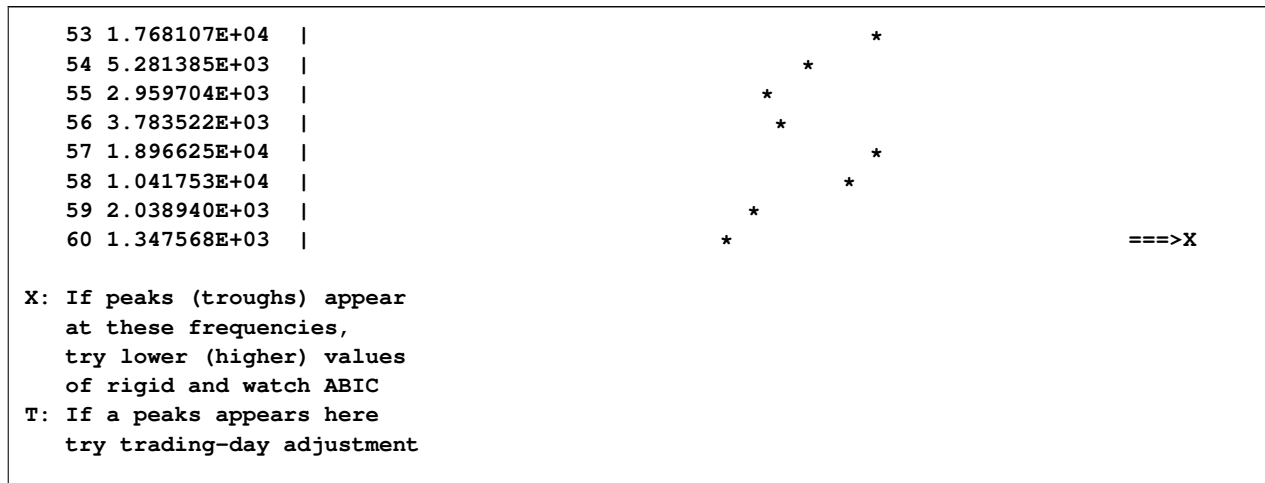
Figure 13.23 Spectrum of Irregular Component

Figure 13.24 continued



Miscellaneous Time Series Analysis Tools

The forecast values of multivariate time series are computed by using the TSPRED call. In the following example, the multistep-ahead forecasts are produced from the VARMA(2,1) estimates. Since the VARMA model is estimated by using the mean deleted series, you should specify the CONSTANT=−1 option. You need to provide the original series instead of the mean deleted series to get the correct predictions. The forecast variance MSE and the impulse response function IMPULSE are also produced.

The VARMA(p, q) model is written

$$\mathbf{y}_t + \sum_{i=1}^p \mathbf{A}_i \mathbf{y}_{t-i} = \epsilon_t + \sum_{i=1}^q \mathbf{M}_i \epsilon_{t-i}$$

Then the COEF matrix is constructed by stacking matrices $\mathbf{A}_1, \dots, \mathbf{A}_p, \mathbf{M}_1, \dots, \mathbf{M}_q$. Here is the code:

```
proc iml;
c = { 264 235 239 239 275 277 274 334 334 306
      308 309 295 271 277 221 223 227 215 223
      241 250 270 303 311 307 322 335 335 334
      309 262 228 191 188 215 215 249 291 296 };
f = { 690 690 688 690 694 702 702 702 700 702
      702 694 708 702 702 708 700 700 702 694
      698 694 700 702 700 702 708 708 710 704
      704 700 700 694 702 694 710 710 710 708 };
t = { 1152 1288 1288 1288 1368 1456 1656 1496 1744 1464
      1560 1376 1336 1336 1296 1296 1280 1264 1280 1272
      1344 1328 1352 1480 1472 1600 1512 1456 1368 1280
      1224 1112 1112 1048 1176 1064 1168 1280 1336 1248 };
p = { 254.14 253.12 251.85 250.41 249.09 249.19 249.52 250.19
      248.74 248.41 249.95 250.64 250.87 250.94 250.96 251.33
      251.18 251.05 251.00 250.99 250.79 250.44 250.12 250.19
      249.77 250.27 250.74 250.90 252.21 253.68 254.47 254.80
      254.92 254.96 254.96 254.96 254.96 254.54 253.21 252.08 };
```

```

y = c` || f` || t` || p`;
ar = { .82028  -.97167  .079386  -5.4382,
        -.39983  .94448  .027938  -1.7477,
        -.42278  -2.3314  1.4682  -70.996,
        .031038  -.019231  -.0004904  1.3677,
        -.029811  .89262  -.047579  4.7873,
        .31476  .0061959  -.012221  1.4921,
        .3813  2.7182  -.52993  67.711,
        -.020818  .01764  .00037981  -.38154 };
ma = { .083035  -1.0509  .055898  -3.9778,
        -.40452  .36876  .026369  -.81146,
        .062379  -2.6506  .80784  -76.952,
        .03273  -.031555  -.00019776  -.025205 };
coef = ar // ma;
ev = { 188.55  6.8082  42.385  .042942,
        6.8082  32.169  37.995  -.062341,
        42.385  37.995  5138.8  -.10757,
        .042942  -.062341  -.10757  .34313 };

nar = 2; nma = 1;
call tspred(forecast,impulse,mse,y,coef,nar,nma,ev,
            5,nrow(y),-1);

```

Figure 13.25 Multivariate ARMA Prediction

observed		predicted	
Y1	Y2	P1	P2
264	690	269.950	700.750
235	690	256.764	691.925
239	688	239.996	693.467
239	690	242.320	690.951
275	694	247.169	693.214
277	702	279.024	696.157
274	702	284.041	700.449
334	702	286.890	701.580
334	700	321.798	699.851
306	702	330.355	702.383
308	702	297.239	700.421
309	694	302.651	701.928
295	708	294.570	696.261
271	702	283.254	703.936
277	702	269.600	703.110
221	708	270.349	701.557
223	700	231.523	705.438
227	700	233.856	701.785
215	702	234.883	700.185
223	694	229.156	701.837
241	698	235.054	697.060
250	694	249.288	698.181
270	700	257.644	696.665
303	702	272.549	699.281
311	700	301.947	701.667
307	702	306.422	700.708
322	708	304.120	701.204
335	708	311.590	704.654
335	710	320.570	706.389
334	704	315.127	706.439
309	704	311.083	703.735
262	700	288.159	702.801
228	700	251.352	700.805
191	694	226.749	700.247
188	702	199.775	696.570
215	694	202.305	700.242
215	710	222.951	696.451
249	710	226.553	704.483
291	710	259.927	707.610
296	708	291.446	707.861
		293.899	707.430
		293.477	706.933
		292.564	706.190
		290.313	705.384
		286.559	704.618

The first 40 forecasts in [Figure 13.25](#) are one-step predictions. The last observation is the five-step forecast values of variables C and F. You can construct the confidence interval for these forecasts by using the mean square error matrix, MSE. See the section “[Multivariate Time Series Analysis](#)” on page 291 for more details about impulse response functions and the mean square error matrix.

The TSROOT call computes the polynomial roots of the AR and MA equations. When the AR(p) process is written

$$y_t = \sum_{i=1}^p \alpha_i y_{t-i} + \epsilon_t$$

you can specify the following polynomial equation:

$$z^p - \sum_{i=1}^p \alpha_i z^{p-i} = 0$$

When all p roots of the preceding equation are inside the unit circle, the AR(p) process is stationary. The MA(q) process is invertible if the following polynomial equation has all roots inside the unit circle:

$$z^q + \sum_{i=1}^q \theta_i z^{q-i} = 0$$

where θ_i are the MA coefficients. For example, the best AR model is selected and estimated by the TSUNIMAR subroutine (see Figure 13.26). You can obtain the roots of the preceding equation by calling the TSROOT subroutine. Since the TSROOT subroutine can handle the complex AR or MA coefficients, note that you should add zero imaginary coefficients for the second column of the MATIN matrix for real coefficients. Here is the code:

```
proc iml;
y = { 2.430 2.506 2.767 2.940 3.169 3.450 3.594 3.774 3.695 3.411
      2.718 1.991 2.265 2.446 2.612 3.359 3.429 3.533 3.261 2.612
      2.179 1.653 1.832 2.328 2.737 3.014 3.328 3.404 2.981 2.557
      2.576 2.352 2.556 2.864 3.214 3.435 3.458 3.326 2.835 2.476
      2.373 2.389 2.742 3.210 3.520 3.828 3.628 2.837 2.406 2.675
      2.554 2.894 3.202 3.224 3.352 3.154 2.878 2.476 2.303 2.360
      2.671 2.867 3.310 3.449 3.646 3.400 2.590 1.863 1.581 1.690
      1.771 2.274 2.576 3.111 3.605 3.543 2.769 2.021 2.185 2.588
      2.880 3.115 3.540 3.845 3.800 3.579 3.264 2.538 2.582 2.907
      3.142 3.433 3.580 3.490 3.475 3.579 2.829 1.909 1.903 2.033
      2.360 2.601 3.054 3.386 3.553 3.468 3.187 2.723 2.686 2.821
      3.000 3.201 3.424 3.531 };

call tsunimar(ar,v,nar,aic) data=y maxlag=5
      opt={-1 1} print=1;
/*-- set up complex coefficient matrix --*/
ar_cx = ar || j(nrow(ar),1,0);
call tsroot(root) matin=ar_cx nar=nar nma=0 print=1;
```

In Figure 13.27, the roots and their lengths from the origin are shown. The roots are also stored in the matrix ROOT. All roots are within the unit circle, while the MOD values of the fourth and fifth roots appear to be sizable (0.9194).

Figure 13.26 Minimum AIC AR Estimation

lag	ar_coef
1	1.3003068
2	-0.72328
3	0.2421928
4	-0.378757
5	0.1377273
aic	innovation_varinace
-318.6138	0.0490554

Figure 13.27 Roots of AR Characteristic Polynomial Equation

Roots of AR Characteristic Polynomial					
I	Real	Imaginary	MOD (Z)	ATAN (I/R)	Degr
1	-0.29755	0.55991	0.6341	2.0593	117.98
2	-0.29755	-0.55991	0.6341	-2.0593	-117.98
3	0.40529	0	0.4053	0	
4	0.74505	0.53866	0.9194	0.6260	35.86
5	0.74505	-0.53866	0.9194	-0.6260	-35.86
$Z^{**5}-AR(1)*Z^{**4}-AR(2)*Z^{**3}-AR(3)*Z^{**2}-AR(4)*Z^{**1}-AR(5)=0$					

The TSROOT subroutine can also recover the polynomial coefficients if the roots are given as an input. You should specify the QCOEF=1 option when you want to compute the polynomial coefficients instead of polynomial roots. You can compare the result with the preceding output of the TSUNIMAR call. Here is the code:

```
call tsroot(ar_cx) matin=root nar=nar qcoef=1
      nma=0 print=1;
```

The results are shown in [Figure 13.28](#).

Figure 13.28 Polynomial Coefficients

Polynomial Coefficients		
I	AR(real)	AR(imag)
1	1.30031	0
2	-0.72328	1.11022E-16
3	0.24219	8.32667E-17
4	-0.37876	2.77556E-17
5	0.13773	0

Syntax

TIMSAC routines are controlled by the following statements:

CALL TSBAYSEA (*trend, season, series, adjust, abic, data <,order, sorder, rigid, npred, opt, cntl, print>*) ;

CALL TSDECOMP (*comp, est, aic, data <,xdata, order, sorder, nar, npred, init, opt, icmp, print>*) ;

CALL TSMLOCAR (*arcoef, ev, nar, aic, start, finish, data <,maxlag, opt, missing, print>*) ;

CALL TSMLOMAR (*arcoef, ev, nar, aic, start, finish, data <,maxlag, opt, missing, print>*) ;

CALL TSMULMAR (*arcoef, ev, nar, aic, data <,maxlag, opt, missing, print>*) ;

CALL TSPEARS (*arcoef, ev, nar, aic, data <,maxlag, opt, missing, print>*) ;

CALL TSPRED (*forecast, impulse, mse, data, coef, nar, nma <,ev, npred, start, constant>*) ;

CALL TSROOT (*matout, matin, nar, nma <,qcoef, print>*) ;

CALL TSTVCAR (*arcoef, variance, est, aic, data <,nar, init, opt, outlier, print>*) ;

CALL TSUNIMAR (*arcoef, ev, nar, aic, data <,maxlag, opt, missing, print>*) ;

Details

This section presents an introductory description of the important topics that are directly related to TIMSAC IML subroutines. The computational details, including algorithms, are described in the section “[Computational Details](#)” on page 295. A detailed explanation of each subroutine is not given; instead, basic ideas and common methodologies for all subroutines are described first and are followed by more technical details. Finally, missing values are discussed in the section “[Missing Values](#)” on page 300.

Minimum AIC Procedure

The AIC statistic is widely used to select the best model among alternative parametric models. The minimum AIC model selection procedure can be interpreted as a maximization of the expected entropy (Akaike 1981). The entropy of a true probability density function (PDF) φ with respect to the fitted PDF f is written as

$$B(\varphi, f) = -I(\varphi, f)$$

where $I(\varphi, f)$ is a Kullback-Leibler information measure, which is defined as

$$I(\varphi, f) = \int \left[\log \left[\frac{\varphi(z)}{f(z)} \right] \right] \varphi(z) dz$$

where the random variable Z is assumed to be continuous. Therefore,

$$B(\varphi, f) = E_Z \log f(Z) - E_Z \log \varphi(Z)$$

where $B(\varphi, f) \leq 0$ and E_Z denotes the expectation concerning the random variable Z . $B(\varphi, f) = 0$ if and only if $\varphi = f$ (a.s.). The larger the quantity $E_Z \log f(Z)$, the closer the function f is to the true PDF φ . Given the data $\mathbf{y} = (y_1, \dots, y_T)'$ that has the same distribution as the random variable Z , let the likelihood function of the parameter vector θ be $\prod_{t=1}^T f(y_t|\theta)$. Then the average of the log-likelihood function $\frac{1}{T} \sum_{t=1}^T \log f(y_t|\theta)$ is an estimate of the expected value of $\log f(Z)$. Akaike (1981) derived the alternative estimate of $E_Z \log f(Z)$ by using the Bayesian predictive likelihood. The AIC is the bias-corrected estimate of $-2TE_Z \log f(Z|\hat{\theta})$, where $\hat{\theta}$ is the maximum likelihood estimate.

$$\text{AIC} = -2(\text{maximum log} - \text{likelihood}) + 2(\text{number of free parameters})$$

Let $\theta = (\theta_1, \dots, \theta_K)'$ be a $K \times 1$ parameter vector that is contained in the parameter space Θ_K . Given the data \mathbf{y} , the log-likelihood function is

$$\ell(\theta) = \sum_{t=1}^T \log f(y_t|\theta)$$

Suppose the probability density function $f(y|\theta)$ has the true PDF $\varphi(y) = f(y|\theta^0)$, where the true parameter vector θ^0 is contained in Θ_K . Let $\hat{\theta}_K$ be a maximum likelihood estimate. The maximum of the log-likelihood function is denoted as $\ell(\hat{\theta}_K) = \max_{\theta \in \Theta_K} \ell(\theta)$. The expected log-likelihood function is defined by

$$\ell^*(\theta) = TE_Z \log f(Z|\theta)$$

The Taylor series expansion of the expected log-likelihood function around the true parameter θ^0 gives the following asymptotic relationship:

$$\ell^*(\theta) \stackrel{A}{=} \ell^*(\theta^0) + T(\theta - \theta^0)' E_Z \frac{\partial \log f(Z|\theta^0)}{\partial \theta} - \frac{T}{2} (\theta - \theta^0)' I(\theta^0) (\theta - \theta^0)$$

where $I(\theta^0)$ is the information matrix and $\stackrel{A}{=}$ stands for asymptotic equality. Note that $\frac{\partial \log f(z|\theta^0)}{\partial \theta} = 0$ since $\log f(z|\theta)$ is maximized at θ^0 . By substituting $\hat{\theta}_K$, the expected log-likelihood function can be written as

$$\ell^*(\hat{\theta}_K) \stackrel{A}{=} \ell^*(\theta^0) - \frac{T}{2} (\hat{\theta}_K - \theta^0)' I(\theta^0) (\hat{\theta}_K - \theta^0)$$

The maximum likelihood estimator is asymptotically normally distributed under the regularity conditions

$$\sqrt{T} I(\theta^0)^{1/2} (\hat{\theta}_K - \theta^0) \xrightarrow{d} N(0, I_K)$$

Therefore,

$$T(\hat{\theta}_K - \theta^0)' I(\theta^0) (\hat{\theta}_K - \theta^0) \stackrel{a}{\sim} \chi_K^2$$

The mean expected log-likelihood function, $\ell^*(K) = E_Y \ell^*(\hat{\theta}_K)$, becomes

$$\ell^*(K) \stackrel{A}{=} \ell^*(\theta^0) - \frac{K}{2}$$

When the Taylor series expansion of the log-likelihood function around $\hat{\theta}_K$ is used, the log-likelihood function $\ell(\theta)$ is written

$$\ell(\theta) \stackrel{A}{=} \ell(\hat{\theta}_K) + (\theta - \hat{\theta}_K)' \frac{\partial \ell(\theta)}{\partial \theta} \Big|_{\hat{\theta}_K} + \frac{1}{2} (\theta - \hat{\theta}_K)' \frac{\partial^2 \ell(\theta)}{\partial \theta \partial \theta'} \Big|_{\hat{\theta}_K} (\theta - \hat{\theta}_K)$$

Since $\ell(\hat{\theta}_K)$ is the maximum log-likelihood function, $\frac{\partial \ell(\theta)}{\partial \theta} \Big|_{\hat{\theta}_K} = 0$. Note that $\text{plim} \left[-\frac{1}{T} \frac{\partial^2 \ell(\theta)}{\partial \theta \partial \theta'} \Big|_{\hat{\theta}_K} \right] = I(\theta^0)$ if the maximum likelihood estimator $\hat{\theta}_K$ is a consistent estimator of θ . Replacing θ with the true parameter θ^0 and taking expectations with respect to the random variable Y ,

$$\mathbb{E}_Y \ell(\theta^0) \stackrel{A}{=} \mathbb{E}_Y \ell(\hat{\theta}_K) - \frac{K}{2}$$

Consider the following relationship:

$$\begin{aligned} \ell^*(\theta^0) &= T \mathbb{E}_Z \log f(Z|\theta^0) \\ &= \mathbb{E}_Y \sum_{t=1}^T \log f(Y_t|\theta^0) \\ &= \mathbb{E}_Y \ell(\theta^0) \end{aligned}$$

From the previous derivation,

$$\ell^*(K) \stackrel{A}{=} \ell^*(\theta^0) - \frac{K}{2}$$

Therefore,

$$\ell^*(K) \stackrel{A}{=} \mathbb{E}_Y \ell(\hat{\theta}_K) - K$$

The natural estimator for $\mathbb{E}_Y \ell(\hat{\theta}_K)$ is $\ell(\hat{\theta}_K)$. Using this estimator, you can write the mean expected log-likelihood function as

$$\ell^*(K) \stackrel{A}{=} \ell(\hat{\theta}_K) - K$$

Consequently, the AIC is defined as an asymptotically unbiased estimator of $-2(\text{mean expected log} - \text{likelihood})$

$$\text{AIC}(K) = -2\ell(\hat{\theta}_K) + 2K$$

In practice, the previous asymptotic result is expected to be valid in finite samples if the number of free parameters does not exceed $2\sqrt{T}$ and the upper bound of the number of free parameters is $\frac{T}{2}$. It is worth noting that the amount of AIC is not meaningful in itself, since this value is not the Kullback-Leibler information measure. The difference of AIC values can be used to select the model. The difference of the two AIC values is considered insignificant if it is far less than 1. It is possible to find a better model when the minimum AIC model contains many free parameters.

Smoothness Priors Modeling

Consider the time series y_t :

$$y_t = f(t) + \epsilon_t$$

where $f(t)$ is an unknown smooth function and ϵ_t is an *iid* random variable with zero mean and positive variance σ^2 . Whittaker (1923) provides the solution, which balances a tradeoff between closeness to the data and the k th-order difference equation. For a fixed value of λ and k , the solution \hat{f} satisfies

$$\min_f \sum_{t=1}^T \left\{ [y_t - f(t)]^2 + \lambda^2 [\nabla^k f(t)]^2 \right\}$$

where ∇^k denotes the k th-order difference operator. The value of λ can be viewed as the smoothness tradeoff measure. Akaike (1980a) proposed the Bayesian posterior PDF to solve this problem.

$$\ell(f) = \exp \left\{ -\frac{1}{2\sigma^2} \sum_{t=1}^T [y_t - f(t)]^2 \right\} \exp \left\{ -\frac{\lambda^2}{2\sigma^2} \sum_{t=1}^T [\nabla^k f(t)]^2 \right\}$$

Therefore, the solution can be obtained when the function $\ell(f)$ is maximized.

Assume that time series is decomposed as follows:

$$y_t = T_t + S_t + \epsilon_t$$

where T_t denotes the trend component and S_t is the seasonal component. The trend component follows the k th-order stochastically perturbed difference equation.

$$\nabla^k T_t = w_{1t}, w_{1t} \sim N(0, \tau_1^2)$$

For example, the polynomial trend component for $k = 2$ is written as

$$T_t = 2T_{t-1} - T_{t-2} + w_{1t}$$

To accommodate regular seasonal effects, the stochastic seasonal relationship is used.

$$\sum_{i=0}^{L-1} S_{t-i} = w_{2t}, w_{2t} \sim N(0, \tau_2^2)$$

where L is the number of seasons within a period. In the context of Whittaker and Akaike, the smoothness priors problem can be solved by the maximization of

$$\begin{aligned} \ell(f) = & \exp \left[-\frac{1}{2\sigma^2} \sum_{t=1}^T (y_t - T_t - S_t)^2 \right] \exp \left[-\frac{\tau_1^2}{2\sigma^2} \sum_{t=1}^T (\nabla^k T_t)^2 \right] \\ & \times \exp \left[-\frac{\tau_2^2}{2\sigma^2} \sum_{t=1}^T \left(\sum_{i=0}^{L-1} S_{t-i} \right)^2 \right] \end{aligned}$$

The values of hyperparameters τ_1^2 and τ_2^2 refer to a measure of uncertainty of prior information. For example, the large value of τ_1^2 implies a relatively smooth trend component. The ratio $\frac{\tau_i^2}{\sigma^2}$ ($i = 1, 2$) can be considered as a signal-to-noise ratio.

Kitagawa and Gersch (1984) use the Kalman filter recursive computation for the likelihood of the tradeoff parameters. The hyperparameters are estimated by combining the grid search and optimization method. The state space model and Kalman filter recursive computation are discussed in the section “[State Space and Kalman Filter Method](#)” on page 298.

Bayesian Seasonal Adjustment

Seasonal phenomena are frequently observed in many economic and business time series. For example, consumption expenditure might have strong seasonal variations because of Christmas spending. The seasonal phenomena are repeatedly observed after a regular period of time. The number of seasons within a

period is defined as the smallest time span for this repetitive observation. Monthly consumption expenditure shows a strong increase during the Christmas season, with 12 seasons per period.

There are three major approaches to seasonal time series: the regression model, the moving average model, and the seasonal ARIMA model.

Regression Model

Let the trend component be $T_t = \sum_{i=1}^{m_\alpha} \alpha_i U_{it}$ and the seasonal component be $S_t = \sum_{j=1}^{m_\beta} \beta_j V_{jt}$. Then the additive time series can be written as the regression model

$$y_t = \sum_{i=1}^{m_\alpha} \alpha_i U_{it} + \sum_{j=1}^{m_\beta} \beta_j V_{jt} + \epsilon_t$$

In practice, the trend component can be written as the m_α th-order polynomial, such as

$$T_t = \sum_{i=0}^{m_\alpha} \alpha_i t^i$$

The seasonal component can be approximated by the seasonal dummies (D_{jt})

$$S_t = \sum_{j=1}^{L-1} \beta_j D_{jt}$$

where L is the number of seasons within a period. The least squares method is applied to estimate parameters α_i and β_j .

The seasonally adjusted series is obtained by subtracting the estimated seasonal component from the original series. Usually, the error term ϵ_t is assumed to be white noise, while sometimes the autocorrelation of the regression residuals needs to be allowed. However, the regression method is not robust to the regression function type, especially at the beginning and end of the series.

Moving Average Model

If you assume that the annual sum of a seasonal time series has small seasonal fluctuations, the nonseasonal component $N_t = T_t + \epsilon_t$ can be estimated by using the moving average method.

$$\hat{N}_t = \sum_{i=-m}^m \lambda_i y_{t-i}$$

where m is the positive integer and λ_i is the symmetric constant such that $\lambda_i = \lambda_{-i}$ and $\sum_{i=-m}^m \lambda_i = 1$.

When the data are not available, either an asymmetric moving average is used, or the forecast data are augmented to use the symmetric weight. The X-11 procedure is a complex modification of this moving-average method.

Seasonal ARIMA Model

The regression and moving-average approaches assume that the seasonal component is deterministic and independent of other nonseasonal components. The time series approach is used to handle the stochastic trend and seasonal components.

The general ARIMA model can be written

$$\prod_{j=1}^m \phi_j(B) \prod_{i=1}^k (1 - B^{s_i})^{d_i} \tilde{y}_t = \theta_0 + \prod_{i=1}^q \theta_i(B) \epsilon_t$$

where B is the backshift operator and

$$\begin{aligned} \phi_j(B) &= 1 - \phi_1 B - \dots - \phi_j B^{p_j} \\ \theta_i(B) &= 1 - \theta_1 B - \dots - \theta_i B^{q_i} \end{aligned}$$

and $\tilde{y}_t = y_t - E(Y_t)$ if $d_i = 0$; otherwise, $\tilde{y}_t = y_t$. The power of B , s_i , can be considered as a seasonal factor. Specifically, the Box-Jenkins multiplicative seasonal ARIMA(p, d, q)(P, D, Q) $_s$ model is written as

$$\phi_p(B) \Phi_P(B^s) (1 - B)^d (1 - B^s)^D \tilde{y}_t = \theta_q(B) \Theta_Q(B^s) \epsilon_t$$

ARIMA modeling is appropriate for particular time series and requires burdensome computation.

The TSBAYSEA subroutine combines the simple characteristics of the regression approach and time series modeling. The TSBAYSEA and X-11 procedures use the model-based seasonal adjustment. The symmetric weights of the standard X-11 option can be approximated by using the integrated MA form

$$(1 - B)(1 - B^{12})y_t = \theta(B)\epsilon_t$$

With a fixed value ϕ , the TSBAYSEA subroutine is approximated as

$$(1 - \phi B)(1 - B)(1 - B^{12})y_t = \theta(B)\epsilon_t$$

The subroutine is flexible enough to handle trading-day or leap-year effects, the shift of the base observation, and missing values. The TSBAYSEA-type modeling approach has some advantages: it clearly defines the statistical model of the time series; modification of the basic model can be an efficient method of choosing a particular procedure for the seasonal adjustment of a given time series; and the use of the concept of the likelihood provides a minimum AIC model selection approach.

Nonstationary Time Series

The subroutines TSMLOCAR, TSMLOMAR, and TSTVCAR are used to analyze nonstationary time series models. The AIC statistic is extensively used to analyze the locally stationary model.

Locally Stationary AR Model

When the time series is nonstationary, the TSMLOCAR (univariate) and TSMLOMAR (multivariate) subroutines can be employed. The whole span of the series is divided into locally stationary blocks of data,

and then the TSMLOCAR and TSMLOMAR subroutines estimate a stationary AR model by using the least squares method on this stationary block. The homogeneity of two different blocks of data is tested by using the AIC.

Given a set of data $\{y_1, \dots, y_T\}$, the data can be divided into k blocks of sizes t_1, \dots, t_k , where $t_1 + \dots + t_k = T$, and k and t_i are unknown. The locally stationary model is fitted to the data

$$y_t = \alpha_0^i + \sum_{j=1}^{p_i} \alpha_j^i y_{t-j} + \epsilon_t^i$$

where

$$T_{i-1} = \sum_{j=1}^{i-1} t_j < t \leq T_i = \sum_{j=1}^i t_j \text{ for } i = 1, \dots, k$$

where ϵ_t^i is a Gaussian white noise with $E\epsilon_t^i = 0$ and $E(\epsilon_t^i)^2 = \sigma_i^2$. Therefore, the log-likelihood function of the locally stationary series is

$$\ell = -\frac{1}{2} \sum_{i=1}^k \left[t_i \log(2\pi\sigma_i^2) + \frac{1}{\sigma_i^2} \sum_{t=T_{i-1}+1}^{T_i} \left(y_t - \alpha_0^i - \sum_{j=1}^{p_i} \alpha_j^i y_{t-j} \right)^2 \right]$$

Given α_j^i , $j = 0, \dots, p_i$, the maximum of the log-likelihood function is attained at

$$\hat{\sigma}_i^2 = \frac{1}{t_i} \sum_{t=T_{i-1}+1}^{T_i} \left(y_t - \hat{\alpha}_0^i - \sum_{j=1}^{p_i} \hat{\alpha}_j^i y_{t-j} \right)^2$$

The concentrated log-likelihood function is given by

$$\ell^* = -\frac{T}{2} [1 + \log(2\pi)] - \frac{1}{2} \sum_{i=1}^k t_i \log(\hat{\sigma}_i^2)$$

Therefore, the maximum likelihood estimates, $\hat{\alpha}_j^i$ and $\hat{\sigma}_i^2$, are obtained by minimizing the following local SSE:

$$\text{SSE} = \sum_{t=T_{i-1}+1}^{T_i} \left(y_t - \hat{\alpha}_0^i - \sum_{j=1}^{p_i} \hat{\alpha}_j^i y_{t-j} \right)^2$$

The least squares estimation of the stationary model is explained in the section “[Least Squares and Householder Transformation](#)” on page 295.

The AIC for the locally stationary model over the pooled data is written as

$$\sum_{i=1}^k t_i \log(\hat{\sigma}_i^2) + 2 \sum_{i=1}^k (p_i + \text{intercept} + 1)$$

where $\text{intercept} = 1$ if the intercept term (α_0^i) is estimated; otherwise, $\text{intercept} = 0$. The number of stationary blocks (k), the size of each block (t_i), and the order of the locally stationary model is determined by the

AIC. Consider the autoregressive model fitted over the block of data, $\{y_1, \dots, y_T\}$, and let this model M_1 be an $AR(p_1)$ process. When additional data, $\{y_{T+1}, \dots, y_{T+T_1}\}$, are available, a new model M_2 , an $AR(p_2)$ process, is fitted over this new data set, assuming that these data are independent of the previous data. Then AICs for models M_1 and M_2 are defined as

$$\begin{aligned} \text{AIC}_1 &= T \log(\sigma_1^2) + 2(p_1 + \text{intercept} + 1) \\ \text{AIC}_2 &= T_1 \log(\sigma_2^2) + 2(p_2 + \text{intercept} + 1) \end{aligned}$$

The joint model AIC for M_1 and M_2 is obtained by summation

$$\text{AIC}_J = \text{AIC}_1 + \text{AIC}_2$$

When the two data sets are pooled and estimated over the pooled data set, $\{y_1, \dots, y_{T+T_1}\}$, the AIC of the pooled model is

$$\text{AIC}_A = (T + T_1) \log(\hat{\sigma}_A^2) + 2(p_A + \text{intercept} + 1)$$

where σ_A^2 is the pooled error variance and p_A is the order chosen to fit the pooled data set.

Decision

- If $\text{AIC}_J < \text{AIC}_A$, switch to the new model, since there is a change in the structure of the time series.
- If $\text{AIC}_J \geq \text{AIC}_A$, pool the two data sets, since two data sets are considered to be homogeneous.

If new observations are available, repeat the preceding steps to determine the homogeneity of the data. The basic idea of locally stationary AR modeling is that, if the structure of the time series is not changed, you should use the additional information to improve the model fitting, but you need to follow the new structure of the time series if there is any change.

Time-Varying AR Coefficient Model

Another approach to nonstationary time series, especially those that are nonstationary in the covariance, is time-varying AR coefficient modeling. When the time series is nonstationary in the covariance, the problem in modeling this series is related to an efficient parameterization. It is possible for a Bayesian approach to estimate the model with a large number of implicit parameters of the complex structure by using a relatively small number of hyperparameters.

The TSTVCAR subroutine uses smoothness priors by imposing stochastically perturbed difference equation constraints on each AR coefficient and frequency response function. The variance of each AR coefficient distribution constitutes a hyperparameter included in the state space model. The likelihood of these hyperparameters is computed by the Kalman filter recursive algorithm.

The time-varying AR coefficient model is written

$$y_t = \sum_{i=1}^m \alpha_{it} y_{t-i} + \epsilon_t$$

where time-varying coefficients α_{it} are assumed to change gradually with time. The following simple stochastic difference equation constraint is imposed on each coefficient:

$$\nabla^k \alpha_{it} = w_{it}, w_{it} \sim N(0, \tau^2), i = 1, \dots, m$$

The frequency response function of the AR process is written

$$A(f) = 1 - \sum_{j=1}^m \alpha_{jt} \exp(-2\pi j i f)$$

The smoothness of this function can be measured by the k th derivative smoothness constraint,

$$R_k = \int_{-1/2}^{1/2} \left| \frac{d^k A(f)}{df^k} \right|^2 df = (2\pi)^{2k} \sum_{j=1}^m j^{2k} \alpha_{jt}^2$$

Then the TSTVCAR call imposes zero and second derivative smoothness constraints. The time-varying AR coefficients are the solution of the following constrained least squares:

$$\sum_{t=1}^T \left(y_t - \sum_{i=1}^m \alpha_{it} y_{t-i} \right)^2 + \tau^2 \sum_{t=1}^T \sum_{i=1}^m \left(\nabla^k \alpha_{it} \right)^2 + \lambda^2 \sum_{t=1}^T \sum_{i=1}^m i^2 \alpha_{it}^2 + \nu^2 \sum_{t=1}^T \sum_{i=1}^m \alpha_{it}^2$$

where τ^2 , λ^2 , and ν^2 are hyperparameters of the prior distribution.

Using a state space representation, the model is

$$\begin{aligned} \mathbf{x}_t &= \mathbf{F} \mathbf{x}_{t-1} + \mathbf{G} \mathbf{w}_t \\ y_t &= \mathbf{H}_t \mathbf{x}_t + \epsilon_t \end{aligned}$$

where

$$\begin{aligned} \mathbf{x}_t &= (\alpha_{1t}, \dots, \alpha_{mt}, \dots, \alpha_{1,t-k+1}, \dots, \alpha_{m,t-k+1})' \\ \mathbf{H}_t &= (y_{t-1}, \dots, y_{t-m}, \dots, 0, \dots, 0) \\ \mathbf{w}_t &= (w_{1t}, \dots, w_{mt})' \\ k &= 1 : \mathbf{F} = \mathbf{I}_m \mathbf{G} = \mathbf{I}_m \\ k &= 2 : \mathbf{F} = \begin{bmatrix} 2\mathbf{I}_m & -\mathbf{I}_m \\ \mathbf{I}_m & 0 \end{bmatrix} \mathbf{G} = \begin{bmatrix} \mathbf{I}_m \\ 0 \end{bmatrix} \\ k &= 3 : \mathbf{F} = \begin{bmatrix} 3\mathbf{I}_m & -3\mathbf{I}_m & \mathbf{I}_m \\ \mathbf{I}_m & 0 & 0 \\ 0 & \mathbf{I}_m & 0 \end{bmatrix} \mathbf{G} = \begin{bmatrix} \mathbf{I}_m \\ 0 \\ 0 \end{bmatrix} \\ \begin{bmatrix} \mathbf{w}_t \\ \epsilon_t \end{bmatrix} &\sim N \left(\mathbf{0}, \begin{bmatrix} \tau^2 \mathbf{I} & 0 \\ 0 & \sigma^2 \end{bmatrix} \right) \end{aligned}$$

The computation of the likelihood function is straightforward. See the section “[State Space and Kalman Filter Method](#)” on page 298 for the computation method.

Multivariate Time Series Analysis

The subroutines TSMULMAR, TSMLOMAR, and TSPRED analyze multivariate time series. The periodic AR model, TSPEARS, can also be estimated by using a vector AR procedure, since the periodic AR series can be represented as the covariance-stationary vector autoregressive model.

The stationary vector AR model is estimated and the order of the model (or each variable) is automatically determined by the minimum AIC procedure. The stationary vector AR model is written

$$\begin{aligned} \mathbf{y}_t &= \mathbf{A}_0 + \mathbf{A}_1 \mathbf{y}_{t-1} + \cdots + \mathbf{A}_p \mathbf{y}_{t-p} + \epsilon_t \\ \epsilon_t &\sim N(\mathbf{0}, \Sigma) \end{aligned}$$

Using the \mathbf{LDL}' factorization method, the error covariance is decomposed as

$$\Sigma = \mathbf{LDL}'$$

where \mathbf{L} is a unit lower triangular matrix and \mathbf{D} is a diagonal matrix. Then the instantaneous response model is defined as

$$\mathbf{C}\mathbf{y}_t = \mathbf{A}_0^* + \mathbf{A}_1^* \mathbf{y}_{t-1} + \cdots + \mathbf{A}_p^* \mathbf{y}_{t-p} + \epsilon_t^*$$

where $\mathbf{C} = \mathbf{L}^{-1}$, $\mathbf{A}_i^* = \mathbf{L}^{-1} \mathbf{A}_i$ for $i = 0, 1, \dots, p$, and $\epsilon_t^* = \mathbf{L}^{-1} \epsilon_t$. Each equation of the instantaneous response model can be estimated independently, since its error covariance matrix has a diagonal covariance matrix \mathbf{D} . Maximum likelihood estimates are obtained through the least squares method when the disturbances are normally distributed and the presample values are fixed.

The TSMULMAR subroutine estimates the instantaneous response model. The VAR coefficients are computed by using the relationship between the VAR and instantaneous models.

The general VARMA model can be transformed as an infinite-order MA process under certain conditions.

$$\mathbf{y}_t = \mu + \epsilon_t + \sum_{m=1}^{\infty} \Psi_m \epsilon_{t-m}$$

In the context of the VAR(p) model, the coefficient Ψ_m can be interpreted as the m -lagged response of a unit increase in the disturbances at time t .

$$\Psi_m = \frac{\partial \mathbf{y}_{t+m}}{\partial \epsilon_t^*}$$

The lagged response on the one-unit increase in the orthogonalized disturbances ϵ_t^* is denoted

$$\frac{\partial \mathbf{y}_{t+m}}{\partial \epsilon_{jt}^*} = \frac{\partial E(\mathbf{y}_{t+m} | y_{jt}, y_{j-1,t}, \dots, \mathbf{X}_t)}{\partial y_{jt}} = \Psi_m \mathbf{L}_j$$

where \mathbf{L}_j is the j th column of the unit triangular matrix \mathbf{L} and $\mathbf{X}_t = [\mathbf{y}_{t-1}, \dots, \mathbf{y}_{t-p}]$. When you estimate the VAR model by using the TSMULMAR call, it is easy to compute this impulse response function.

The MSE of the m -step prediction is computed as

$$E(\mathbf{y}_{t+m} - \mathbf{y}_{t+m|t})(\mathbf{y}_{t+m} - \mathbf{y}_{t+m|t})' = \Sigma + \Psi_1 \Sigma \Psi_1' + \cdots + \Psi_{m-1} \Sigma \Psi_{m-1}'$$

Note that $\epsilon_t = \mathbf{L}\epsilon_t^*$. Then the covariance matrix of ϵ_t is decomposed

$$\Sigma = \sum_{i=1}^n \mathbf{L}_i \mathbf{L}_i' d_{ii}$$

where d_{ii} is the i th diagonal element of the matrix \mathbf{D} and n is the number of variables. The MSE matrix can be written

$$\sum_{i=1}^n d_{ii} [\mathbf{L}_i \mathbf{L}_i' + \Psi_1 \mathbf{L}_i \mathbf{L}_i' \Psi_1' + \cdots + \Psi_{m-1} \mathbf{L}_i \mathbf{L}_i' \Psi_{m-1}']$$

Therefore, the contribution of the i th orthogonalized innovation to the MSE is

$$\mathbf{V}_i = d_{ii} [\mathbf{L}_i \mathbf{L}_i' + \Psi_1 \mathbf{L}_i \mathbf{L}_i' \Psi_1' + \cdots + \Psi_{m-1} \mathbf{L}_i \mathbf{L}_i' \Psi_{m-1}']$$

The i th forecast error variance decomposition is obtained from diagonal elements of the matrix \mathbf{V}_i .

The nonstationary multivariate series can be analyzed by the TSMLOMAR subroutine. The estimation and model identification procedure is analogous to the univariate nonstationary procedure, which is explained in the section “Nonstationary Time Series” on page 287.

A time series y_t is periodically correlated with period d if $E y_t = E y_{t+d}$ and $E y_s y_t = E y_{s+d} y_{t+d}$. Let y_t be autoregressive of period d with AR orders (p_1, \dots, p_d) —that is,

$$y_t = \sum_{j=1}^{p_t} \alpha_{jt} y_{t-j} + \epsilon_t$$

where ϵ_t is uncorrelated with mean zero and $E \epsilon_t^2 = \sigma_t^2$, $p_t = p_{t+d}$, $\sigma_t^2 = \sigma_{t+d}^2$, and $\alpha_{jt} = \alpha_{j,t+d}$ ($j = 1, \dots, p_t$). Define the new variable such that $x_{jt} = y_{j+d(t-1)}$. The vector series, $\mathbf{x}_t = (x_{1t}, \dots, x_{dt})'$, is autoregressive of order p , where $p = \max_j \text{int}((p_j - j)/d) + 1$. The TSPEARS subroutine estimates the periodic autoregressive model by using minimum AIC vector AR modeling.

The TSPRED subroutine computes the one-step or multistep forecast of the multivariate ARMA model if the ARMA parameter estimates are provided. In addition, the subroutine TSPRED produces the (intermediate and permanent) impulse response function and performs forecast error variance decomposition for the vector AR model.

Spectral Analysis

The autocovariance function of the random variable Y_t is defined as

$$C_{YY}(k) = E(Y_{t+k} Y_t)$$

where $E Y_t = 0$. When the real valued process Y_t is stationary and its autocovariance is absolutely summable, the population spectral density function is obtained by using the Fourier transform of the autocovariance function

$$f(g) = \frac{1}{2\pi} \sum_{k=-\infty}^{\infty} C_{YY}(k) \exp(-i g k) \quad -\pi \leq g \leq \pi$$

where $i = \sqrt{-1}$ and $C_{YY}(k)$ is the autocovariance function such that $\sum_{k=-\infty}^{\infty} |C_{YY}(k)| < \infty$.

Consider the autocovariance generating function

$$\gamma(z) = \sum_{k=-\infty}^{\infty} C_{YY}(k) z^k$$

where $C_{YY}(k) = C_{YY}(-k)$ and z is a complex scalar. The spectral density function can be represented as

$$f(g) = \frac{1}{2\pi} \gamma(\exp(-ig))$$

The stationary ARMA(p, q) process is denoted

$$\phi(B)y_t = \theta(B)\epsilon_t \epsilon_t \sim (0, \sigma^2)$$

where $\phi(B)$ and $\theta(B)$ do not have common roots. Note that the autocovariance generating function of the linear process $y_t = \psi(B)\epsilon_t$ is given by

$$\gamma(B) = \sigma^2 \psi(B) \psi(B^{-1})$$

For the ARMA(p, q) process, $\psi(B) = \frac{\theta(B)}{\phi(B)}$. Therefore, the spectral density function of the stationary ARMA(p, q) process becomes

$$f(g) = \frac{\sigma^2}{2\pi} \left| \frac{\theta(\exp(-ig))\theta(\exp(ig))}{\phi(\exp(-ig))\phi(\exp(ig))} \right|^2$$

The spectral density function of a white noise is a constant.

$$f(g) = \frac{\sigma^2}{2\pi}$$

The spectral density function of the AR(1) process ($\phi(B) = 1 - \phi_1 B$) is given by

$$f(g) = \frac{\sigma^2}{2\pi(1 - \phi_1 \cos(g) + \phi_1^2)}$$

The spectrum of the AR(1) process has its minimum at $g = 0$ and its maximum at $g = \pm\pi$ if $\phi_1 < 0$, while the spectral density function attains its maximum at $g = 0$ and its minimum at $g = \pm\pi$, if $\phi_1 > 0$. When the series is positively autocorrelated, its spectral density function is dominated by low frequencies. It is interesting to observe that the spectrum approaches $\frac{\sigma^2}{4\pi} \frac{1}{1 - \cos(g)}$ as $\phi_1 \rightarrow 1$. This relationship shows that the series is difference-stationary if its spectral density function has a remarkable peak near 0.

The spectrum of AR(2) process ($\phi(B) = 1 - \phi_1 B - \phi_2 B^2$) equals

$$f(g) = \frac{\sigma^2}{2\pi} \frac{1}{\left\{ -4\phi_2 \left[\cos(g) + \frac{\phi_1(1-\phi_2)}{4\phi_2} \right]^2 + \frac{(1+\phi_2)^2(4\phi_2+\phi_1^2)}{4\phi_2} \right\}}$$

Refer to Anderson (1971) for details of the characteristics of this spectral density function of the AR(2) process.

In practice, the population spectral density function cannot be computed. There are many ways of computing the sample spectral density function. The TSBAYSEA and TSMLOCAR subroutines compute the power spectrum by using AR coefficients and the white noise variance.

The power spectral density function of Y_t is derived by using the Fourier transformation of $C_{YY}(k)$.

$$f_{YY}(g) = \sum_{k=-\infty}^{\infty} \exp(-2\pi i g k) C_{YY}(k), -\frac{1}{2} \leq g \leq \frac{1}{2}$$

where $i = \sqrt{-1}$ and g denotes frequency. The autocovariance function can also be written as

$$C_{YY}(k) = \int_{-1/2}^{1/2} \exp(2\pi i g k) f_{YY}(g) dg$$

Consider the following stationary AR(p) process:

$$y_t - \sum_{i=1}^p \phi_i y_{t-i} = \epsilon_t$$

where ϵ_t is a white noise with mean zero and constant variance σ^2 .

The autocovariance function of white noise ϵ_t equals

$$C_{\epsilon\epsilon}(k) = \delta_{k0} \sigma^2$$

where $\delta_{k0} = 1$ if $k = 0$; otherwise, $\delta_{k0} = 0$. Therefore, the power spectral density of the white noise is $f_{\epsilon\epsilon}(g) = \sigma^2$, $-\frac{1}{2} \leq g \leq \frac{1}{2}$. Note that, with $\phi_0 = -1$,

$$C_{\epsilon\epsilon}(k) = \sum_{m=0}^p \sum_{n=0}^p \phi_m \phi_n C_{YY}(k - m + n)$$

Using the following autocovariance function of Y_t ,

$$C_{YY}(k) = \int_{-1/2}^{1/2} \exp(2\pi i g k) f_{YY}(g) dg$$

the autocovariance function of the white noise is denoted as

$$\begin{aligned} C_{\epsilon\epsilon}(k) &= \sum_{m=0}^p \sum_{n=0}^p \phi_m \phi_n \int_{-1/2}^{1/2} \exp(2\pi i g(k - m + n)) f_{YY}(g) dg \\ &= \int_{-1/2}^{1/2} \exp(2\pi i g k) \left| 1 - \sum_{m=1}^p \phi_m \exp(-2\pi i g m) \right|^2 f_{YY}(g) dg \end{aligned}$$

On the other hand, another formula of the $C_{\epsilon\epsilon}(k)$ gives

$$C_{\epsilon\epsilon}(k) = \int_{-1/2}^{1/2} \exp(2\pi i g k) f_{\epsilon\epsilon}(g) dg$$

Therefore,

$$f_{\epsilon\epsilon}(g) = \left| 1 - \sum_{m=1}^p \phi_m \exp(-2\pi i g m) \right|^2 f_{YY}(g)$$

Since $f_{\epsilon\epsilon}(g) = \sigma^2$, the rational spectrum of Y_t is

$$f_{YY}(g) = \frac{\sigma^2}{\left| 1 - \sum_{m=1}^p \phi_m \exp(-2\pi i g m) \right|^2}$$

To compute the power spectrum, estimated values of white noise variance $\hat{\sigma}^2$ and AR coefficients $\hat{\phi}_m$ are used. The order of the AR process can be determined by using the minimum AIC procedure.

Computational Details

Least Squares and Householder Transformation

Consider the univariate AR(p) process

$$y_t = \alpha_0 + \sum_{i=1}^p \alpha_i y_{t-i} + \epsilon_t$$

Define the design matrix \mathbf{X} .

$$\mathbf{X} = \begin{bmatrix} 1 & y_p & \cdots & y_1 \\ \vdots & \vdots & \ddots & \vdots \\ 1 & y_{T-1} & \cdots & y_{T-p} \end{bmatrix}$$

Let $\mathbf{y} = (y_{p+1}, \dots, y_T)'$. The least squares estimate, $\hat{\mathbf{a}} = (\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\mathbf{y}$, is the approximation to the maximum likelihood estimate of $\mathbf{a} = (\alpha_0, \alpha_1, \dots, \alpha_p)$ if ϵ_t is assumed to be Gaussian error disturbances. Combining \mathbf{X} and \mathbf{y} as

$$\mathbf{Z} = [\mathbf{X} : \mathbf{y}]$$

the \mathbf{Z} matrix can be decomposed as

$$\mathbf{Z} = \mathbf{Q}\mathbf{U} = \mathbf{Q} \begin{bmatrix} \mathbf{R} & \mathbf{w}_1 \\ \mathbf{0} & \mathbf{w}_2 \end{bmatrix}$$

where \mathbf{Q} is an orthogonal matrix and \mathbf{R} is an upper triangular matrix, $\mathbf{w}_1 = (w_1, \dots, w_{p+1})'$, and $\mathbf{w}_2 = (w_{p+2}, 0, \dots, 0)'$.

$$\mathbf{Q}'\mathbf{y} = \begin{bmatrix} w_1 \\ w_2 \\ \vdots \\ w_{T-p} \end{bmatrix}$$

The least squares estimate that uses Householder transformation is computed by solving the linear system

$$\mathbf{R}\mathbf{a} = \mathbf{w}_1$$

The unbiased residual variance estimate is

$$\hat{\sigma}^2 = \frac{1}{T-p} \sum_{i=p+2}^{T-p} w_i^2 = \frac{w_{p+2}^2}{T-p}$$

and

$$\text{AIC} = (T-p) \log(\hat{\sigma}^2) + 2(p+1)$$

In practice, least squares estimation does not require the orthogonal matrix \mathbf{Q} . The TIMSAC subroutines compute the upper triangular matrix without computing the matrix \mathbf{Q} .

Bayesian Constrained Least Squares

Consider the additive time series model

$$y_t = T_t + S_t + \epsilon_t, \epsilon_t \sim N(0, \sigma^2)$$

Practically, it is not possible to estimate parameters $\mathbf{a} = (T_1, \dots, T_T, S_1, \dots, S_T)'$, since the number of parameters exceeds the number of available observations. Let ∇_L^m denote the seasonal difference operator with L seasons and degree of m ; that is, $\nabla_L^m = (1 - B^L)^m$. Suppose that $T = L * n$. Some constraints on the trend and seasonal components need to be imposed such that the sum of squares of $\nabla^k T_t$, $\nabla_L^m S_t$, and $(\sum_{i=0}^{L-1} S_{t-i})$ is small. The constrained least squares estimates are obtained by minimizing

$$\sum_{t=1}^T \left\{ (y_t - T_t - S_t)^2 + d^2 \left[s^2 (\nabla^k T_t)^2 + (\nabla_L^m S_t)^2 + z^2 (S_t + \dots + S_{t-L+1})^2 \right] \right\}$$

Using matrix notation,

$$(\mathbf{y} - \mathbf{M}\mathbf{a})'(\mathbf{y} - \mathbf{M}\mathbf{a}) + (\mathbf{a} - \mathbf{a}_0)' \mathbf{D}' \mathbf{D} (\mathbf{a} - \mathbf{a}_0)$$

where $\mathbf{M} = [\mathbf{I}_T : \mathbf{I}_T]$, $\mathbf{y} = (y_1, \dots, y_T)'$, and \mathbf{a}_0 is the initial guess of \mathbf{a} . The matrix \mathbf{D} is a $3T \times 2T$ control matrix in which structure varies according to the order of differencing in trend and season.

$$\mathbf{D} = d \begin{bmatrix} \mathbf{E}_m & \mathbf{0} \\ z\mathbf{F} & \mathbf{0} \\ \mathbf{0} & s\mathbf{G}_k \end{bmatrix}$$

where

$$\begin{aligned}
 \mathbf{E}_m &= \mathbf{C}_m \otimes \mathbf{I}_L, m = 1, 2, 3 \\
 \mathbf{F} &= \begin{bmatrix} 1 & 0 & \cdots & 0 \\ 1 & 1 & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ 1 & \cdots & 1 & 1 \end{bmatrix}_{T \times T} \\
 \mathbf{G}_1 &= \begin{bmatrix} 1 & 0 & 0 & \cdots & 0 \\ -1 & 1 & 0 & \cdots & 0 \\ 0 & -1 & 1 & \ddots & \vdots \\ \vdots & \ddots & \ddots & \ddots & 0 \\ 0 & \cdots & 0 & -1 & 1 \end{bmatrix}_{T \times T} \\
 \mathbf{G}_2 &= \begin{bmatrix} 1 & 0 & 0 & 0 & \cdots & 0 \\ -2 & 1 & 0 & 0 & \cdots & 0 \\ 1 & -2 & 1 & 0 & \cdots & 0 \\ 0 & 1 & -2 & 1 & \ddots & \vdots \\ \vdots & \ddots & \ddots & \ddots & \ddots & 0 \\ 0 & \cdots & 0 & 1 & -2 & 1 \end{bmatrix}_{T \times T} \\
 \mathbf{G}_3 &= \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & \cdots & 0 \\ -3 & 1 & 0 & 0 & 0 & \cdots & 0 \\ 3 & -3 & 1 & 0 & 0 & \cdots & 0 \\ -1 & 3 & -3 & 1 & 0 & \cdots & 0 \\ 0 & -1 & 3 & -3 & 1 & \ddots & \vdots \\ \vdots & \ddots & \ddots & \ddots & \ddots & \ddots & 0 \\ 0 & \cdots & 0 & -1 & 3 & -3 & 1 \end{bmatrix}_{T \times T}
 \end{aligned}$$

The $n \times n$ matrix \mathbf{C}_m has the same structure as the matrix \mathbf{G}_m , and \mathbf{I}_L is the $L \times L$ identity matrix. The solution of the constrained least squares method is equivalent to that of maximizing the function

$$L(\mathbf{a}) = \exp \left\{ -\frac{1}{2\sigma^2} (\mathbf{y} - \mathbf{Ma})' (\mathbf{y} - \mathbf{Ma}) \right\} \exp \left\{ -\frac{1}{2\sigma^2} (\mathbf{a} - \mathbf{a}_0)' \mathbf{D}' \mathbf{D} (\mathbf{a} - \mathbf{a}_0) \right\}$$

Therefore, the PDF of the data \mathbf{y} is

$$f(\mathbf{y} | \sigma^2, \mathbf{a}) = \left(\frac{1}{2\pi} \right)^{T/2} \left(\frac{1}{\sigma} \right)^T \exp \left\{ -\frac{1}{2\sigma^2} (\mathbf{y} - \mathbf{Ma})' (\mathbf{y} - \mathbf{Ma}) \right\}$$

The prior PDF of the parameter vector \mathbf{a} is

$$\pi(\mathbf{a} | \mathbf{D}, \sigma^2, \mathbf{a}_0) = \left(\frac{1}{2\pi} \right)^T \left(\frac{1}{\sigma} \right)^{2T} |\mathbf{D}' \mathbf{D}| \exp \left\{ -\frac{1}{2\sigma^2} (\mathbf{a} - \mathbf{a}_0)' \mathbf{D}' \mathbf{D} (\mathbf{a} - \mathbf{a}_0) \right\}$$

When the constant d is known, the estimate $\hat{\mathbf{a}}$ of \mathbf{a} is the mean of the posterior distribution, where the posterior PDF of the parameter \mathbf{a} is proportional to the function $L(\mathbf{a})$. It is obvious that $\hat{\mathbf{a}}$ is the minimizer

of $\|\mathbf{g}(\mathbf{a}|d)\|^2 = (\tilde{\mathbf{y}} - \tilde{\mathbf{D}}\mathbf{a})'(\tilde{\mathbf{y}} - \tilde{\mathbf{D}}\mathbf{a})$, where

$$\tilde{\mathbf{y}} = \begin{bmatrix} \mathbf{y} \\ \mathbf{D}\mathbf{a}_0 \end{bmatrix}$$

$$\tilde{\mathbf{D}} = \begin{bmatrix} \mathbf{M} \\ \mathbf{D} \end{bmatrix}$$

The value of d is determined by the minimum ABIC procedure. The ABIC is defined as

$$\text{ABIC} = T \log \left[\frac{1}{T} \|\mathbf{g}(\mathbf{a}|d)\|^2 \right] + 2\{\log[\det(\mathbf{D}'\mathbf{D} + \mathbf{M}'\mathbf{M})] - \log[\det(\mathbf{D}'\mathbf{D})]\}$$

State Space and Kalman Filter Method

In this section, the mathematical formulas for state space modeling are introduced. The Kalman filter algorithms are derived from the state space model. As an example, the state space model of the TSDECOMP subroutine is formulated.

Define the following state space model:

$$\begin{aligned} \mathbf{x}_t &= \mathbf{F}\mathbf{x}_{t-1} + \mathbf{G}\mathbf{w}_t \\ y_t &= \mathbf{H}_t\mathbf{x}_t + \epsilon_t \end{aligned}$$

where $\epsilon_t \sim N(0, \sigma^2)$ and $\mathbf{w}_t \sim N(\mathbf{0}, \mathbf{Q})$. If the observations, (y_1, \dots, y_T) , and the initial conditions, $\mathbf{x}_{0|0}$ and $\mathbf{P}_{0|0}$, are available, the one-step predictor $(\mathbf{x}_{t|t-1})$ of the state vector \mathbf{x}_t and its mean square error (MSE) matrix $\mathbf{P}_{t|t-1}$ are written as

$$\begin{aligned} \mathbf{x}_{t|t-1} &= \mathbf{F}\mathbf{x}_{t-1|t-1} \\ \mathbf{P}_{t|t-1} &= \mathbf{F}\mathbf{P}_{t-1|t-1}\mathbf{F}' + \mathbf{G}\mathbf{Q}\mathbf{G}' \end{aligned}$$

Using the current observation, the filtered value of \mathbf{x}_t and its variance $\mathbf{P}_{t|t}$ are updated.

$$\begin{aligned} \mathbf{x}_{t|t} &= \mathbf{x}_{t|t-1} + \mathbf{K}_t e_t \\ \mathbf{P}_{t|t} &= (\mathbf{I} - \mathbf{K}_t \mathbf{H}_t) \mathbf{P}_{t|t-1} \end{aligned}$$

where $e_t = y_t - \mathbf{H}_t \mathbf{x}_{t|t-1}$ and $\mathbf{K}_t = \mathbf{P}_{t|t-1} \mathbf{H}_t' [\mathbf{H}_t \mathbf{P}_{t|t-1} \mathbf{H}_t' + \sigma^2 \mathbf{I}]^{-1}$. The log-likelihood function is computed as

$$\ell = -\frac{1}{2} \sum_{t=1}^T \log(2\pi v_{t|t-1}) - \sum_{t=1}^T \frac{e_t^2}{2v_{t|t-1}}$$

where $v_{t|t-1}$ is the conditional variance of the one-step prediction error e_t .

Consider the additive time series decomposition

$$y_t = T_t + S_t + TD_t + u_t + \mathbf{x}_t' \boldsymbol{\beta}_t + \epsilon_t$$

where \mathbf{x}_t is a $(K \times 1)$ regressor vector and β_t is a $(K \times 1)$ time-varying coefficient vector. Each component has the following constraints:

$$\begin{aligned}\nabla^k T_t &= w_{1t}, w_{1t} \sim N(0, \tau_1^2) \\ \nabla_L^m S_t &= w_{2t}, w_{2t} \sim N(0, \tau_2^2) \\ u_t &= \sum_{i=1}^p \alpha_i u_{t-i} + w_{3t}, w_{3t} \sim N(0, \tau_3^2) \\ \beta_{jt} &= \beta_{j,t-1} + w_{3+j,t}, w_{3+j,t} \sim N(0, \tau_{3+j}^2), j = 1, \dots, K \\ \sum_{i=1}^7 \gamma_{it} TD_t(i) &= \sum_{i=1}^6 \gamma_{it} (TD_t(i) - TD_t(7)) \\ \gamma_{it} &= \gamma_{i,t-1}\end{aligned}$$

where $\nabla^k = (1 - B)^k$ and $\nabla_L^m = (1 - B^L)^m$. The AR component u_t is assumed to be stationary. The trading-day component $TD_t(i)$ represents the number of the i th day of the week in time t . If $k = 3$, $p = 3$, $m = 1$, and $L = 12$ (monthly data),

$$\begin{aligned}T_t &= 3T_{t-1} - 3T_{t-2} + T_{t-3} + w_{1t} \\ \sum_{i=0}^{11} S_{t-i} &= w_{2t} \\ u_t &= \sum_{i=1}^3 \alpha_i u_{t-i} + w_{3t}\end{aligned}$$

The state vector is defined as

$$\mathbf{x}_t = (T_t, T_{t-1}, T_{t-2}, S_t, \dots, S_{t-11}, u_t, u_{t-1}, u_{t-2}, \gamma_{1t}, \dots, \gamma_{6t})'$$

The matrix \mathbf{F} is

$$\mathbf{F} = \begin{bmatrix} \mathbf{F}_1 & 0 & 0 & 0 \\ 0 & \mathbf{F}_2 & 0 & 0 \\ 0 & 0 & \mathbf{F}_3 & 0 \\ 0 & 0 & 0 & \mathbf{F}_4 \end{bmatrix}$$

where

$$\begin{aligned}\mathbf{F}_1 &= \begin{bmatrix} 3 & -3 & 1 \\ 1 & 0 & 0 \\ 0 & 1 & 0 \end{bmatrix} \\ \mathbf{F}_2 &= \begin{bmatrix} -\mathbf{1}' & -1 \\ \mathbf{I}_{10} & 0 \end{bmatrix} \\ \mathbf{F}_3 &= \begin{bmatrix} \alpha_1 & \alpha_2 & \alpha_3 \\ 1 & 0 & 0 \\ 0 & 1 & 0 \end{bmatrix}\end{aligned}$$

$$\mathbf{F}_4 = \mathbf{I}_6$$

$$\mathbf{1}' = (1, 1, \dots, 1)$$

The matrix G can be denoted as

$$G = \begin{bmatrix} \mathbf{g}_1 & 0 & 0 \\ 0 & \mathbf{g}_2 & 0 \\ 0 & 0 & \mathbf{g}_3 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix}$$

where

$$\mathbf{g}_1 = \mathbf{g}_3 = \begin{bmatrix} 1 & 0 & 0 \end{bmatrix}'$$

$$\mathbf{g}_2 = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}'$$

Finally, the matrix \mathbf{H}_t is time-varying,

$$\mathbf{H}_t = \begin{bmatrix} 1 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & \mathbf{h}_t' \end{bmatrix}$$

where

$$\begin{aligned} \mathbf{h}_t &= \begin{bmatrix} D_t(1) & D_t(2) & D_t(3) & D_t(4) & D_t(5) & D_t(6) \end{bmatrix}' \\ D_t(i) &= TD_t(i) - TD_t(7), i = 1, \dots, 6 \end{aligned}$$

Missing Values

The TIMSAC subroutines skip any missing values at the beginning of the data set. When the univariate and multivariate AR models are estimated via least squares (TSMLOCAR, TSMLOMAR, TSUNIMAR, TSMULMAR, and TSPEARS), there are three options available; that is, MISSING=0, MISSING=1, or MISSING=2. When the MISSING=0 (default) option is specified, the first contiguous observations with no missing values are used. The MISSING=1 option specifies that only nonmissing observations should be used by ignoring the observations with missing values. If the MISSING=2 option is specified, the missing values are filled with the sample mean. The least squares estimator with the MISSING=2 option is biased in general.

The BAYSEA subroutine assumes the same prior distribution of the trend and seasonal components that correspond to the missing observations. A modification is made to skip the components of the vector $\mathbf{g}(\mathbf{a}|d)$ that correspond to the missing observations. The vector $\mathbf{g}(\mathbf{a}|d)$ is defined in the section “[Bayesian Constrained Least Squares](#)” on page 296. In addition, the TSBAYSEA subroutine considers outliers as missing values. The TSDECOMP and TSTVCAR subroutines skip the Kalman filter updating equation when the current observation is missing.

ISM TIMSAC Packages

A description of each TIMSAC package follows. Each description includes a list of the programs provided in the TIMSAC version.

TIMSAC-72

The TIMSAC-72 package analyzes and controls feedback systems (for example, a cement kiln process). Univariate- and multivariate-AR models are employed in this original TIMSAC package. The final prediction error (FPE) criterion is used for model selection.

- AUSPEC estimates the power spectrum by the Blackman-Tukey procedure.
- AUTCOR computes autocovariance and autocorrelation.
- DECONV computes the impulse response function.
- FFTCOR computes autocorrelation and crosscorrelation via the fast Fourier transform.
- FPEAUT computes AR coefficients and FPE for the univariate AR model.
- FPEC computes AR coefficients and FPE for the control system or multivariate AR model.
- MULCOR computes multiple covariance and correlation.
- MULNOS computes relative power contribution.
- MULRSP estimates the rational spectrum for multivariate data.
- MULSPE estimates the cross spectrum by Blackman-Tukey procedure.
- OPTDES performs optimal controller design.
- OPTSIM performs optimal controller simulation.
- RASPEC estimates the rational spectrum for univariate data.
- SGLFRE computes the frequency response function.
- WNOISE performs white noise simulation.

TIMSAC-74

The TIMSAC-74 package estimates and forecasts univariate and multivariate ARMA models by fitting the canonical Markovian model. A locally stationary autoregressive model is also analyzed. Akaike's information criterion (AIC) is used for model selection.

- AUTARM performs automatic univariate ARMA model fitting.
- BISPEC computes bispectrum.
- CANARM performs univariate canonical correlation analysis.
- CANOCA performs multivariate canonical correlation analysis.
- COVGEN computes the covariance from gain function.
- FRDPLY plots the frequency response function.
- MARKOV performs automatic multivariate ARMA model fitting.
- NONST estimates the locally stationary AR model.
- PRDCTR performs ARMA model prediction.
- PWDPLY plots the power spectrum.

- SIMCON performs optimal controller design and simulation.
- THIRMO computes the third-order moment.

TIMSAC-78

The TIMSAC-78 package uses the Householder transformation to estimate time series models. This package also contains Bayesian modeling and the exact maximum likelihood estimation of the ARMA model. Minimum AIC or Akaike Bayesian information criterion (ABIC) modeling is extensively used.

- BLOCAR estimates the locally stationary univariate AR model by using the Bayesian method.
- BLOMAR estimates the locally stationary multivariate AR model by using the Bayesian method.
- BSUBST estimates the univariate subset regression model by using the Bayesian method.
- EXSAR estimates the univariate AR model by using the exact maximum likelihood method.
- MLOCAR estimates the locally stationary univariate AR model by using the minimum AIC method.
- MLOMAR estimates the locally stationary multivariate AR model by using the minimum AIC method.
- MULBAR estimates the multivariate AR model by using the Bayesian method.
- MULMAR estimates the multivariate AR model by using the minimum AIC method.
- NADCON performs noise adaptive control.
- PERARS estimates the periodic AR model by using the minimum AIC method.
- UNIBAR estimates the univariate AR model by using the Bayesian method.
- UNIMAR estimates the univariate AR model by using the minimum AIC method.
- XSARMA estimates the univariate ARMA model by using the exact maximum likelihood method.

In addition, the following test subroutines are available: TSSBST, TSWIND, TSROOT, TSTIMS, and TSCANC.

TIMSAC-84

The TIMSAC-84 package contains the Bayesian time series modeling procedure, the point process data analysis, and the seasonal adjustment procedure.

- ADAR estimates the amplitude dependent AR model.
- BAYSEA performs Bayesian seasonal adjustments.
- BAYTAP performs Bayesian tidal analysis.
- DECOMP performs time series decomposition analysis by using state space modeling.
- EPTREN estimates intensity rates of either the exponential polynomial or exponential Fourier series of the nonstationary Poisson process model.
- LINLIN estimates linear intensity models of the self-exciting point process with another process input and with cyclic and trend components.
- LINSIM performs simulation of the point process estimated by the subroutine LINLIN.

- LOCCAR estimates the locally constant AR model.
- MULCON performs simulation, control, and prediction of the multivariate AR model.
- NONSPA performs nonstationary spectrum analysis by using the minimum Bayesian AIC procedure.
- PGRAPH performs graphical analysis for point process data.
- PTSPEC computes periodograms of point process data with significant bands.
- SIMBVH performs simulation of bivariate Hawkes' mutually exciting point process.
- SNDE estimates the stochastic nonlinear differential equation model.
- TVCAR estimates the time-varying AR coefficient model by using state space modeling.

Refer to Kitagawa and Akaike (1981) and Ishiguro (1987) for more information about TIMSAC programs.

Example 13.1: VAR Estimation and Variance Decomposition

In this example, a VAR model is estimated and forecast. The VAR(3) model is estimated by using investment, durable consumption, and consumption expenditures. The data are found in the appendix to Lütkepohl (1993). The stationary VAR(3) process is specified as

$$\mathbf{y}_t = \mathbf{A}_0 + \mathbf{A}_1\mathbf{y}_{t-1} + \mathbf{A}_2\mathbf{y}_{t-2} + \mathbf{A}_3\mathbf{y}_{t-3} + \epsilon_t$$

The matrix ARCOEF contains the AR coefficients ($\mathbf{A}_1, \mathbf{A}_2$, and \mathbf{A}_3), and the matrix EV contains error covariance estimates. An intercept vector \mathbf{A}_0 is included in the first row of the matrix ARCOEF if OPT[1]=1 is specified. Here is the code:

```
data one;
  input invest income consum @@;
datalines;
180 451 415 179 465 421 185 485 434 192 493 448
211 509 459 202 520 458 207 521 479 214 540 487
231 548 497 229 558 510 234 574 516 237 583 525
206 591 529 250 599 538 259 610 546 263 627 555
264 642 574 280 653 574 282 660 586 292 694 602
286 709 617 302 734 639 304 751 653 307 763 668
317 766 679 314 779 686 306 808 697 304 785 688
292 794 704 275 799 699 273 799 709 301 812 715
280 837 724 289 853 746 303 876 758 322 897 779
315 922 798 339 949 816 364 979 837 371 988 858
375 1025 881 432 1063 905 453 1104 934 460 1131 968
475 1137 983 496 1178 1013 494 1211 1034 498 1256 1064
526 1290 1101 519 1314 1102 516 1346 1145 531 1385 1173
573 1416 1216 551 1436 1229 538 1462 1242 532 1493 1267
558 1516 1295 524 1557 1317 525 1613 1355 519 1642 1371
526 1690 1402 510 1759 1452 519 1756 1485 538 1780 1516
549 1807 1549 570 1831 1567 559 1873 1588 584 1897 1631
```

```

611 1910 1650 597 1943 1685 603 1976 1722 619 2018 1752
635 2040 1774 658 2070 1807 675 2121 1831 700 2132 1842
692 2199 1890 759 2253 1958 782 2276 1948 816 2318 1994
844 2369 2061 830 2423 2056 853 2457 2102 852 2470 2121
833 2521 2145 860 2545 2164 870 2580 2206 830 2620 2225
801 2639 2235 824 2618 2237 831 2628 2250 830 2651 2271
;

proc iml;
use one;
read all into y var{invest income consum};
mdel = 1;
maice = 0;
misw = 0; /*-- instantaneous modeling ? --*/
call tsmulmar(arcoef,ev,nar,aic) data=y maxlag=3
    opt=(mdel || maice || misw) print=1;
arcoef = j(9,3,0);
do i=1 to 9;
    do j=1 to 3;
        arcoef[i,j] = arcoef_l[i+1,j];
    end;
end;
print arcoef;
misw = 1;
call tsmulmar(arcoef,ev,nar,aic) data=y maxlag=3
    opt=(mdel || maice || misw) print=1;
print ev;

```

To obtain the unit triangular matrix \mathbf{L}^{-1} and diagonal matrix \mathbf{D}_t , you need to estimate the instantaneous response model. When you specify the OPT[3]=1 option, the first row of the output matrix EV contains error variances of the instantaneous response model, while the unit triangular matrix is in the second through the fifth rows. See [Output 13.1.1](#). Here is the code:

Output 13.1.1 Error Variance and Unit Triangular Matrix

VAR Estimation and Variance Decomposition			
ev			
295.21042	190.94664	59.361516	
1	0	0	
-0.02239	1	0	
-0.256341	-0.500803	1	

In [Output 13.1.2](#) and [Output 13.1.3](#), you can see the relationship between the instantaneous response model and the VAR model. The VAR coefficients are computed as $\mathbf{A}_i = \mathbf{L}\mathbf{A}_i^*$ ($i = 0, 1, 2, 3$), where \mathbf{A}_i^* is a coefficient matrix of the instantaneous model. For example, you can verify this result by using the first lag coefficient matrix (\mathbf{A}_1).

$$\begin{bmatrix} 0.886 & 0.340 & -0.014 \\ 0.168 & 1.050 & 0.107 \\ 0.089 & 0.459 & 0.447 \end{bmatrix} = \begin{bmatrix} 1.000 & 0 & 0 \\ -0.022 & 1.000 & 0 \\ -0.256 & -0.501 & 1.000 \end{bmatrix}^{-1} \begin{bmatrix} 0.886 & 0.340 & -0.014 \\ 0.149 & 1.043 & 0.107 \\ -0.222 & -0.154 & 0.397 \end{bmatrix}$$

```
proc iml;
mdel = 1;
maice = 0;
misw = 0;
call tsmulmar(arcoef,ev,nar,aic) data=y maxlag=3
    opt=(mdel || maice || misw);
call tspred(forecast,impulse0,mse,y,arcoef,nar,0,ev)
    npred=10 start=nrow(y) constant=mdel;
```

Output 13.1.2 VAR Estimates

arcoef		
0.8855926	0.3401741	-0.014398
0.1684523	1.0502619	0.107064
0.0891034	0.4591573	0.4473672
-0.059195	-0.298777	0.1629818
0.1128625	-0.044039	-0.088186
0.1684932	-0.025847	-0.025671
0.0637227	-0.196504	0.0695746
-0.226559	0.0532467	-0.099808
-0.303697	-0.139022	0.2576405

Output 13.1.3 Instantaneous Response Model Estimates

arcoef		
0.885593	0.340174	-0.014398
0.148624	1.042645	0.107386
-0.222272	-0.154018	0.39744
-0.059195	-0.298777	0.162982
0.114188	-0.037349	-0.091835
0.127145	0.072796	-0.023287
0.063723	-0.196504	0.069575
-0.227986	0.057646	-0.101366
-0.20657	-0.115316	0.28979

When the VAR estimates are available, you can forecast the future values by using the TSPRED call. As a default, the one-step predictions are produced until the START= point is reached. The NPRED= h option specifies how far you want to predict. The prediction error covariance matrix MSE contains h mean square error matrices. The output matrix IMPULSE contains the estimate of the coefficients (Ψ_i) of the infinite MA process. The following IML code estimates the VAR(3) model and performs 10-step-ahead prediction.

```
mdel = 1;
```

```

maice = 0;
misw = 0;
call tsmulmar(arcoef,ev,nar,aic) data=y maxlag=3
      opt=(mdel || maice || misw);
call tspredd(forecast,impulse,mse,y,arcoef,nar,0,ev)
      npred=10 start=nrow(y) constant=mdel;
print impulse;

```

The lagged effects of a unit increase in the error disturbances are included in the matrix IMPULSE. For example:

$$\frac{\partial \mathbf{y}_{t+2}}{\partial \epsilon_t'} = \begin{bmatrix} 0.781100 & 0.353140 & 0.180211 \\ 0.448501 & 1.165474 & 0.069731 \\ 0.364611 & 0.692111 & 0.222342 \end{bmatrix}$$

Output 13.1.4 displays the first 15 rows of the matrix IMPULSE.

Output 13.1.4 Moving-Average Coefficients: MA(0)–MA(4)

impulse			
	1	0	0
	0	1	0
	0	0	1
0.8855926	0.3401741	-0.014398	
0.1684523	1.0502619	0.107064	
0.0891034	0.4591573	0.4473672	
0.7810999	0.3531397	0.1802109	
0.4485013	1.1654737	0.0697311	
0.3646106	0.6921108	0.2223425	
0.8145483	0.243637	0.2914643	
0.4997732	1.3625363	-0.018202	
0.2775237	0.7555914	0.3885065	
0.7960884	0.2593068	0.260239	
0.5275069	1.4134792	0.0335483	
0.267452	0.8659426	0.3190203	

In addition, you can compute the lagged response on the one-unit increase in the orthogonalized disturbances ϵ_t^* .

$$\frac{\partial \mathbf{y}_{t+m}}{\partial \epsilon_{jt}^*} = \frac{\partial E(\mathbf{y}_{t+m} | y_{jt}, y_{j-1,t}, \dots, \mathbf{X}_t)}{\partial y_{jt}} = \Psi_m \mathbf{L}_j$$

When the error matrix EV is obtained from the instantaneous response model, you need to convert the matrix IMPULSE. The first 15 rows of the matrix ORTH_IMP are shown in Output 13.1.5. Note that the matrix constructed from the last three rows of EV become the matrix \mathbf{L}^{-1} . Here is the code:

```

call tsmulmar(arcoef,ev,nar,aic) data=y maxlag=3
      opt={1 0 1};
lmtx = inv(ev[2:nrow(ev),]);
orth_imp = impulse * lmtx;

```

```
print orth_imp;
```

Output 13.1.5 Transformed Moving-Average Coefficients

orth_imp			
	1	0	0
0.0223902		1	0
0.267554	0.5008031		1
0.889357	0.3329638	-0.014398	
0.2206132	1.1038799	0.107064	
0.219079	0.6832001	0.4473672	
0.8372229	0.4433899	0.1802109	
0.4932533	1.2003953	0.0697311	
0.4395957	0.8034606	0.2223425	
0.8979858	0.3896033	0.2914643	
0.5254106	1.3534206	-0.018202	
0.398388	0.9501566	0.3885065	
0.8715223	0.3896353	0.260239	
0.5681309	1.4302804	0.0335483	
0.3721958	1.025709	0.3190203	

You can verify the result for the case of

$$\frac{\partial \mathbf{y}_{t+2}}{\partial \epsilon_{2t}^*} = \frac{\partial E(\mathbf{y}_{t+2} | y_{2t}, y_{1t}, \dots, \mathbf{X}_t)}{\partial y_{2t}} = \Psi_2 \mathbf{L}_2$$

using the simple computation

$$\begin{bmatrix} 0.443390 \\ 1.200395 \\ 0.803461 \end{bmatrix} = \begin{bmatrix} 0.781100 & 0.353140 & 0.180211 \\ 0.448501 & 1.165474 & 0.069731 \\ 0.364611 & 0.692111 & 0.222342 \end{bmatrix} \begin{bmatrix} 0.000000 \\ 1.000000 \\ 0.500803 \end{bmatrix}$$

The contribution of the i th orthogonalized innovation to the mean square error matrix of the 10-step forecast is computed by using the formula

$$d_{ii} [\mathbf{L}_i \mathbf{L}_i' + \Psi_1 \mathbf{L}_i \mathbf{L}_i' \Psi_1' + \dots + \Psi_9 \mathbf{L}_i \mathbf{L}_i' \Psi_9']$$

In [Output 13.1.6](#), diagonal elements of each decomposed MSE matrix are displayed as the matrix CONTRIB as well as those of the MSE matrix (VAR). Here is the code:

```
mse1 = j(3,3,0);
mse2 = j(3,3,0);
mse3 = j(3,3,0);
do i = 1 to 5;
    psi = impulse[(i-1)*3+1:3*i,];
    mse1 = mse1 + psi*lmtx[,1]*lmtx[,1]`*psi`;
    mse2 = mse2 + psi*lmtx[,2]*lmtx[,2]`*psi`;
    mse3 = mse3 + psi*lmtx[,3]*lmtx[,3]`*psi`;
end;
```

```

mse1 = ev[1,1]#mse1;
mse2 = ev[1,2]#mse2;
mse3 = ev[1,3]#mse3;
contrib = vecdiag(mse1) || vecdiag(mse2) || vecdiag(mse3);
var = vecdiag(mse[28:30,]);
print contrib var;

```

Output 13.1.6 Orthogonal Innovation Contribution

contrib			var
1197.9131	116.68096	11.003194	2163.7104
263.12088	1439.1551	1.0555626	4573.9809
180.09836	633.55931	89.177905	2466.506

The investment innovation contribution to its own variable is 1879.3774, and the income innovation contribution to the consumption expenditure is 1916.1676. It is easy to understand the contribution of innovations in the i th variable to MSE when you compute the innovation account. In [Output 13.1.7](#), innovations in the first variable (investment) explain 20.45% of the error variance of the second variable (income), while the innovations in the second variable explain 79.5% of its own error variance. It is straightforward to construct the general multistep forecast error variance decomposition. Here is the code:

```

account = contrib * 100 / (var@j(1,3,1));
print account;

```

Output 13.1.7 Innovation Account

account		
55.363835	5.3926331	0.5085336
5.7525574	31.463951	0.0230775
7.3017604	25.68651	3.615556

Kalman Filter Subroutines

This section describes a collection of Kalman filtering and smoothing subroutines for time series analysis; immediately following are three examples using Kalman filtering subroutines. The state space model is a method for analyzing a wide range of time series models. When the time series is represented by the state space model (SSM), the Kalman filter is used for filtering, prediction, and smoothing of the state vector. The state space model is composed of the measurement and transition equations.

The following Kalman filtering and smoothing subroutines are supported:

KALCVF performs covariance filtering and prediction.

KALCVS	performs fixed-interval smoothing.
KALDFF	performs diffuse covariance filtering and prediction.
KALDFS	performs diffuse fixed-interval smoothing.

Getting Started

The measurement (or observation) equation can be written

$$\mathbf{y}_t = \mathbf{b}_t + \mathbf{H}_t \mathbf{z}_t + \epsilon_t$$

where \mathbf{b}_t is an $N_y \times 1$ vector, \mathbf{H}_t is an $N_y \times N_z$ matrix, the sequence of observation noise ϵ_t is independent, \mathbf{z}_t is an $N_z \times 1$ state vector, and \mathbf{y}_t is an $N_y \times 1$ observed vector.

The transition (or state) equation is denoted as a first-order Markov process of the state vector.

$$\mathbf{z}_{t+1} = \mathbf{a}_t + \mathbf{F}_t \mathbf{z}_t + \eta_t$$

where \mathbf{a}_t is an $N_z \times 1$ vector, \mathbf{F}_t is an $N_z \times N_z$ transition matrix, and the sequence of transition noise η_t is independent. This equation is often called a *shifted transition equation* because the state vector is shifted forward one time period. The transition equation can also be denoted by using an alternative specification

$$\mathbf{z}_t = \mathbf{a}_t + \mathbf{F}_t \mathbf{z}_{t-1} + \eta_t$$

There is no real difference between the shifted transition equation and this alternative equation if the observation noise and transition equation noise are uncorrelated—that is, $E(\eta_t \epsilon'_t) = 0$. It is assumed that

$$\begin{aligned} E(\eta_t \eta'_s) &= \mathbf{V}_t \delta_{ts} \\ E(\epsilon_t \epsilon'_s) &= \mathbf{R}_t \delta_{ts} \\ E(\eta_t \epsilon'_s) &= \mathbf{G}_t \delta_{ts} \end{aligned}$$

where

$$\delta_{ts} = \begin{cases} 1 & \text{if } t = s \\ 0 & \text{if } t \neq s \end{cases}$$

De Jong (1991) proposed a diffuse Kalman filter that can handle an arbitrarily large initial state covariance matrix. The diffuse initial state assumption is reasonable if you encounter the case of parameter uncertainty or SSM nonstationarity. The SSM of the diffuse Kalman filter is written

$$\begin{aligned} \mathbf{y}_t &= \mathbf{X}_t \boldsymbol{\beta} + \mathbf{H}_t \mathbf{z}_t + \epsilon_t \\ \mathbf{z}_{t+1} &= \mathbf{W}_t \boldsymbol{\beta} + \mathbf{F}_t \mathbf{z}_t + \eta_t \\ \mathbf{z}_0 &= \mathbf{a} + \mathbf{A} \delta \\ \boldsymbol{\beta} &= \mathbf{b} + \mathbf{B} \delta \end{aligned}$$

where δ is a random variable with a mean of μ and a variance of $\sigma^2 \Sigma$. When $\Sigma \rightarrow \infty$, the SSM is said to be diffuse.

The KALCVF call computes the one-step prediction $\mathbf{z}_{t+1|t}$ and the filtered estimate $\mathbf{z}_{t|t}$, together with their covariance matrices $\mathbf{P}_{t+1|t}$ and $\mathbf{P}_{t|t}$, using forward recursions. You can obtain the k -step prediction $\mathbf{z}_{t+k|t}$ and its covariance matrix $\mathbf{P}_{t+k|t}$ with the KALCVF call. The KALCVS call uses backward recursions to compute the smoothed estimate $\mathbf{z}_{t|T}$ and its covariance matrix $\mathbf{P}_{t|T}$ when there are T observations in the complete data.

The KALDFF call produces one-step prediction of the state and the unobserved random vector δ as well as their covariance matrices. The KALDFS call computes the smoothed estimate $\mathbf{z}_{t|T}$ and its covariance matrix $\mathbf{P}_{t|T}$.

Syntax

CALL KALCVF (*pred, vpred, filt, vfilt, data, lead, a, f, b, h, var <, z0, vz0>*) ;

CALL KALCVS (*sm, vsm, data, a, f, b, h, var, pred, vpred <, un, vun>*) ;

CALL KALDFF (*pred, vpred, initial, s2, data, lead, int, coef, var, intd, coefd <, n0, at, mt, qt>*) ;

CALL KALDFS (*sm, vsm, data, int, coef, var, bvec, bmat, initial, at, mt, s2 <, un, vun>*) ;

Example 13.2: Kalman Filtering: Likelihood Function Evaluation

In the following example, the log-likelihood function of the SSM is computed by using prediction error decomposition. The annual real GNP series, y_t , can be decomposed as

$$y_t = \mu_t + \epsilon_t$$

where μ_t is a trend component and ϵ_t is a white noise error with $\epsilon_t \sim (0, \sigma_\epsilon^2)$. Refer to Nelson and Plosser (1982) for more details about these data. The trend component is assumed to be generated from the following stochastic equations:

$$\begin{aligned}\mu_t &= \mu_{t-1} + \beta_{t-1} + \eta_{1t} \\ \beta_t &= \beta_{t-1} + \eta_{2t}\end{aligned}$$

where η_{1t} and η_{2t} are independent white noise disturbances with $\eta_{1t} \sim (0, \sigma_{\eta_1}^2)$ and $\eta_{2t} \sim (0, \sigma_{\eta_2}^2)$.

It is straightforward to construct the SSM of the real GNP series.

$$\begin{aligned}y_t &= \mathbf{H}\mathbf{z}_t + \epsilon_t \\ \mathbf{z}_t &= \mathbf{F}\mathbf{z}_{t-1} + \boldsymbol{\eta}_t\end{aligned}$$

where

$$\begin{aligned}\mathbf{H} &= (1, 0) \\ \mathbf{F} &= \begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix} \\ \mathbf{z}_t &= (\mu_t, \beta_t)' \\ \eta_t &= (\eta_{1t}, \eta_{2t})' \\ \text{Var} \left(\begin{bmatrix} \eta_t \\ \epsilon_t \end{bmatrix} \right) &= \begin{bmatrix} \sigma_{\eta_1}^2 & 0 & 0 \\ 0 & \sigma_{\eta_2}^2 & 0 \\ 0 & 0 & \sigma_{\epsilon}^2 \end{bmatrix}\end{aligned}$$

When the observation noise ϵ_t is normally distributed, the average log-likelihood function of the SSM is

$$\begin{aligned}\ell &= \frac{1}{T} \sum_{t=1}^T \ell_t \\ \ell_t &= -\frac{N_y}{2} \log(2\pi) - \frac{1}{2} \log(|\mathbf{C}_t|) - \frac{1}{2} \hat{\epsilon}_t' \mathbf{C}_t^{-1} \hat{\epsilon}_t\end{aligned}$$

where \mathbf{C}_t is the mean square error matrix of the prediction error $\hat{\epsilon}_t$, such that $\mathbf{C}_t = \mathbf{H}\mathbf{P}_{t|t-1}\mathbf{H}' + \mathbf{R}_t$.

The LIK module computes the average log-likelihood function. First, the average log-likelihood function is computed by using the default initial values: $\mathbf{Z0}=0$ and $\mathbf{VZ0}=10^6\mathbf{I}$. The second call of module LIK produces the average log-likelihood function with the given initial conditions: $\mathbf{Z0}=0$ and $\mathbf{VZ0}=10^{-3}\mathbf{I}$. You can notice a sizable difference between the uncertain initial condition ($\mathbf{VZ0}=10^6\mathbf{I}$) and the almost deterministic initial condition ($\mathbf{VZ0}=10^{-3}\mathbf{I}$) in [Output 13.2.1](#).

Finally, the first 15 observations of one-step predictions, filtered values, and real GNP series are produced under the moderate initial condition ($\mathbf{VZ0}=10\mathbf{I}$). The data are the annual real GNP for the years 1909 to 1969. Here is the code:

```
title 'Likelihood Evaluation of SSM';
title2 'DATA: Annual Real GNP 1909-1969';
data gnp;
    input y @@;
datalines;
116.8 120.1 123.2 130.2 131.4 125.6 124.5 134.3
135.2 151.8 146.4 139.0 127.8 147.0 165.9 165.5
179.4 190.0 189.8 190.9 203.6 183.5 169.3 144.2
141.5 154.3 169.5 193.0 203.2 192.9 209.4 227.2
263.7 297.8 337.1 361.3 355.2 312.6 309.9 323.7
324.1 355.3 383.4 395.1 412.8 406.0 438.0 446.1
452.5 447.3 475.9 487.7 497.2 529.8 551.0 581.1
617.8 658.1 675.2 706.6 724.7
;
```

```

proc iml;
start lik(y,a,b,f,h,var,z0,vz0);
  nz = nrow(f);
  n = nrow(y);
  k = ncol(y);
  const = k*log(8*atan(1));
  if ( sum(z0 = .) | sum(vz0 = .) ) then
    call kalcvf(pred,vpred,filt,vfilt,y,0,a,f,b,h,var);
  else
    call kalcvf(pred,vpred,filt,vfilt,y,0,a,f,b,h,var,z0,vz0);
  et = y - pred*h`;
  sum1 = 0;
  sum2 = 0;
  do i = 1 to n;
    vpred_i = vpred[(i-1)*nz+1:i*nz,];
    et_i = et[i,];
    ft = h*vpred_i*h` + var[nz+1:nz+k,nz+1:nz+k];
    sum1 = sum1 + log(det(ft));
    sum2 = sum2 + et_i*inv(ft)*et_i`;
  end;
  return(-.5*const-.5*(sum1+sum2)/n);
finish;

use gnp;
read all var {y};
close gnp;

f = {1 1, 0 1};
h = {1 0};
a = j(nrow(f),1,0);
b = j(nrow(h),1,0);
var = diag(j(1,nrow(f)+ncol(y),1e-3));
/*-- initial values are computed --*/
z0 = j(1,nrow(f),.);
vz0 = j(nrow(f),nrow(f),.);
logl = lik(y,a,b,f,h,var,z0,vz0);
print 'No initial values are given', logl;
/*-- initial values are given --*/
z0 = j(1,nrow(f),0);
vz0 = 1e-3#i(nrow(f));
logl = lik(y,a,b,f,h,var,z0,vz0);
print 'Initial values are given', logl;
z0 = j(1,nrow(f),0);
vz0 = 10#i(nrow(f));
call kalcvf(pred0,vpred,filt0,vfilt,y,1,a,f,b,h,var,z0,vz0);

y0 = y;
free y;
y = j(16,1,0);
pred = j(16,2,0);
filt = j(16,2,0);
do i=1 to 16;
  y[i] = y0[i];

```



```

    pred[i,] = pred0[i,];
    filt[i,] = filt0[i,];
end;
print y pred filt;
quit;

```

Output 13.2.1 Average Log Likelihood of SSM

```

Likelihood Evaluation of SSM
DATA: Annual Real GNP 1909-1969

No initial values are given

logl

-26313.74

Initial values are given

logl

-91883.49

```

Output 13.2.2 shows the observed data, the predicted state vectors, and the filtered state vectors for the first 16 observations.

Output 13.2.2 Filtering and One-Step Prediction

	y	pred		filt
	116.8	0	0	116.78832 0
	120.1	116.78832	0	120.09967 3.3106857
	123.2	123.41035	3.3106857	123.22338 3.1938303
	130.2	126.41721	3.1938303	129.59203 4.8825531
	131.4	134.47459	4.8825531	131.93806 3.5758561
	125.6	135.51391	3.5758561	127.36247 -0.610017
	124.5	126.75246	-0.610017	124.90123 -1.560708
	134.3	123.34052	-1.560708	132.34754 3.0651076
	135.2	135.41265	3.0651076	135.23788 2.9753526
	151.8	138.21324	2.9753526	149.37947 8.7100967
	146.4	158.08957	8.7100967	148.48254 3.7761324
	139	152.25867	3.7761324	141.36208 -1.82012
	127.8	139.54196	-1.82012	129.89187 -6.776195
	147	123.11568	-6.776195	142.74492 3.3049584
	165.9	146.04988	3.3049584	162.36363 11.683345
	165.5	174.04698	11.683345	167.02267 8.075817

Example 13.3: Kalman Filtering: SSM Estimation With the EM Algorithm

The following example estimates the normal SSM of the mink-muskrat data by using the EM algorithm. The mink-muskrat series are detrended. Refer to Harvey (1989) for details of this data set. Since this EM algorithm uses filtering and smoothing, you can learn how to use the KALCVF and KALCVS calls to analyze the data. Consider the bivariate SSM:

$$\begin{aligned} \mathbf{y}_t &= \mathbf{H}\mathbf{z}_t + \epsilon_t \\ \mathbf{z}_t &= \mathbf{F}\mathbf{z}_{t-1} + \eta_t \end{aligned}$$

where \mathbf{H} is a 2×2 identity matrix, the observation noise has a time-invariant covariance matrix \mathbf{R} , and the covariance matrix of the transition equation is also assumed to be time invariant. The initial state \mathbf{z}_0 has mean μ and covariance Σ . For estimation, the Σ matrix is fixed as

$$\begin{bmatrix} 0.1 & 0.0 \\ 0.0 & 0.1 \end{bmatrix}$$

while the mean vector μ is updated by the smoothing procedure such that $\hat{\mu} = \mathbf{z}_{0|T}$. Note that this estimation requires an extra smoothing step since the usual smoothing procedure does not produce $\mathbf{z}_{T|0}$.

The EM algorithm maximizes the expected log-likelihood function given the current parameter estimates. In practice, the log-likelihood function of the normal SSM is evaluated while the parameters are updated by using the M-step of the EM maximization

$$\begin{aligned} \mathbf{F}^{i+1} &= \mathbf{S}_t(1)[\mathbf{S}_{t-1}(0)]^{-1} \\ \mathbf{V}^{i+1} &= \frac{1}{T} (\mathbf{S}_t(0) - \mathbf{S}_t(1)[\mathbf{S}_{t-1}(0)]^{-1}\mathbf{S}_t'(1)) \\ \mathbf{R}^{i+1} &= \frac{1}{T} \sum_{t=1}^T [(\mathbf{y}_t - \mathbf{H}\mathbf{z}_{t|T})(\mathbf{y}_t - \mathbf{H}\mathbf{z}_{t|T})' + \mathbf{H}\mathbf{P}_{t|T}\mathbf{H}'] \\ \mu^{i+1} &= \mathbf{z}_{0|T} \end{aligned}$$

where the index i represents the current iteration number, and

$$\begin{aligned} \mathbf{S}_t(0) &= \sum_{t=1}^T (\mathbf{P}_{t|T} + \mathbf{z}_{t|T}\mathbf{z}_{t|T}'), \\ \mathbf{S}_t(1) &= \sum_{t=1}^T (\mathbf{P}_{t,t-1|T} + \mathbf{z}_{t|T}\mathbf{z}_{t-1|T}') \end{aligned}$$

It is necessary to compute the value of $\mathbf{P}_{t,t-1|T}$ recursively such that

$$\mathbf{P}_{t-1,t-2|T} = \mathbf{P}_{t-1|t-1}\mathbf{P}_{t-2}^{*'} + \mathbf{P}_{t-1}^*(\mathbf{P}_{t,t-1|T} - \mathbf{F}\mathbf{P}_{t-1|t-1})\mathbf{P}_{t-2}^{*}$$

where $\mathbf{P}_t^* = \mathbf{P}_{t|t}\mathbf{F}'\mathbf{P}_{t+1|t}^{-}$ and the initial value $\mathbf{P}_{T,T-1|T}$ is derived by using the formula

$$\mathbf{P}_{T,T-1|T} = [\mathbf{I} - \mathbf{P}_{t|t-1}\mathbf{H}'(\mathbf{H}\mathbf{P}_{t|t-1}\mathbf{H}' + \mathbf{R})^{-1}\mathbf{H}]\mathbf{F}\mathbf{P}_{T-1|T-1}$$

Note that the initial value of the state vector is updated for each iteration

$$\begin{aligned}\mathbf{z}_{1|0} &= \mathbf{F}\mu^i \\ \mathbf{P}_{1|0} &= \mathbf{F}^i \Sigma \mathbf{F}^{i'} + \mathbf{V}^i\end{aligned}$$

The objective function value is computed as -2ℓ in the IML module LIK. The log-likelihood function is written

$$\ell = -\frac{1}{2} \sum_{t=1}^T \log(|\mathbf{C}_t|) - \frac{1}{2} \sum_{t=1}^T (\mathbf{y}_t - \mathbf{H}\mathbf{z}_{t|t-1}) \mathbf{C}_t^{-1} (\mathbf{y}_t - \mathbf{H}\mathbf{z}_{t|t-1})'$$

where $\mathbf{C}_t = \mathbf{H}\mathbf{P}_{t|t-1}\mathbf{H}' + \mathbf{R}$.

The iteration history is shown in [Output 13.3.1](#). As shown in [Output 13.3.2](#), the eigenvalues of \mathbf{F} are within the unit circle, which indicates that the SSM is stationary. However, the muskrat series (Y1) is reported to be difference stationary. The estimated parameters are almost identical to those of the VAR(1) estimates. Refer to Harvey (1989). Finally, multistep forecasts of \mathbf{y}_t are computed by using the KALCVF call. Here is the code:

```
call kalcvf(pred,vpred,filt,vfilt,y,15,a,f,b,h,var,z0,vz0);
```

The predicted values of the state vector \mathbf{z}_t and their standard errors are shown in [Output 13.3.3](#). Here is the code:

```
title 'SSM Estimation using EM Algorithm';
data one;
  input y1 y2 @@;
datalines;
  0.10609 0.16794 -0.16852 0.06242 -0.23700 -0.13344
-0.18022 -0.50616 0.18094 -0.37943 0.65983 -0.40132
  0.65235 0.08789 0.21594 0.23877 -0.11515 0.40043
-0.00067 0.37758 -0.00387 0.55735 -0.25202 0.34444
-0.65011 -0.02749 -0.53646 -0.41519 -0.08462 0.02591
-0.05640 -0.11348 0.26630 0.20544 0.03641 0.16331
-0.26030 -0.01498 -0.03995 0.09657 0.33612 0.31096
-0.11672 0.30681 -0.69775 -0.69351 -0.07569 -0.56212
  0.36149 -0.36799 0.42341 -0.24725 0.26721 0.04478
-0.00363 0.21637 0.08333 0.30188 -0.22480 0.29493
-0.13728 0.35463 -0.12698 0.05490 -0.18770 -0.52573
  0.34741 -0.49541 0.54947 -0.26250 0.57423 -0.21936
  0.57493 -0.12012 0.28188 0.63556 -0.58438 0.27067
-0.50236 0.10386 -0.60766 0.36748 -1.04784 -0.33493
-0.68857 -0.46525 -0.11450 -0.63648 0.22005 -0.26335
  0.36533 0.07017 -0.00151 -0.04977 0.03740 -0.02411
  0.22438 0.30790 -0.16196 0.41050 -0.12862 0.34929
  0.08448 -0.14995 0.17945 -0.03320 0.37502 0.02953
  0.95727 0.24090 0.86188 0.41096 0.39464 0.24157
  0.53794 0.29385 0.13054 0.39336 -0.39138 -0.00323
-1.23825 -0.56953 -0.66286 -0.72363
;
run;
```

```

proc iml;
start lik(y,pred,vpred,h,rt);
  n = nrow(y);
  nz = ncol(h);
  et = y - pred*h`;
  sum1 = 0;
  sum2 = 0;
  do i = 1 to n;
    vpred_i = vpred[(i-1)*nz+1:i*nz,];
    et_i = et[i,];
    ft = h*vpred_i*h` + rt;
    sum1 = sum1 + log(det(ft));
    sum2 = sum2 + et_i*inv(ft)*et_i`;
  end;
  return(sum1+sum2);
finish;

use one;
read all into y var {y1 y2};
close one;
/*-- mean adjust series --*/
t = nrow(y);
ny = ncol(y);
nz = ny;
f = i(nz);
h = i(ny);

/*-- observation noise variance is diagonal --*/
rt = 1e-5#i(ny);

/*-- transition noise variance --*/
vt = .1#i(nz);
a = j(nz,1,0);
b = j(ny,1,0);
myu = j(nz,1,0);
sigma = .1#i(nz);
converge = 0;
logl0 = 0.0;
do iter = 1 to 100 while( converge = 0 );

/*-- construct big cov matrix --*/
var = ( vt || j(nz,ny,0) ) //
      ( j(ny,nz,0) || rt );

/*-- initial values are changed --*/
z0 = myu` * f`;
vz0 = f * sigma * f` + vt;

/*-- filtering to get one-step prediction and filtered value --*/
call kalcvf(pred,vpred,filt,vfilt,y,0,a,f,b,h,var,z0,vz0);

/*-- smoothing using one-step prediction values --*/

```

```

call kalcvs(sm,vsm,y,a,f,b,h,var,pred,vpred);

/*-- compute likelihood values --*/
logl = lik(y,pred,vpred,h,rt);

/*-- store old parameters and function values --*/
myu0 = myu;
f0 = f;
vt0 = vt;
rt0 = rt;
diflog = logl - logl0;
logl0 = logl;
itermat = itermat // ( iter || logl0 || shape(f0,1) || myu0` );

/*-- obtain P*(t) to get P_T_0 and Z_T_0 --*/
/*-- these values are not usually needed --*/
/*-- See Harvey (1989 p154) or Shumway (1988, p177) --*/
jt1 = sigma * f` * inv(vpred[1:nz,]);
p_t_0 = sigma + jt1*(vsm[1:nz,] - vpred[1:nz,])*jt1`;
z_t_0 = myu + jt1*(sm[1,]` - pred[1,]`);
p_t1_t = vpred[(t-1)*nz+1:t*nz,];
p_t1_t1 = vfilt[(t-2)*nz+1:(t-1)*nz,];
kt = p_t1_t*h`*inv(h*p_t1_t*h`+rt);

/*-- obtain P_T_TT1. See Shumway (1988, p180) --*/
p_t_i1 = (i(nz)-kt*h)*f*p_t1_t1;
st0 = vsm[(t-1)*nz+1:t*nz,] + sm[t,]*sm[t,];
st1 = p_t_i1 + sm[t,]*sm[t-1,];
st00 = p_t_0 + z_t_0 * z_t_0`;
cov = (y[t,]` - h*sm[t,]`) * (y[t,]` - h*sm[t,]`)` +
      h*vsm[(t-1)*nz+1:t*nz,]*h`;
do i = t to 2 by -1;
  p_i1_i1 = vfilt[(i-2)*nz+1:(i-1)*nz,];
  p_i1_i = vpred[(i-1)*nz+1:i*nz,];
  jt1 = p_i1_i1 * f` * inv(p_i1_i);
  p_i1_i = vpred[(i-2)*nz+1:(i-1)*nz,];
  if ( i > 2 ) then
    p_i2_i2 = vfilt[(i-3)*nz+1:(i-2)*nz,];
  else
    p_i2_i2 = sigma;
  jt2 = p_i2_i2 * f` * inv(p_i1_i);
  p_t_ili2 = p_i1_i1*jt2` + jt1*(p_t_i1 - f*p_i1_i1)*jt2`;
  p_t_i1 = p_t_ili2;
  temp = vsm[(i-2)*nz+1:(i-1)*nz,];
  sm1 = sm[i-1,]`;
  st0 = st0 + ( temp + sm1 * sm1` );
  if ( i > 2 ) then
    st1 = st1 + ( p_t_i1 + sm1 * sm[i-2,] );
  else st1 = st1 + ( p_t_i1 + sm1 * z_t_0` );
  st00 = st00 + ( temp + sm1 * sm1` );
  cov = cov + ( h * temp * h` +
    (y[i-1,]` - h * sm1)*(y[i-1,]` - h * sm1)` );
end;

```

```

/*-- M-step: update the parameters --*/
myu = z_t_0;
f = st1 * inv(st00);
vt = (st0 - st1 * inv(st00) * st1`)/t;
rt = cov / t;

/*-- check convergence --*/
if ( max(abs((myu - myu0)/(myu0+1e-6))) < 1e-2 &
      max(abs((f - f0)/(f0+1e-6))) < 1e-2 &
      max(abs((vt - vt0)/(vt0+1e-6))) < 1e-2 &
      max(abs((rt - rt0)/(rt0+1e-6))) < 1e-2 &
      abs((diflog)/(logl0+1e-6)) < 1e-3 ) then
  converge = 1;
end;

reset noname;
  colnm = {'Iter' '-2*log L' 'F11' 'F12' 'F21' 'F22'
           'MYU11' 'MYU22'};
print itermat[colname=colnm format=8.4];

eval = eigval(f0);
colnm = {'Real' 'Imag' 'MOD'};
eval = eval || sqrt((eval#eval)[,+]);
print eval[colname=colnm];
var = ( vt || j(nz,ny,0) ) //
      ( j(ny,nz,0) || rt );

/*-- initial values are changed --*/
z0 = myu` * f`;
vz0 = f * sigma * f` + vt;
free itermat;

/*-- multistep prediction --*/
call kalcvf(pred,vpred,filt,vfilt,y,15,a,f,b,h,var,z0,vz0);
do i = 1 to 15;
  itermat = itermat // ( i || pred[t+i,] ||
                        sqrt(vecdiag(vpred[(t+i-1)*nz+1:(t+i)*nz,]))` );
end;
colnm = {'n-Step' 'Z1_T_n' 'Z2_T_n' 'SE_Z1' 'SE_Z2'};
print itermat[colname=colnm];
quit;

```

Output 13.3.1 Iteration History

SSM Estimation using EM Algorithm							
Iter	-2*log L	F11	F12	F21	F22	MYU11	MYU22
1.0000	-154.010	1.0000	0.0000	0.0000	1.0000	0.0000	0.0000
2.0000	-237.962	0.7952	-0.6473	0.3263	0.5143	0.0530	0.0840
3.0000	-238.083	0.7967	-0.6514	0.3259	0.5142	0.1372	0.0977
4.0000	-238.126	0.7966	-0.6517	0.3259	0.5139	0.1853	0.1159
5.0000	-238.143	0.7964	-0.6519	0.3257	0.5138	0.2143	0.1304
6.0000	-238.151	0.7963	-0.6520	0.3255	0.5136	0.2324	0.1405
7.0000	-238.153	0.7962	-0.6520	0.3254	0.5135	0.2438	0.1473
8.0000	-238.155	0.7962	-0.6521	0.3253	0.5135	0.2511	0.1518
9.0000	-238.155	0.7962	-0.6521	0.3253	0.5134	0.2558	0.1546
10.0000	-238.155	0.7961	-0.6521	0.3253	0.5134	0.2588	0.1565

Output 13.3.2 Eigenvalues of F Matrix

Real	Imag	MOD
0.6547534	0.438317	0.7879237
0.6547534	-0.438317	0.7879237

Output 13.3.3 Multistep Prediction

n-Step	Z1_T_n	Z2_T_n	SE_Z1	SE_Z2
1	-0.055792	-0.587049	0.2437666	0.237074
2	0.3384325	-0.319505	0.3140478	0.290662
3	0.4778022	-0.053949	0.3669731	0.3104052
4	0.4155731	0.1276996	0.4021048	0.3218256
5	0.2475671	0.2007098	0.419699	0.3319293
6	0.0661993	0.1835492	0.4268943	0.3396153
7	-0.067001	0.1157541	0.430752	0.3438409
8	-0.128831	0.0376316	0.4341532	0.3456312
9	-0.127107	-0.022581	0.4369411	0.3465325
10	-0.086466	-0.052931	0.4385978	0.3473038
11	-0.034319	-0.055293	0.4393282	0.3479612
12	0.0087379	-0.039546	0.4396666	0.3483717
13	0.0327466	-0.017459	0.439936	0.3485586
14	0.0374564	0.0016876	0.4401753	0.3486415
15	0.0287193	0.0130482	0.440335	0.3487034

Example 13.4: Diffuse Kalman Filtering

The nonstationary SSM is simulated to analyze the diffuse Kalman filter call KALDFF. The transition equation is generated by using the following formula:

$$\begin{bmatrix} z_{1t} \\ z_{2t} \end{bmatrix} = \begin{bmatrix} 1.5 & -0.5 \\ 1.0 & 0.0 \end{bmatrix} \begin{bmatrix} z_{1t-1} \\ z_{2t-1} \end{bmatrix} + \begin{bmatrix} \eta_{1t} \\ 0 \end{bmatrix}$$

where $\eta_{1t} \sim N(0, 1)$. The transition equation is nonstationary since the transition matrix \mathbf{F} has one unit root. Here is the code:

```
proc iml;
  z_1 = 0; z_2 = 0;
  do i = 1 to 30;
    z = 1.5*z_1 - .5*z_2 + rannor(1234567);
    z_2 = z_1;
    z_1 = z;
    x = z + .8*rannor(1234578);
    if ( i > 10 ) then y = y // x;
  end;
```

The KALDFF and KALCVF calls produce one-step prediction, and the result shows that two predictions coincide after the fifth observation ([Output 13.4.1](#)). Here is the code:

```
t = nrow(y);
h = { 1 0 };
f = { 1.5 -0.5, 1 0 };
rt = .64;
vt = diag({1 0});
ny = nrow(h);
nz = ncol(h);
nb = nz;
nd = nz;
a = j(nz, 1, 0);
b = j(ny, 1, 0);
int = j(ny+nz, nb, 0);
coef = f // h;
var = ( vt || j(nz, ny, 0) ) //
      ( j(ny, nz, 0) || rt );
intd = j(nz+nb, 1, 0);
coefd = i(nz) // j(nb, nd, 0);
at = j(t*nz, nd+1, 0);
mt = j(t*nz, nz, 0);
qt = j(t*(nd+1), nd+1, 0);
n0 = -1;
call kaldff(kaldff_p, dvpred, initial, s2, y, 0, int,
            coef, var, intd, coefd, n0, at, mt, qt);
call kalcvf(kalcvf_p, vpred, filt, vfilt, y, 0, a, f, b, h, var);
print kalcvf_p kaldff_p;
```


Output 13.4.1 Diffuse Kalman Filtering

Diffuse Kalman Filtering							
kalcvf_p				kaldff_p			
0	0	0	0	0	0	0	0
1.441911	0.961274	1.1214871	0.9612746				
-0.882128	-0.267663	-0.882138	-0.267667				
-0.723156	-0.527704	-0.723158	-0.527706				
1.2964969	0.871659	1.2964968	0.8716585				
-0.035692	0.1379633	-0.035692	0.1379633				
-2.698135	-1.967344	-2.698135	-1.967344				
-5.010039	-4.158022	-5.010039	-4.158022				
-9.048134	-7.719107	-9.048134	-7.719107				
-8.993153	-8.508513	-8.993153	-8.508513				
-11.16619	-10.44119	-11.16619	-10.44119				
-10.42932	-10.34166	-10.42932	-10.34166				
-8.331091	-8.822777	-8.331091	-8.822777				
-9.578258	-9.450848	-9.578258	-9.450848				
-6.526855	-7.241927	-6.526855	-7.241927				
-5.218651	-5.813854	-5.218651	-5.813854				
-5.01855	-5.291777	-5.01855	-5.291777				
-6.5699	-6.284522	-6.5699	-6.284522				
-4.613301	-4.995434	-4.613301	-4.995434				
-5.057926	-5.09007	-5.057926	-5.09007				

The likelihood function for the diffuse Kalman filter under the finite initial covariance matrix Σ_δ is written

$$\lambda(\mathbf{y}) = -\frac{1}{2}[\mathbf{y}^\# \log(\hat{\sigma}^2) + \sum_{t=1}^T \log(|\mathbf{D}_t|)]$$

where $\mathbf{y}^\#$ is the dimension of the matrix $(\mathbf{y}'_1, \dots, \mathbf{y}'_T)'$. The likelihood function for the diffuse Kalman filter under the diffuse initial covariance matrix ($\Sigma_\delta \rightarrow \infty$) is computed as $\lambda(\mathbf{y}) - \frac{1}{2} \log(|\mathbf{S}|)$, where the \mathbf{S} matrix is the upper $N_\delta \times N_\delta$ matrix of \mathbf{Q}_t . **Output 13.4.2** displays the log likelihood and the diffuse log likelihood. Here is the code:

```
d = 0;
do i = 1 to t;
    dt = h*mt[(i-1)*nz+1:i*nz,]*h` + rt;
    d = d + log(det(dt));
end;
s = qt[(t-1)*(nd+1)+1:t*(nd+1)-1,1:nd];
log_l = -(t*log(s2) + d)/2;
dff_logl = log_l - log(det(s))/2;
print log_l dff_logl;
```

Output 13.4.2 Diffuse Likelihood Function

	log_l
Log L	-11.42547
	dff_logl
Diffuse Log L	-9.457596

Vector Time Series Analysis Subroutines

Vector time series analysis involves more than one dependent time series variable, with possible interrelations or feedback between the dependent variables.

The VARMA SIM subroutine generates various time series from the underlying VARMA models. Simulations of time series with known VARMA structure offer learning and developing vector time series analysis skills.

The VARMA COV subroutine provides the pattern of the autocovariance function of VARMA models and helps to identify and fit a proper model.

The VARMA LIK subroutine provides the log-likelihood of a VARMA model and helps to obtain estimates of the parameters of a regression model.

The following subroutines are supported:

VARMA COV	computes the theoretical cross covariances for a multivariate ARMA model
VARMA LIK	evaluates the log-likelihood function for a multivariate ARMA model
VARMA SIM	generates a multivariate ARMA time series
VNORMAL	generates a multivariate normal random series
VTSROOT	computes the characteristic roots of a multivariate ARMA model

Getting Started

Stationary VAR Process

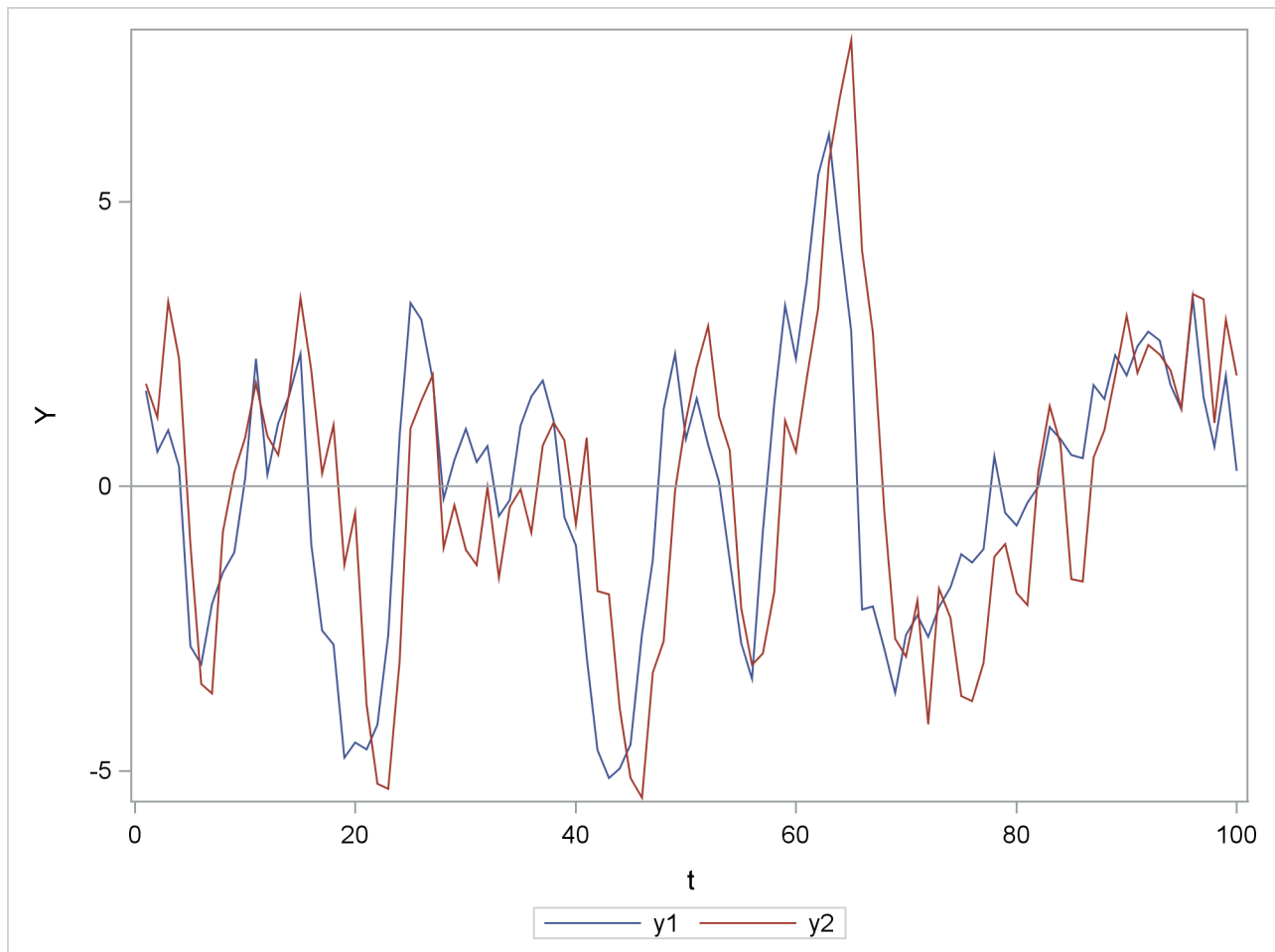
Generate the process following the first-order stationary vector autoregressive model with zero mean

$$\mathbf{y}_t = \begin{pmatrix} 1.2 & -0.5 \\ 0.6 & 0.3 \end{pmatrix} \mathbf{y}_{t-1} + \boldsymbol{\epsilon}_t \text{ with } \Sigma = \begin{pmatrix} 1.0 & 0.5 \\ 0.5 & 1.25 \end{pmatrix}$$

The following statements compute the roots of characteristic function, compute the five lags of cross-covariance matrices, generate 100 observations simulated data, and evaluate the log-likelihood function of the VAR(1) model:

```
proc iml;
  /* Stationary VAR(1) model */
  sig = {1.0 0.5, 0.5 1.25};
  phi = {1.2 -0.5, 0.6 0.3};
  call varmasim(yt,phi) sigma=sig n=100 seed=3243;
  call vtsroot(root,phi);
  print root;
  call varmacov(crosscov,phi) sigma=sig lag=5;
  lag = {'0',' ','1',' ','2',' ','3',' ','4',' ','5',' '};
  print lag crosscov;
  call varmalik(lnl,yt,phi) sigma=sig;
  print lnl;
```

Output 13.4.3 Plot of Generated VAR(1) Process (VARMASIM)



The stationary VAR(1) processes show in [Figure 13.4.3](#).

Output 13.4.4 Roots of VAR(1) Model (VTSROOT)

root				
0.75	0.3122499	0.8124038	0.3945069	22.603583
0.75	-0.31225	0.8124038	-0.394507	-22.60358

In Figure 13.4.4, the first column is the real part (R) of the root of the characteristic function and the second one is the imaginary part (I). The third column is the modulus, the squared root of $R^2 + I^2$. The fourth column is $Tan^{-1}(I/R)$ and the last one is the degree. Since moduli are less than one from the third column, the series is obviously stationary.

Output 13.4.5 Cross-covariance Matrices of VAR(1) Model (VARMACOV)

lag	crosscov	
0	5.3934173	3.8597124
	3.8597124	5.0342051
1	4.5422445	4.3939641
	2.1145523	3.826089
2	3.2537114	4.0435359
	0.6244183	2.4165581
3	1.8826857	3.1652876
	-0.458977	1.0996184
4	0.676579	2.0791977
	-1.100582	0.0544993
5	-0.227704	1.0297067
	-1.347948	-0.643999

In each matrix in Figure 13.4.5, the diagonal elements are corresponding to the autocovariance functions of each time series. The off-diagonal elements are corresponding to the cross-covariance functions of between two series.

Output 13.4.6 Log-Likelihood function of VAR(1) Model (VARMALIK)

lnl
-113.4708
2.5058678
224.43567

In Figure 13.4.6, the first row is the value of log-likelihood function; the second row is the sum of log determinant of the innovation variance; the last row is the weighted sum of squares of residuals.

Nonstationary VAR Process

Generate the process following the error correction model with a cointegrated rank of 1:

$$(1 - B)\mathbf{y}_t = \begin{pmatrix} -0.4 \\ 0.1 \end{pmatrix} (1 - 2)\mathbf{y}_{t-1} + \boldsymbol{\epsilon}_t$$

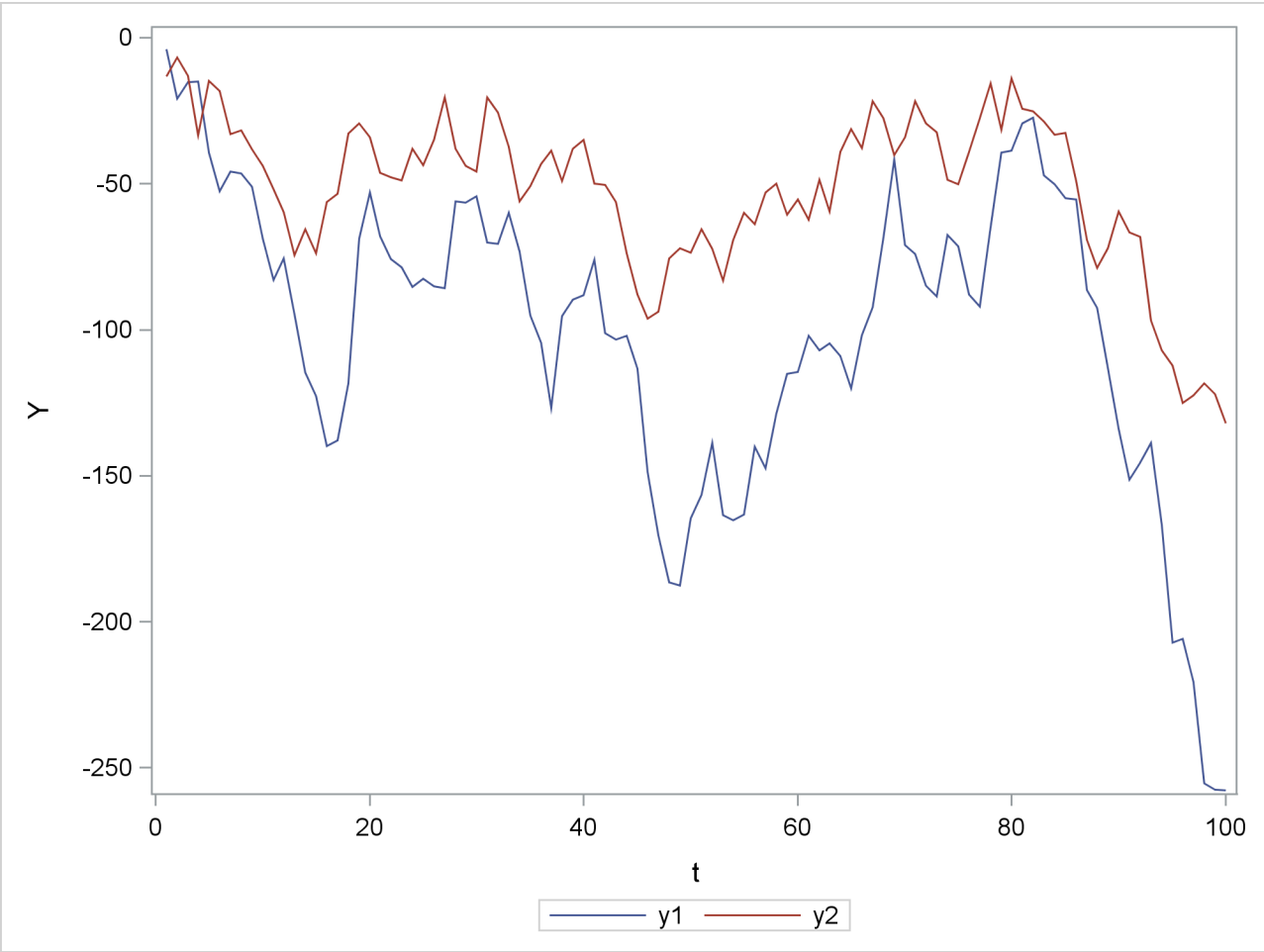
with

$$\Sigma = \begin{pmatrix} 100 & 0 \\ 0 & 100 \end{pmatrix} \text{ and } \mathbf{y}_0 = 0$$

The following statements compute the roots of characteristic function and generate simulated data.

```
proc iml;
/* Nonstationary model */
sig = 100*i(2);
phi = {0.6 0.8, 0.1 0.8};
call varmasim(yt,phi) sigma=sig n=100 seed=1324;
call vtsroot(root,phi);
print root;
```

Output 13.4.7 Plot of Generated Nonstationary Vector Process (VARMASIM)



The nonstationary processes are shown in [Figure 13.4.7](#) and have a comovement.

Output 13.4.8 Roots of Nonstationary VAR(1) Model (VTSROOT)

root				
1	0	1	0	0
0.4	0	0.4	0	0

In [Figure 13.4.8](#), the first column is the real part (R) of the root of the characteristic function and the second one is the imaginary part (I). The third column is the modulus, the squared root of $R^2 + I^2$. The fourth column is $Tan^{-1}(I/R)$ and the last one is the degree. Since the moduli are greater than equal to one from the third column, the series is obviously nonstationary.

Syntax

CALL VARMACOV (*cov, phi, theta, sigma* < , *p, q, lag*>) ;

CALL VARMALIK (*lnl, series, phi, theta, sigma* < , *p, q, opt*>) ;

CALL VARMASIM (*series, phi, theta, mu, sigma, n* < , *p, q, initial, seed*>) ;

CALL VNORMAL (*series, mu, sigma, n* < , *seed*>) ;

CALL VTSROOT *root, phi, theta* < , *p, q*>) ;

Fractionally Integrated Time Series Analysis

This section describes subroutines related to fractionally integrated time series analysis. The phenomenon of long memory can be observed in hydrology, finance, economics, and so on. Unlike with a stationary process, the correlations between observations of a long memory series are slowly decaying to zero.

The following subroutines are supported:

FARMACOV	computes the autocovariance function for a fractionally integrated ARMA model.
FARMAFIT	estimates the parameters for a fractionally integrated ARMA model.
FARMALIK	computes the log-likelihood function for a fractionally integrated ARMA model.
FARMASIM	generates a fractionally integrated ARMA process.
FDIF	computes a fractionally differenced process.

Getting Started

The fractional differencing enables the degree of differencing d to take any real value rather than being restricted to integer values. The fractionally differenced processes are capable of modeling long-term persistence. The process

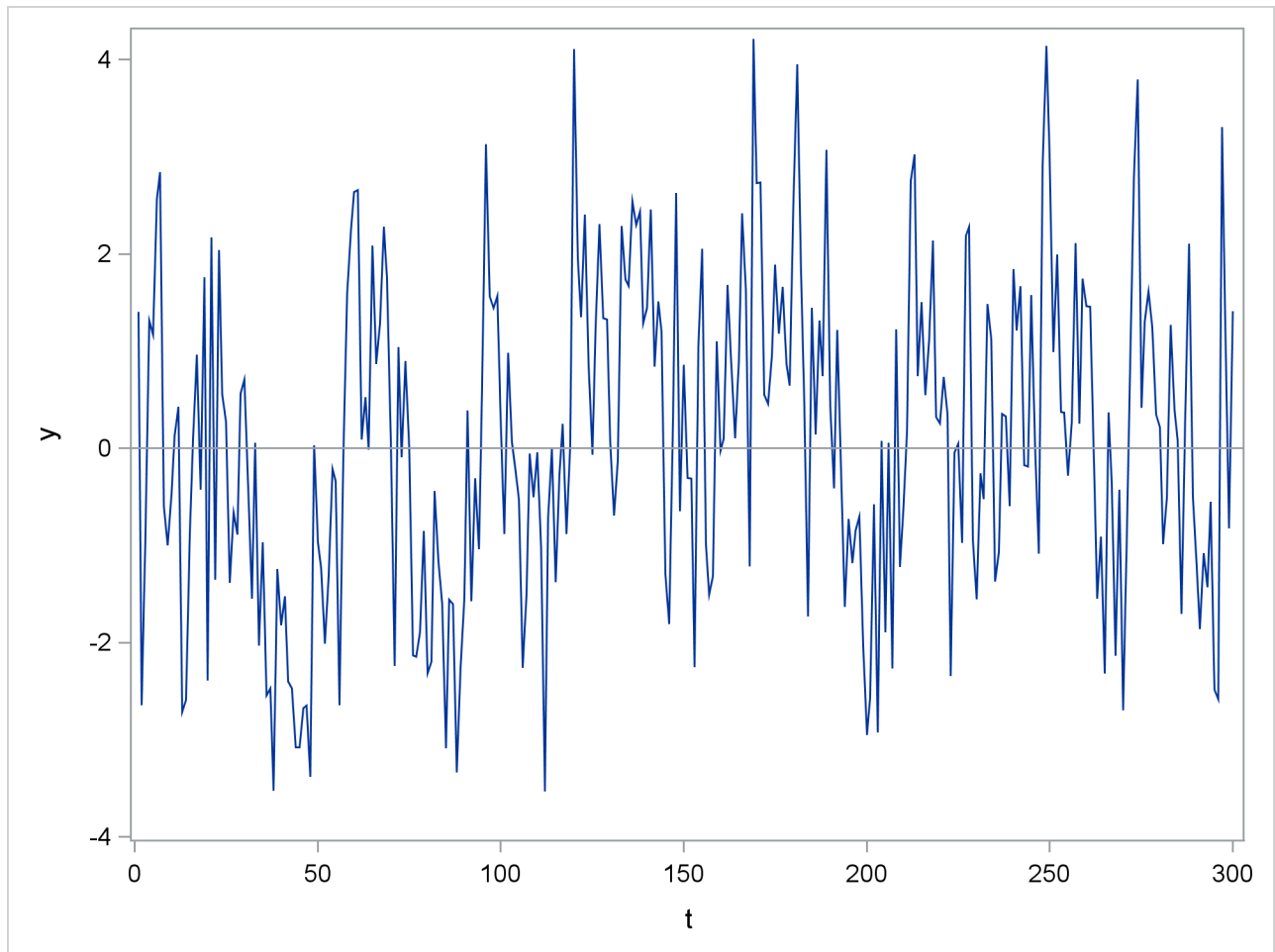
$$(1 - B)^d y_t = \epsilon_t$$

is known as a fractional Gaussian noise process or an ARFIMA(0, d , 0) process, where $d \in (-1, 1)$, ϵ_t is a white noise process with mean zero and variance σ_ϵ^2 , and B is the back-shift operator such that $B^j \mathbf{y}_t = \mathbf{y}_{t-j}$. The extension of an ARFIMA(0, d , 0) model combines fractional differencing with an ARMA(p , q) model, known as an ARFIMA(p , d , q) model.

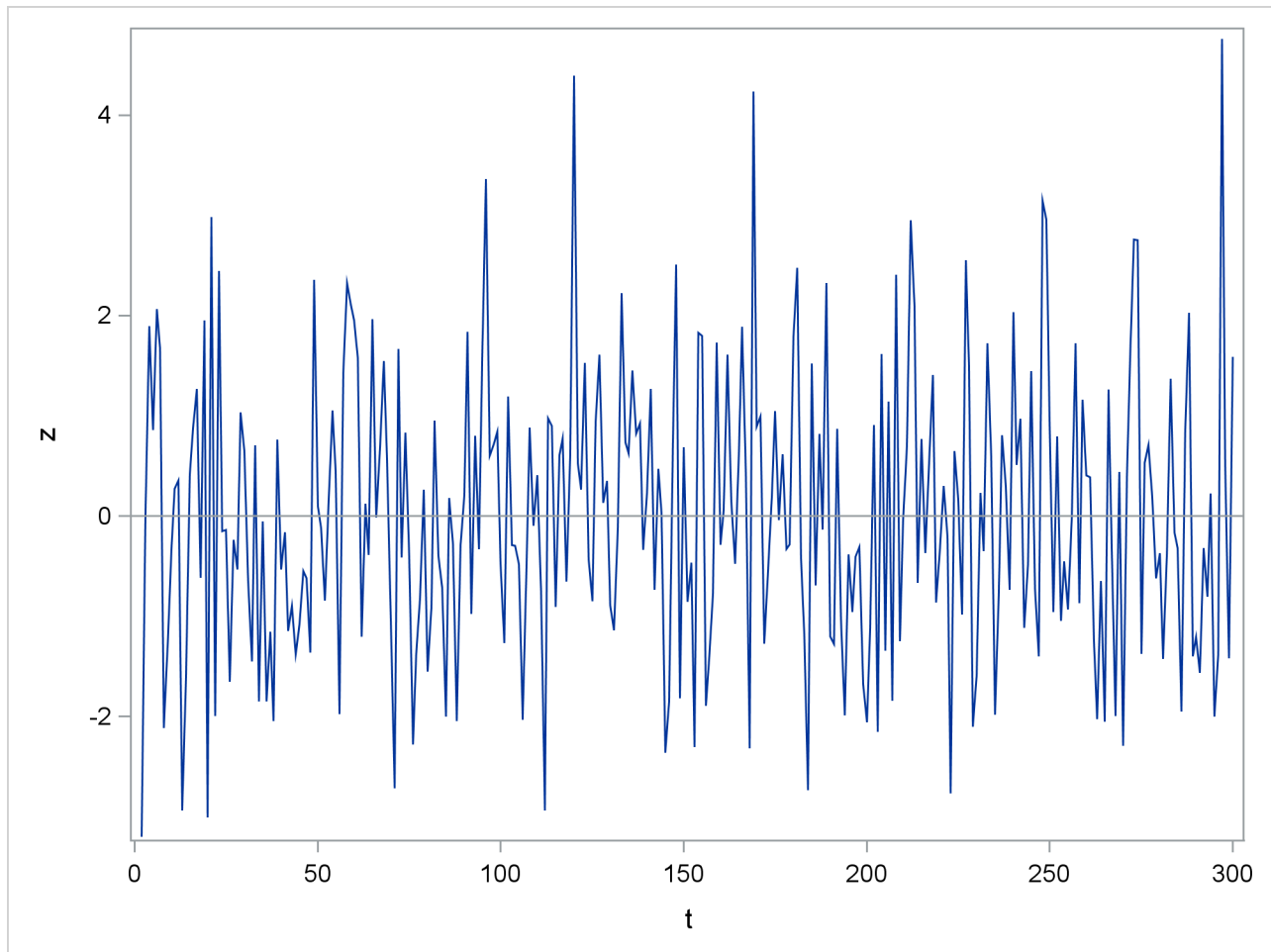
Consider an ARFIMA(0, 0.4, 0) represented as $(1 - B)^{0.4} y_t = \epsilon_t$ where $\epsilon_t \sim iid N(0, 2)$. With the following statements you can

- generate the simulated 300 observations data
- obtain the fractionally differenced data
- compute the autocovariance function
- compute the log-likelihood function
- fit a fractionally integrated time series model to the data

```
proc iml;
/* ARFIMA(0,0.4,0) */
lag = (0:12)`;
call farmacov(autocov_D_IS_04, 0.4);
call farmacov(D_IS_005, 0.05);
print lag autocov_D_IS_04 D_IS_005;
d = 0.4;
call farmasim(yt, d) n=300 sigma=2 seed=5345;
call fdif(zt, yt, d);
*print zt;
call farmalik(lnl, yt, d);
print lnl;
call farmafit(d, ar, ma, sigma, yt);
print d sigma;
```


Output 13.4.9 Plot of Generated ARFIMA(0,0.4,0) Process (FARMASIM)

The FARMASIM function generates the data shown in [Figure 13.4.9](#).

Output 13.4.10 Plot of Fractionally Differenced Process (FDIF)

The FDIF function creates the fractionally differenced process. [Figure 13.4.10](#) shows a white noise series.

Output 13.4.11 Autocovariance Functions of ARFIMA(0,0.4,0) and ARFIMA(0,0.05,0) Models (FARMACOV)

lag	autocov_D_IS_04	D_IS_005
0	2.0700983	1.0044485
1	1.3800656	0.0528657
2	1.2075574	0.0284662
3	1.1146683	0.0197816
4	1.0527423	0.0152744
5	1.0069709	0.0124972
6	0.9710077	0.0106069
7	0.9415832	0.0092333
8	0.9168047	0.008188
9	0.8954836	0.0073647
10	0.8768277	0.0066985
11	0.8602838	0.006148
12	0.8454513	0.0056849

The first column is the autocovariance function of the ARFIMA(0,0.4,0) model, and the second column is the autocovariance function of the ARFIMA(0,0.05,0) model. The first column decays to zero more slowly than the second column.

Output 13.4.12 Log-Likelihood Function of ARFIMA(0,0.4,0) Model (FARMALIK)

lnl
-101.0599
.
.

The first row value is the log-likelihood function of the ARFIMA(0,0.4,0) model. Because the default option of the estimates method is the conditional sum of squares, the last two rows of [Figure 13.4.12](#) contain missing values.

Output 13.4.13 Parameter Estimation of ARFIMA(0,0.4,0) Model (FARMAFIT)

d	sigma
0.386507	1.9610507

The final estimates of the parameters are $d = 0.387$ and $\sigma^2 = 1.96$, while the true values of the data generating process are $d = 0.4$ and $\sigma^2 = 2$.

Syntax

CALL FARMACOV (*cov*, *d* < , *phi*, *theta*, *sigma*, *p*, *q*, *lag*>) ;

CALL FARMAFIT (*d*, *phi*, *theta*, *sigma*, *series* < , *p*, *q*, *opt*>) ;

CALL FARMALIK (*lnl*, *series*, *d* < , *phi*, *theta*, *sigma*, *p*, *q*, *opt*>) ;

CALL FARMASIM (*series*, *d* < , *phi*, *theta*, *mu*, *sigma*, *n*, *p*, *q*, *initial*, *seed*>) ;

CALL FDIF (*out*, *series*, *d*) ;

References

- Affi, A. A. and Elashoff, R. M. (1967), “Missing Observations in Multivariate Statistics II. Point Estimation in Simple Linear Regression,” *Journal of the American Statistical Association*, 62, 10–29.
- Akaike, H. (1974), “A New Look at Statistical Model Identification,” *IEEE Transactions on Automatic Control*, 19, 716–723.

- Akaike, H. (1977), "On Entropy Maximization Principle," in P. R. Krishnaiah, ed., *Applications of Statistics*, 27–41, Amsterdam: North Holland Publishing.
- Akaike, H. (1978a), "A Bayesian Analysis of the Minimum AIC Procedure," *Ann. Inst. Statist. Math.*, 30, 9–14.
- Akaike, H. (1978b), "Time Series Analysis and Control through Parametric Models," in D. F. Findley, ed., *Applied Time Series Analysis*, 1–23, New York: Academic Press.
- Akaike, H. (1979), "A Bayesian Extension of the Minimum AIC Procedure of Autoregressive Model Fitting," *Biometrika*, 66, 237–242.
- Akaike, H. (1980a), "Likelihood and the Bayes Procedure," in J. M. Bernardo, M. H. DeGroot, D. V. Lindley, and M. Smith, eds., *Bay Statistics*, 143–166, Valencia, Spain: University Press.
- Akaike, H. (1980b), "Seasonal Adjustment by a Bayesian Modeling," *Journal of Time Series Analysis*, 1, 1–13.
- Akaike, H. (1981), "Likelihood of a Model and Information Criteria," *Journal of Econometrics*, 16, 3–14.
- Akaike, H. (1986), "The Selection of Smoothness Priors for Distributed Lag Estimation," in P. Goel and A. Zellner, eds., *Bayesian Inference and Decision Techniques*, 109–118, Elsevier Science.
- Akaike, H. and Ishiguro, M. (1980), "Trend Estimation with Missing Observations," *Ann. Inst. Statist. Math.*, 32, 481–488.
- Akaike, H. and Nakagawa, T. (1988), *Statistical Analysis and Control of Dynamic Systems*, Tokyo: KTK Scientific.
- Anderson, T. W. (1971), *The Statistical Analysis of Time Series*, New York: John Wiley & Sons.
- Ansley, C. F. (1980), "Computation of the Theoretical Autocovariance Function for a Vector ARMA Process," *Journal of Statistical Computation and Simulation*, 12, 15–24.
- Ansley, C. F. and Kohn, R. (1986), "A Note on Reparameterizing a Vector Autoregressive Moving Average Model to Enforce Stationary," *Journal of Statistical Computation and Simulation*, 24, 99–106.
- Brockwell, P. J. and Davis, R. A. (1991), *Time Series: Theory and Methods*, Second Edition, New York: Springer-Verlag.
- Chung, C. F. (1996), "A Generalized Fractionally Integrated ARMA Process," *Journal of Time Series Analysis*, 2, 111–140.
- De Jong, P. (1991), "The Diffuse Kalman Filter," *Annals of Statistics*, 19, 1073–1083.
- Doan, T., Litterman, R., and Sims, C. (1984), "Forecasting and Conditional Projection Using Realistic Prior Distributions," *Econometric Reviews*.
- Gersch, W. and Kitagawa, G. (1983), "The Prediction of Time Series with Trends and Seasonalities," *Journal of Business and Economic Statistics*, 1, 253–264.
- Geweke, J. and Porter-Hudak, S. (1983), "The Estimation and Application of Long Memory Time Series Models," *Journal of Time Series Analysis*, 4, 221–238.

- Granger, C. W. J. and Joyeux, R. (1980), "An Introduction to Long Memory Time Series Models and Fractional Differencing," *Journal of Time Series Analysis*, 1, 15–39.
- Harvey, A. C. (1989), *Forecasting, Structural Time Series Models and the Kalman Filter*, Cambridge: Cambridge University Press.
- Hosking, J. R. M. (1981), "Fractional Differencing," *Biometrika*, 68, 165–176.
- Ishiguro, M. (1984), "Computationally Efficient Implementation of a Bayesian Seasonal Adjustment Procedure," *Journal of Time Series Analysis*, 5, 245–253.
- Ishiguro, M. (1987), "TIMSAC-84: A New Time Series Analysis and Control Package," *Proceedings of American Statistical Association: Business and Economic Section*.
- Jones, R. H. and Brelsford, W. M. (1967), "Time Series with Periodic Structure," *Biometrika*, 54, 403–408.
- Kitagawa, G. (1981), "A Nonstationary Time Series Model and Its Fitting by a Recursive Filter," *Journal of Time Series Analysis*, 2, 103–116.
- Kitagawa, G. (1983), "Changing Spectrum Estimation," *Journal of Sound and Vibration*, 89, 433–445.
- Kitagawa, G. and Akaike, H. (1978), "A Procedure for the Modeling of Non-stationary Time Series," *Ann. Inst. Statist. Math.*, 30, 351–363.
- Kitagawa, G. and Akaike, H. (1981), "On TIMSAC-78," in D. F. Findley, ed., *Applied Time Series Analysis II*, 499–547, New York: Academic Press.
- Kitagawa, G. and Akaike, H. (1982), "A Quasi Bayesian Approach to Outlier Detection," *Ann. Inst. Statist. Math.*, 34, 389–398.
- Kitagawa, G. and Gersch, W. (1984), "A Smoothness Priors-State Space Modeling of Time Series with Trend and Seasonality," *Journal of the American Statistical Association*, 79, 378–389.
- Kitagawa, G. and Gersch, W. (1985a), "A Smoothness Priors Long AR Model Method for Spectral Estimation," *IEEE Transactions on Automatic Control*, 30, 57–65.
- Kitagawa, G. and Gersch, W. (1985b), "A Smoothness Priors Time-Varying AR Coefficient Modeling of Nonstationary Covariance Time Series," *IEEE Transactions on Automatic Control*, 30, 48–56.
- Kohn, R. and Ansley, C. F. (1982), "A Note on Obtaining the Theoretical Autocovariances of an ARMA Process," *Journal of Statistical Computation and Simulation*, 15, 273–283.
- Li, W. K. and McLeod, A. I. (1986), "Fractional Time Series Modeling," *Biometrika*, 73, 217–221.
- Lütkepohl, H. (1993), *Introduction to Multiple Time Series Analysis*, Berlin: Springer-Verlag.
- Mittnik, S. (1990), "Computation of Theoretical Autocovariance Matrices of Multivariate Autoregressive Moving Average Time Series," *Journal of Royal Statistical Society*.
- Nelson, C. R. and Plosser, C. I. (1982), "Trends and Random Walks in Macroeconomic Time Series: Some Evidence and Implications," *Journal of Monetary Economics*, 10, 139–162.
- Pagano, M. (1978), "On Periodic and Multiple Autoregressions," *The Annals of Statistics*, 6, 1310–1317.

- Reinsel, G. C. (1997), *Elements of Multivariate Time Series Analysis*, Second Edition, New York: Springer-Verlag.
- Sakamoto, Y., Ishiguro, M., and Kitagawa, G. (1986), *Akaike Information Criterion Statistics*, Tokyo: KTK Scientific.
- Shiller, R. J. (1973), "A Distributed Lag Estimator Derived from Smoothness Priors," *Econometrica*, 41, 775–788.
- Shumway, R. H. (1988), *Applied Statistical Time Series Analysis*, Englewood Cliffs, NJ: Prentice-Hall.
- Sowell, F. (1992), "Maximum Likelihood Estimation of Stationary Univariate Fractionally Integrated Time Series Models," *Journal of Econometrics*, 53, 165–188.
- Tamura, Y. H. (1986), "An Approach to the Nonstationary Process Analysis," *Ann. Inst. Statist. Math.*, 39, 227–241.
- Wei, W. W. S. (1990), *Time Series Analysis: Univariate and Multivariate Methods*, Redwood: Addison-Wesley.
- Whittaker, E. T. (1923), "On a New Method of Graduation," *Proceedings of the Edinburgh Mathematical Society*, 41, 63–75.
- Whittaker, E. T. and Robinson, G. (1944), *Calculus of Observation*, Fourth Edition, London: Blackie & Son Limited.
- Zellner, A. (1971), *An Introduction to Bayesian Inference in Econometrics*, New York: John Wiley & Sons.

Chapter 14

Nonlinear Optimization Examples

Contents

Overview	335
Getting Started	337
Details	344
Global versus Local Optima	344
Kuhn-Tucker Conditions	346
Definition of Return Codes	346
Objective Function and Derivatives	347
Finite-Difference Approximations of Derivatives	352
Parameter Constraints	354
Options Vector	356
Termination Criteria	360
Control Parameters Vector	367
Printing the Optimization History	369
Nonlinear Optimization Examples	370
Example 14.1: Chemical Equilibrium	370
Example 14.2: Network Flow and Delay	374
Example 14.3: Compartmental Analysis	378
Example 14.4: MLEs for Two-Parameter Weibull Distribution	387
Example 14.5: Profile-Likelihood-Based Confidence Intervals	390
Example 14.6: Survival Curve for Interval Censored Data	392
Example 14.7: A Two-Equation Maximum Likelihood Problem	398
Example 14.8: Time-Optimal Heat Conduction	402
References	406

Overview

The IML procedure offers a set of optimization subroutines for minimizing or maximizing a continuous nonlinear function $f = f(x)$ of n parameters, where $x = (x_1, \dots, x_n)^T$. The parameters can be subject to boundary constraints and linear or nonlinear equality and inequality constraints. The following set of optimization subroutines is available:

NLPCG	Conjugate Gradient Method
NLPDD	Double Dogleg Method
NLPNMS	Nelder-Mead Simplex Method
NLPNRA	Newton-Raphson Method
NLPNRR	Newton-Raphson Ridge Method
NLPQN	(Dual) Quasi-Newton Method
NLPQUA	Quadratic Optimization Method
NLPTR	Trust-Region Method

The following subroutines are provided for solving nonlinear least squares problems:

NLPLM	Levenberg-Marquardt Least Squares Method
NLPHQN	Hybrid Quasi-Newton Least Squares Methods

A least squares problem is a special form of minimization problem where the objective function is defined as a sum of squares of other (nonlinear) functions.

$$f(x) = \frac{1}{2} \{f_1^2(x) + \cdots + f_m^2(x)\}$$

Least squares problems can usually be solved more efficiently by the least squares subroutines than by the other optimization subroutines.

The following subroutines are provided for the related problems of computing finite difference approximations for first- and second-order derivatives and of determining a feasible point subject to boundary and linear constraints:

NLPFDD	Approximate Derivatives by Finite Differences
NLPFEA	Feasible Point Subject to Constraints

Each optimization subroutine works iteratively. If the parameters are subject only to linear constraints, all optimization and least squares techniques are *feasible-point methods*; that is, they move from feasible point $x^{(k)}$ to a better feasible point $x^{(k+1)}$ by a step in the search direction $s^{(k)}$, $k = 1, 2, 3, \dots$. If you do not provide a feasible starting point $x^{(0)}$, the optimization methods call the algorithm used in the NLPFEA subroutine, which tries to compute a starting point that is feasible with respect to the boundary and linear constraints.

The NLPNMS and NLPQN subroutines permit nonlinear constraints on parameters. For problems with nonlinear constraints, these subroutines do not use a feasible-point method; instead, the algorithms begin with whatever starting point you specify, whether feasible or infeasible.

Each optimization technique requires a continuous objective function $f = f(x)$, and all optimization subroutines except the NLPNMS subroutine require continuous first-order derivatives of the objective function f . If you do not provide the derivatives of f , they are approximated by finite-difference formulas. You can use the NLPFDD subroutine to check the correctness of analytical derivative specifications.

Most of the results obtained from the IML procedure optimization and least squares subroutines can also be obtained by using the OPTMODEL procedure or the NLP procedure in SAS/OR software.

The advantages of the IML procedure are as follows:

- You can use matrix algebra to specify the objective function, nonlinear constraints, and their derivatives in IML modules.

- The IML procedure offers several subroutines that can be used to specify the objective function or nonlinear constraints, many of which would be very difficult to write for the NLP procedure.
- You can formulate your own termination criteria by using the “*ptit*” module argument.

The advantages of the NLP procedure are as follows:

- Although identical optimization algorithms are used, the NLP procedure can be much faster because of the interactive and more general nature of the IML product.
- Analytic first- and second-order derivatives can be computed with a special compiler.
- Additional optimization methods are available in the NLP procedure that do not fit into the framework of this package.
- Data set processing is much easier than in the IML procedure. You can save results in output data sets and use them in subsequent runs.
- The printed output contains more information.

Getting Started

Unconstrained Rosenbrock Function

The Rosenbrock function is defined as

$$\begin{aligned} f(x) &= \frac{1}{2} \{100(x_2 - x_1^2)^2 + (1 - x_1)^2\} \\ &= \frac{1}{2} \{f_1^2(x) + f_2^2(x)\}, \quad x = (x_1, x_2) \end{aligned}$$

The minimum function value $f^* = f(x^*) = 0$ is at the point $x^* = (1, 1)$.

The following code calls the NLPTR subroutine to solve the optimization problem:

The NLPTR is a trust-region optimization method. The F_ROSEN module represents the Rosenbrock function, and the G_ROSEN module represents its gradient. Specifying the gradient can reduce the number of function calls by the optimization subroutine. The optimization begins at the initial point $x = (-1.2, 1)$. For more information about the NLPTR subroutine and its arguments, see the section “[NLPTR Call](#)” on page 855. For details about the options vector, which is given by the OPTN vector in the preceding code, see the section “[Options Vector](#)” on page 356.

A portion of the output produced by the NLPTR subroutine is shown in [Figure 14.1](#).

Figure 14.1 NLPTR Solution to the Rosenbrock Problem

Optimization Start								
Parameter Estimates								
N Parameter	Estimate	Gradient Objective Function						
1 X1	-1.200000	-107.800000						
2 X2	1.000000	-44.000000						
Value of Objective Function = 12.1								
Trust Region Optimization								
Without Parameter Scaling								
CRP Jacobian Computed by Finite Differences								
Parameter Estimates		2						
Optimization Start								
Active Constraints	0 Objective Function	12.1						
Max Abs Gradient Element	107.8 Radius	1						
Iter	Rest arts	Func Calls	Act Con	Objective Function	Obj Fun Change	Max Abs Gradient Element	Lambda	Trust Region Radius
1	0	2	0	2.36594	9.7341	2.3189	0	1.000
2	0	5	0	2.05926	0.3067	5.2875	0.385	1.526
3	0	8	0	1.74390	0.3154	5.9934	0	1.086
4	0	9	0	1.43279	0.3111	6.5134	0.918	0.372
5	0	10	0	1.13242	0.3004	4.9245	0	0.373
6	0	11	0	0.86905	0.2634	2.9302	0	0.291
7	0	12	0	0.66711	0.2019	3.6584	0	0.205
8	0	13	0	0.47959	0.1875	1.7354	0	0.208
9	0	14	0	0.36337	0.1162	1.7589	2.916	0.132
10	0	15	0	0.26903	0.0943	3.4089	0	0.270
11	0	16	0	0.16280	0.1062	0.6902	0	0.201
12	0	19	0	0.11590	0.0469	1.1456	0	0.316
13	0	20	0	0.07616	0.0397	0.8462	0.931	0.134
14	0	21	0	0.04873	0.0274	2.8063	0	0.276
15	0	22	0	0.01862	0.0301	0.2290	0	0.232
16	0	25	0	0.01005	0.00858	0.4553	0	0.256
17	0	26	0	0.00414	0.00590	0.4297	0.247	0.104
18	0	27	0	0.00100	0.00314	0.4323	0.0453	0.104
19	0	28	0	0.0000961	0.000906	0.1134	0	0.104
20	0	29	0	1.67873E-6	0.000094	0.0224	0	0.0569
21	0	30	0	6.9582E-10	1.678E-6	0.000336	0	0.0248
22	0	31	0	1.3128E-16	6.96E-10	1.977E-7	0	0.00314

Figure 14.1 *continued*

Optimization Results			
Iterations	22	Function Calls	32
Hessian Calls	23	Active Constraints	0
Objective Function	1.312814E-16	Max Abs Gradient Element	1.9773384E-7
Lambda	0	Actual Over Pred Change	0
Radius	0.003140192		
ABSGCONV convergence criterion satisfied.			
Optimization Results Parameter Estimates			
N Parameter	Estimate	Gradient Objective Function	
1 X1	1.000000	0.000000198	
2 X2	1.000000	-0.000000105	
Value of Objective Function = 1.312814E-16			

Since $f(x) = \frac{1}{2}\{f_1^2(x) + f_2^2(x)\}$, you can also use least squares techniques in this situation. The following code calls the NLPLM subroutine to solve the problem. The output is shown in Figure 14.2.

Figure 14.2 NLPLM Solution Using the Least Squares Technique

Optimization Start Parameter Estimates			
N Parameter	Estimate	Gradient Objective Function	
1 X1	-1.200000	-107.799999	
2 X2	1.000000	-44.000000	
Value of Objective Function = 12.1			
Levenberg-Marquardt Optimization			
Scaling Update of More (1978)			
Gradient Computed by Finite Differences			
CRP Jacobian Computed by Finite Differences			
Parameter Estimates		2	
Functions (Observations)		2	
Optimization Start			
Active Constraints	0	Objective Function	12.1
Max Abs Gradient Element	107.7999987	Radius	2626.5613171

Figure 14.2 continued

Iter	Rest arts	Func Calls	Act Con	Objective Function	Obj Fun Change	Max Abs Gradient Element	Lambda	Actual Over Pred Change
1	0	4	0	2.18185	9.9181	17.4704	0.00804	0.964
2	0	6	0	1.59370	0.5881	3.7015	0.0190	0.988
3	0	7	0	1.32848	0.2652	7.0843	0.00830	0.678
4	0	8	0	1.03891	0.2896	6.3092	0.00753	0.593
5	0	9	0	0.78943	0.2495	7.2617	0.00634	0.486
6	0	10	0	0.58838	0.2011	7.8837	0.00462	0.393
7	0	11	0	0.34224	0.2461	6.6815	0.00307	0.524
8	0	12	0	0.19630	0.1459	8.3857	0.00147	0.469
9	0	13	0	0.11626	0.0800	9.3086	0.00016	0.409
10	0	14	0	0.0000396	0.1162	0.1781	0	1.000
11	0	15	0	2.4652E-30	0.000040	4.44E-14	0	1.000

Optimization Results

Iterations	11	Function Calls	16
Jacobian Calls	12	Active Constraints	0
Objective Function	2.46519E-30	Max Abs Gradient Element	4.440892E-14
Lambda	0	Actual Over Pred Change	1
Radius	0.0178062912		

ABSGCONV convergence criterion satisfied.

Optimization Results
Parameter Estimates

N	Parameter	Estimate	Gradient Objective Function
1	X1	1.000000	-4.44089E-14
2	X2	1.000000	2.220446E-14

Value of Objective Function = 2.46519E-30

The Levenberg-Marquardt least squares method, which is the method used by the NLPLM subroutine, is a modification of the trust-region method for nonlinear least squares problems. The F_ROSEN module represents the Rosenbrock function. Note that for least squares problems, the m functions $f_1(x), \dots, f_m(x)$ are specified as elements of a vector; this is different from the manner in which $f(x)$ is specified for the other optimization techniques. No derivatives are specified in the preceding code, so the NLPLM subroutine computes finite-difference approximations. For more information about the NLPLM subroutine, see the section “NLPLM Call” on page 836.

Constrained Betts Function

The linearly constrained Betts function (Hock and Schittkowski 1981) is defined as

$$f(x) = 0.01x_1^2 + x_2^2 - 100$$

The boundary constraints are

$$\begin{aligned} 2 &\leq x_1 \leq 50 \\ -50 &\leq x_2 \leq 50 \end{aligned}$$

The linear constraint is

$$10x_1 - x_2 \geq 10$$

The following code calls the NLPCG subroutine to solve the optimization problem. The infeasible initial point $x^0 = (-1, -1)$ is specified, and a portion of the output is shown in [Figure 14.3](#).

The NLPCG subroutine performs conjugate gradient optimization. It requires only function and gradient calls. The F_BETTS module represents the Betts function, and since no module is defined to specify the gradient, first-order derivatives are computed by finite-difference approximations. For more information about the NLPCG subroutine, see the section “[NLPCG Call](#)” on page 826. For details about the constraint matrix, which is represented by the CON matrix in the preceding code, see the section “[Parameter Constraints](#)” on page 354.

Figure 14.3 NLPCG Solution to Betts Problem

Optimization Start				
Parameter Estimates				
		Gradient	Lower	Upper
N	Parameter	Estimate	Bound	Bound
		Function	Constraint	Constraint
1	X1	6.800000	0.136000	2.000000
2	X2	-1.000000	-2.000000	-50.000000
				50.000000
Linear Constraints				
1	59.00000 :	10.0000	<= + 10.0000 * X1	- 1.0000 *
	X2			
	Parameter Estimates	2		
	Lower Bounds	2		
	Upper Bounds	2		
	Linear Constraints	1		
Optimization Start				
Active Constraints		0	Objective Function	-98.5376
Max Abs Gradient Element		2		

Figure 14.3 continued

Iter	Rest arts	Func Calls	Act Con	Objective Function	Obj Fun Change	Max Abs Gradient Element	Step Size	Slope Search Direc
1	0	3	0	-99.54682	1.0092	0.1346	0.502	-4.018
2	1	7	1	-99.96000	0.4132	0.00272	34.985	-0.0182
3	2	9	1	-99.96000	1.851E-6	0	0.500	-74E-7

Optimization Results			
Iterations	3	Function Calls	10
Gradient Calls	9	Active Constraints	1
Objective Function	-99.96	Max Abs Gradient Element	0
Slope of Search Direction	-7.398365E-6		

Optimization Results Parameter Estimates			
N Parameter	Estimate	Gradient Objective Function	Active Bound Constraint
1 X1	2.000000	0.040000	Lower BC
2 X2	-1.24028E-10	0	

Linear Constraints Evaluated at Solution			
1	10.00000	= -10.0000 + 10.0000 * X1 - 1.0000 * X2	

Since the initial point $(-1, -1)$ is infeasible, the subroutine first computes a feasible starting point. Convergence is achieved after three iterations, and the optimal point is given to be $x^* = (2, 0)$ with an optimal function value of $f^* = f(x^*) = -99.96$. For more information about the printed output, see the section “Printing the Optimization History” on page 369.

Rosen-Suzuki Problem

The Rosen-Suzuki problem is a function of four variables with three nonlinear constraints on the variables. It is taken from problem 43 of Hock and Schittkowski (1981). The objective function is

$$f(x) = x_1^2 + x_2^2 + 2x_3^2 + x_4^2 - 5x_1 - 5x_2 - 21x_3 + 7x_4$$

The nonlinear constraints are

$$\begin{aligned} 0 &\leq 8 - x_1^2 - x_2^2 - x_3^2 - x_4^2 - x_1 + x_2 - x_3 + x_4 \\ 0 &\leq 10 - x_1^2 - 2x_2^2 - x_3^2 - 2x_4^2 + x_1 + x_4 \\ 0 &\leq 5 - 2x_1^2 - x_2^2 - x_3^2 - 2x_1 + x_2 + x_4 \end{aligned}$$

Since this problem has nonlinear constraints, only the NLPQN and NLPNMS subroutines are available to perform the optimization. The following code solves the problem with the NLPQN subroutine:

The F_HS43 module specifies the objective function, and the C_HS43 module specifies the nonlinear constraints. The OPTN vector is passed to the subroutine as the OPT input argument. See the section “Options Vector” on page 356 for more information. The value of OPTN[10] represents the total number of nonlinear constraints, and the value of OPTN[11] represents the number of equality constraints. In the preceding code, OPTN[10]=3 and OPTN[11]=0, which indicate that there are three constraints, all of which are inequality constraints. In the subroutine calls, instead of separating missing input arguments with commas, you can specify optional arguments with keywords, as in the CALL NLPQN statement in the preceding code. For details about the CALL NLPQN statement, see the section “NLPQN Call” on page 847.

The initial point for the optimization procedure is $x = (1, 1, 1, 1)$, and the optimal point is $x^* = (0, 1, 2, -1)$, with an optimal function value of $f(x^*) = -44$. Part of the output produced is shown in Figure 14.4.

Figure 14.4 Solution to the Rosen-Suzuki Problem by the NLPQN Subroutine

Optimization Start			
Parameter Estimates			
		Gradient	Gradient
		Objective	Lagrange
N	Parameter	Estimate	Function
1	X1	1.000000	-3.000000
2	X2	1.000000	-3.000000
3	X3	1.000000	-17.000000
4	X4	1.000000	9.000000
Parameter Estimates		4	
Nonlinear Constraints		3	
Optimization Start			
Objective Function		-19	Maximum Constraint
			Violation
Maximum Gradient of the		17	
Lagran Func			
Maximum			
Gradient			
Element			
of the			
Iter	Restarts	Function	Step Lagrange
		Objective	Size Function
		Function	Violation
		Reduction	
1	0	2	-41.88007
2	0	3	-48.83264
3	0	4	-45.33515
4	0	5	-44.08667
5	0	6	-44.00011
6	0	7	-44.00001
7	0	8	-44.00000
			1.8988
			3.0280
			0.5452
			0.0427
			0.000099
			2.573E-6
			9.118E-8
			13.6803
			9.5464
			2.6179
			0.1732
			0.000218
			0.000014
			5.097E-7
			1.000
			5.647
			5.041
			1.061
			0.0297
			0.00906
			0.00219
			0.00022

Figure 14.4 continued

Optimization Results			
Iterations	7	Function Calls	9
Gradient Calls	9	Active Constraints	2
Objective Function	-44.00000026	Maximum Constraint Violation	9.1176306E-8
Maximum Projected Gradient	0.0002265341	Value Lagrange Function	-44
Maximum Gradient of the Lagran Func	0.00022158	Slope of Search Direction	-5.097332E-7

Optimization Results			
Parameter Estimates			
N Parameter	Estimate	Gradient Objective Function	Gradient Lagrange Function
1 X1	-0.000001248	-5.000002	-0.000012804
2 X2	1.000027	-2.999945	0.000222
3 X3	1.999993	-13.000027	-0.000054166
4 X4	-1.000003	4.999995	-0.000020681

In addition to the standard iteration history, the NLPQN subroutine includes the following information for problems with nonlinear constraints:

- CONMAX is the maximum value of all constraint violations.
- PRED is the value of the predicted function reduction used with the GTOL and FTOL2 termination criteria.
- ALFA is the step size α of the quasi-Newton step.
- LFGMAX is the maximum element of the gradient of the Lagrange function.

Details

Global versus Local Optima

All the IML optimization algorithms converge toward local rather than global optima. The smallest local minimum of an objective function is called the global minimum, and the largest local maximum of an objective function is called the global maximum. Hence, the subroutines can occasionally fail to find the global optimum. Suppose you have the function $f(x) = \frac{1}{27}(3x_1^4 - 28x_1^3 + 84x_1^2 - 96x_1 + 64) + x_2^2$, which has a local minimum at $f(1, 0) = 1$ and a global minimum at the point $f(4, 0) = 0$.

The following statements use two calls of the NLPTR subroutine to minimize the preceding function. The first call specifies the initial point $xa = (0.5, 1.5)$, and the second call specifies the initial point $xb = (3, 1)$. The first call finds the local optimum $x^* = (1, 0)$, and the second call finds the global optimum $x^* = (4, 0)$.

```
proc iml;
  start F_GLOBAL(x);
    f=(3*x[1]**4-28*x[1]**3+84*x[1]**2-96*x[1]+64)/27 + x[2]**2;
    return(f);
  finish F_GLOBAL;
  xa = {.5 1.5};
  xb = {3 -1};
  optn = {0 2};
  call nlpnr(rca,xra,"F_GLOBAL",xa,optn);
  call nlpnr(rcb,xrb,"F_GLOBAL",xb,optn);
  print xra xrb;
```

One way to find out whether the objective function has more than one local optimum is to run various optimizations with a pattern of different starting points.

For a more mathematical definition of optimality, refer to the *Kuhn-Tucker theorem* in standard optimization literature. Using rather nonmathematical language, a local minimizer x^* satisfies the following conditions:

- There exists a small, feasible neighborhood of x^* that does not contain any point x with a smaller function value $f(x) < f(x^*)$.
- The vector of first derivatives (gradient) $g(x^*) = \nabla f(x^*)$ of the objective function f (projected toward the feasible region) at the point x^* is zero.
- The matrix of second derivatives $G(x^*) = \nabla^2 f(x^*)$ (Hessian matrix) of the objective function f (projected toward the feasible region) at the point x^* is positive definite.

A local maximizer has the largest value in a feasible neighborhood and a negative definite Hessian.

The iterative optimization algorithm terminates at the point x^t , which should be in a small neighborhood (in terms of a user-specified termination criterion) of a local optimizer x^* . If the point x^t is located on one or more active boundary or general linear constraints, the local optimization conditions are valid only for the feasible region. That is,

- the projected gradient, $Z^T g(x^t)$, must be sufficiently small
- the projected Hessian, $Z^T G(x^t) Z$, must be positive definite for minimization problems or negative definite for maximization problems

If there are n active constraints at the point x^t , the nullspace Z has zero columns and the projected Hessian has zero rows and columns. A matrix with zero rows and columns is considered positive as well as negative definite.

Kuhn-Tucker Conditions

The nonlinear programming (NLP) problem with one objective function f and m constraint functions c_i , which are continuously differentiable, is defined as follows:

$$\begin{aligned} &\text{minimize } f(x), & x \in \mathcal{R}^n, & \text{ subject to} \\ &c_i(x) = 0, & i = 1, \dots, m_e \\ &c_i(x) \geq 0, & i = m_e + 1, \dots, m \end{aligned}$$

In the preceding notation, n is the dimension of the function $f(x)$, and m_e is the number of equality constraints. The linear combination of objective and constraint functions

$$L(x, \lambda) = f(x) - \sum_{i=1}^m \lambda_i c_i(x)$$

is the *Lagrange function*, and the coefficients λ_i are the *Lagrange multipliers*.

If the functions f and c_i are twice differentiable, the point x^* is an *isolated local minimizer* of the NLP problem, if there exists a vector $\lambda^* = (\lambda_1^*, \dots, \lambda_m^*)$ that meets the following conditions:

- Kuhn-Tucker conditions

$$\begin{aligned} &c_i(x^*) = 0, & i = 1, \dots, m_e \\ &c_i(x^*) \geq 0, \quad \lambda_i^* \geq 0, \quad \lambda_i^* c_i(x^*) = 0, & i = m_e + 1, \dots, m \\ &\nabla_x L(x^*, \lambda^*) = 0 \end{aligned}$$

- second-order condition

Each nonzero vector $y \in \mathcal{R}^n$ with

$$y^T \nabla_x c_i(x^*) = 0 \quad i = 1, \dots, m_e, \quad \text{and } \forall i \in m_e + 1, \dots, m; \lambda_i^* > 0$$

satisfies

$$y^T \nabla_x^2 L(x^*, \lambda^*) y > 0$$

In practice, you cannot expect the constraint functions $c_i(x^*)$ to vanish within machine precision, and determining the set of active constraints at the solution x^* might not be simple.

Definition of Return Codes

The return code, which is represented by the output parameter rc in the optimization subroutines, indicates the reason for optimization termination. A positive value indicates successful termination, while a negative value indicates unsuccessful termination. Table 14.1 gives the reason for termination associated with each return code.

Table 14.1 Summary of Return Codes

Code	Reason for Optimization Termination
1	ABSTOL criterion satisfied (absolute F convergence)
2	ABSFTOL criterion satisfied (absolute F convergence)
3	ABSGTOL criterion satisfied (absolute G convergence)
4	ABSXTOL criterion satisfied (absolute X convergence)
5	FTOL criterion satisfied (relative F convergence)
6	GTOL criterion satisfied (relative G convergence)
7	XTOL criterion satisfied (relative X convergence)
8	FTOL2 criterion satisfied (relative F convergence)
9	GTOL2 criterion satisfied (relative G convergence)
10	n linear independent constraints are active at xr and none of them could be released to improve the function value
-1	objective function cannot be evaluated at starting point
-2	derivatives cannot be evaluated at starting point
-3	objective function cannot be evaluated during iteration
-4	derivatives cannot be evaluated during iteration
-5	optimization subroutine cannot improve the function value (this is a very general formulation and is used for various circumstances)
-6	there are problems in dealing with linearly dependent active constraints (changing the LCSING value in the <i>par</i> vector can be helpful)
-7	optimization process stepped outside the feasible region and the algorithm to return inside the feasible region was not successful (changing the LCEPS value in the <i>par</i> vector can be helpful)
-8	either the number of iterations or the number of function calls is larger than the prespecified values in the <i>tc</i> vector (MAXIT and MAXFU)
-9	this return code is temporarily not used (it is used in PROC NLP where it indicates that more CPU than a prespecified value was used)
-10	a feasible starting point cannot be computed

Objective Function and Derivatives

The input argument *fun* refers to an IML module that specifies a function that returns f , a vector of length m for least squares subroutines or a scalar for other optimization subroutines. The returned f contains the values of the objective function (or the least squares functions) at the point x . Note that for least squares problems, you must specify the number of function values, m , with the first element of the *opt* argument to allocate memory for the return vector. All the modules that you can specify as input arguments (“*fun*,” “*grd*,” “*hes*,” “*jac*,” “*nlc*,” “*jacnlc*,” and “*ptit*”) accept only a single input argument, x , which is the parameter vector. Using the GLOBAL clause, you can provide more input arguments for these modules. Refer to the section “[Numerical Considerations](#)” on page 378 for an example.

All the optimization algorithms assume that f is continuous inside the feasible region. For nonlinearly constrained optimization, this is also required for points outside the feasible region. Sometimes the objective function cannot be computed for all points of the specified feasible region; for example, the function specification might contain the SQRT or LOG function, which cannot be evaluated for negative arguments.

You must make sure that the function and derivatives of the starting point can be evaluated. There are two ways to prevent large steps into infeasible regions of the parameter space during the optimization process:

- The preferred way is to restrict the parameter space by introducing more boundary and linear constraints. For example, the boundary constraint $x_j \geq 1\text{E}-10$ prevents infeasible evaluations of $\log(x_j)$. If the function module takes the square root or the log of an intermediate result, you can use nonlinear constraints to try to avoid infeasible function evaluations. However, this might not ensure feasibility.
- Sometimes the preferred way is difficult to practice, in which case the function module can return a missing value. This can force the optimization algorithm to reduce the step length or the radius of the feasible region.

All the optimization techniques except the NLPNMS subroutine require continuous first-order derivatives of the objective function f . The NLPTR, NLPNRA, and NLPNRR techniques also require continuous second-order derivatives. If you do not provide the derivatives with the IML modules “*grd*,” “*hes*,” or “*jac*,” they are automatically approximated by finite-difference formulas. Approximating first-order derivatives by finite differences usually requires n additional calls of the function module. Approximating second-order derivatives by finite differences using only function calls can be extremely computationally expensive. Hence, if you decide to use the NLPTR, NLPNRA, or NLPNRR subroutines, you should specify at least analytical first-order derivatives. Then, approximating second-order derivatives by finite differences requires only n or $2n$ additional calls of the function and gradient modules.

For all input and output arguments, the subroutines assume that

- the number of parameters n corresponds to the number of columns. For example, x , the input argument to the modules, and g , the output argument returned by the “*grd*” module, are row vectors with n entries, and G , the Hessian matrix returned by the “*hes*” module, must be a symmetric $n \times n$ matrix.
- the number of functions, m , corresponds to the number of rows. For example, the vector f returned by the “*fun*” module must be a column vector with m entries, and in least squares problems, the Jacobian matrix J returned by the “*jac*” module must be an $m \times n$ matrix.

You can verify your analytical derivative specifications by computing finite-difference approximations of the derivatives of f with the NLPFDD subroutine. For most applications, the finite-difference approximations of the derivatives are very precise. Occasionally, difficult objective functions and zero x coordinates cause problems. You can use the *par* argument to specify the number of accurate digits in the evaluation of the objective function; this defines the step size h of the first- and second-order finite-difference formulas. See the section “[Finite-Difference Approximations of Derivatives](#)” on page 352.

NOTE: For some difficult applications, the finite-difference approximations of derivatives that are generated by default might not be precise enough to solve the optimization or least squares problem. In such cases, you might be able to specify better derivative approximations by using a better approximation formula. You can submit your own finite-difference approximations by using the IML module “*grd*,” “*hes*,” “*jac*,” or “*jacnlc*.” See [Example 14.3](#) for an illustration.

In many applications, calculations used in the computation of f can help compute derivatives at the same point efficiently. You can save and reuse such calculations with the GLOBAL clause. As with many other

optimization packages, the subroutines call the “*grd*,” “*hes*,” or “*jac*” modules only after a call of the “*fun*” module.

The following statements specify modules for the function, gradient, and Hessian matrix of the Rosenbrock problem:

```
proc iml;
  start F_ROSEN(x);
    y1 = 10. * (x[2] - x[1] * x[1]);
    y2 = 1. - x[1];
    f = .5 * (y1 * y1 + y2 * y2);
    return(f);
  finish F_ROSEN;

  start G_ROSEN(x);
    g = j(1,2,0.);
    g[1] = -200.*x[1]*(x[2]-x[1]*x[1]) - (1.-x[1]);
    g[2] = 100.*(x[2]-x[1]*x[1]);
    return(g);
  finish G_ROSEN;

  start H_ROSEN(x);
    h = j(2,2,0.);
    h[1,1] = -200.*(x[2] - 3.*x[1]*x[1]) + 1.;
    h[2,2] = 100.;
    h[1,2] = -200. * x[1];
    h[2,1] = h[1,2];
    return(h);
  finish H_ROSEN;
```

The following statements specify a module for the Rosenbrock function when considered as a least squares problem. They also specify the Jacobian matrix of the least squares functions.

```
proc iml;
  start F_ROSEN(x);
    y = j(1,2,0.);
    y[1] = 10. * (x[2] - x[1] * x[1]);
    y[2] = 1. - x[1];
    return(y);
  finish F_ROSEN;

  start J_ROSEN(x);
    jac = j(2,2,0.);
    jac[1,1] = -20. * x[1]; jac[1,2] = 10.;
    jac[2,1] = -1.;          jac[2,2] = 0.;
    return(jac);
  finish J_ROSEN;
```

Diagonal or Sparse Hessian Matrices

In the unconstrained or only boundary constrained case, the NLPNRA algorithm can take advantage of diagonal or sparse Hessian matrices submitted by the “*hes*” module. If the Hessian matrix G of the objective function f has a large proportion of zeros, you can save computer time and memory by specifying a sparse Hessian of dimension $nn \times 3$ rather than a dense $n \times n$ Hessian. Each of the nn rows (i, j, g) of the matrix returned by the sparse Hessian module defines a nonzero element g_{ij} of the Hessian matrix. The row and column location is given by i and j , and g gives the nonzero value. During the optimization process, only the values g can be changed in each call of the Hessian module “*hes*,” the sparsity structure (i, j) must be kept the same. That means that some of the values g can be zero for particular values of x . To allocate sufficient memory before the first call of the Hessian module, you must specify the number of rows, nn , by setting the ninth element of the *opt* argument.

Example 22 of Moré, Garbow, and Hillstom (1981) illustrates the sparse Hessian module input. The objective function, which is the Extended Powell’s Singular Function, for $n = 40$ is a least squares problem:

$$f(x) = \frac{1}{2} \{f_1^2(x) + \cdots + f_m^2(x)\}$$

with

$$\begin{aligned} f_{4i-3}(x) &= x_{4i-3} + 10x_{4i-2} \\ f_{4i-2}(x) &= \sqrt{5}(x_{4i-1} - x_{4i}) \\ f_{4i-1}(x) &= (x_{4i-2} - 2x_{4i-1})^2 \\ f_{4i}(x) &= \sqrt{10}(x_{4i-3} - x_{4i})^2 \end{aligned}$$

The function and gradient modules are as follows:

```
start f_nlp22(x);
  n=ncol(x);
  f = 0.;
  do i=1 to n-3 by 4;
    f1 = x[i] + 10. * x[i+1];
    r2 = x[i+2] - x[i+3];
    f2 = 5. * r2;
    r3 = x[i+1] - 2. * x[i+2];
    f3 = r3 * r3;
    r4 = x[i] - x[i+3];
    f4 = 10. * r4 * r4;
    f = f + f1 * f1 + r2 * f2 + f3 * f3 + r4 * r4 * f4;
  end;
  f = .5 * f;
  return(f);
finish f_nlp22;

start g_nlp22(x);
  n=ncol(x);
  g = j(1,n,0.);
  do i=1 to n-3 by 4;
    f1 = x[i] + 10. * x[i+1];
    f2 = 5. * (x[i+2] - x[i+3]);
```

```

    r3 = x[i+1] - 2. * x[i+2];
    f3 = r3 * r3;
    r4 = x[i] - x[i+3];
    f4 = 10. * r4 * r4;
    g[i] = f1 + 2. * r4 * f4;
    g[i+1] = 10. * f1 + 2. * r3 * f3;
    g[i+2] = f2 - 4. * r3 * f3;
    g[i+3] = -f2 - 2. * r4 * f4;
end;
return(g);
finish g_nlp22;

```

You can specify the sparse Hessian with the following module:

```

start hs_nlp22(x);
  n=ncol(x);
  nnz = 8 * (n / 4);
  h = j(nnz,3,0.);
  j = 0;
  do i=1 to n-3 by 4;
    f1 = x[i] + 10. * x[i+1];
    f2 = 5. * (x[i+2] - x[i+3]);
    r3 = x[i+1] - 2. * x[i+2];
    f3 = r3 * r3;
    r4 = x[i] - x[i+3];
    f4 = 10. * r4 * r4;
    j= j + 1; h[j,1] = i; h[j,2] = i;
    h[j,3] = 1. + 4. * f4;
    h[j,3] = h[j,3] + 2. * f4;
    j= j+1; h[j,1] = i; h[j,2] = i+1;
    h[j,3] = 10.;
    j= j+1; h[j,1] = i; h[j,2] = i+3;
    h[j,3] = -4. * f4;
    h[j,3] = h[j,3] - 2. * f4;
    j= j+1; h[j,1] = i+1; h[j,2] = i+1;
    h[j,3] = 100. + 4. * f3;
    h[j,3] = h[j,3] + 2. * f3;
    j= j+1; h[j,1] = i+1; h[j,2] = i+2;
    h[j,3] = -8. * f3;
    h[j,3] = h[j,3] - 4. * f3;
    j= j+1; h[j,1] = i+2; h[j,2] = i+2;
    h[j,3] = 5. + 16. * f3;
    h[j,3] = h[j,3] + 8. * f3;
    j= j+1; h[j,1] = i+2; h[j,2] = i+3;
    h[j,3] = -5.;
    j= j+1; h[j,1] = i+3; h[j,2] = i+3;
    h[j,3] = 5. + 4. * f4;
    h[j,3] = h[j,3] + 2. * f4;
  end;
  return(h);
finish hs_nlp22;

n = 40;

```

```

x = j(1,n,0.);
do i=1 to n-3 by 4;
    x[i] = 3.; x[i+1] = -1.; x[i+3] = 1.;
end;
opt = j(1,11,.); opt[2]= 3; opt[9]= 8 * (n / 4);
call nlpnra(xr,rc,"f_nlp22",x,opt) grd="g_nlp22" hes="hs_nlp22";

```

NOTE: If the sparse form of Hessian defines a diagonal matrix (that is, $i = j$ in all nn rows), the NLPNRA algorithm stores and processes a diagonal matrix G . If you do not specify any general linear constraints, the NLPNRA subroutine uses only order n memory.

Finite-Difference Approximations of Derivatives

If the optimization technique needs first- or second-order derivatives and you do not specify the corresponding IML module “*grd*,” “*hes*,” “*jac*,” or “*jacnlc*,” the derivatives are approximated by finite-difference formulas using only calls of the module “*fun*.” If the optimization technique needs second-order derivatives and you specify the “*grd*” module but not the “*hes*” module, the subroutine approximates the second-order derivatives by finite differences using n or $2n$ calls of the “*grd*” module.

The eighth element of the *opt* argument specifies the type of finite-difference approximation used to compute first- or second-order derivatives and whether the finite-difference intervals, h , should be computed by an algorithm of Gill et al. (1983). The value of *opt*[8] is a two-digit integer, ij .

- If *opt*[8] is missing or $j = 0$, the fast but not very precise forward-difference formulas are used; if $j \neq 0$, the numerically more expensive central-difference formulas are used.
- If *opt*[8] is missing or $i \neq 1, 2$, or 3, the finite-difference intervals h are based only on the information of *par*[8] or *par*[9], which specifies the number of accurate digits to use in evaluating the objective function and nonlinear constraints, respectively. If $i = 1, 2$, or 3, the intervals are computed with an algorithm by Gill et al. (1983). For $i = 1$, the interval is based on the behavior of the objective function; for $i = 2$, the interval is based on the behavior of the nonlinear constraint functions; and for $i = 3$, the interval is based on the behavior of both the objective function and the nonlinear constraint functions.

Forward-Difference Approximations

- First-order derivatives: n additional function calls are needed.

$$g_i = \frac{\partial f}{\partial x_i} = \frac{f(x + h_i e_i) - f(x)}{h_i}$$

- Second-order derivatives based on function calls only, when the “*grd*” module is not specified (Dennis and Schnabel 1983): for a dense Hessian matrix, $n + n^2/2$ additional function calls are needed.

$$\frac{\partial^2 f}{\partial x_i \partial x_j} = \frac{f(x + h_i e_i + h_j e_j) - f(x + h_i e_i) - f(x + h_j e_j) + f(x)}{h_i h_j}$$

- Second-order derivatives based on gradient calls, when the “*grd*” module is specified (Dennis and Schnabel 1983): n additional gradient calls are needed.

$$\frac{\partial^2 f}{\partial x_i \partial x_j} = \frac{g_i(x + h_j e_j) - g_i(x)}{2h_j} + \frac{g_j(x + h_i e_i) - g_j(x)}{2h_i}$$

Central-Difference Approximations

- First-order derivatives: $2n$ additional function calls are needed.

$$g_i = \frac{\partial f}{\partial x_i} = \frac{f(x + h_i e_i) - f(x - h_i e_i)}{2h_i}$$

- Second-order derivatives based on function calls only, when the “*grd*” module is not specified (Abramowitz and Stegun 1972): for a dense Hessian matrix, $2n + 2n^2$ additional function calls are needed.

$$\begin{aligned} \frac{\partial^2 f}{\partial x_i^2} &= \frac{-f(x + 2h_i e_i) + 16f(x + h_i e_i) - 30f(x) + 16f(x - h_i e_i) - f(x - 2h_i e_i)}{12h_i^2} \\ \frac{\partial^2 f}{\partial x_i \partial x_j} &= \frac{f(x + h_i e_i + h_j e_j) - f(x + h_i e_i - h_j e_j) - f(x - h_i e_i + h_j e_j) + f(x - h_i e_i - h_j e_j)}{4h_i h_j} \end{aligned}$$

- Second-order derivatives based on gradient calls, when the “*grd*” module is specified: $2n$ additional gradient calls are needed.

$$\frac{\partial^2 f}{\partial x_i \partial x_j} = \frac{g_i(x + h_j e_j) - g_i(x - h_j e_j)}{4h_j} + \frac{g_j(x + h_i e_i) - g_j(x - h_i e_i)}{4h_i}$$

The step sizes h_j , $j = 1, \dots, n$, are defined as follows:

- For the forward-difference approximation of first-order derivatives using only function calls and for second-order derivatives using only gradient calls, $h_j = \sqrt[3]{\eta_j}(1 + |x_j|)$.
- For the forward-difference approximation of second-order derivatives using only function calls and for central-difference formulas, $h_j = \sqrt[3]{\eta_j}(1 + |x_j|)$.

If the algorithm of Gill et al. (1983) is not used to compute η_j , a constant value $\eta = \eta_j$ is used depending on the value of *par*[8].

- If the number of accurate digits is specified by *par*[8] = k_1 , then η is set to 10^{-k_1} .
- If *par*[8] is not specified, η is set to the machine precision, ϵ .

If central-difference formulas are not specified, the optimization algorithm switches automatically from the forward-difference formula to a corresponding central-difference formula during the iteration process if one of the following two criteria is satisfied:

- The absolute maximum gradient element is less than or equal to 100 times the ABSGTOL threshold.
- The term on the left of the GTOL criterion is less than or equal to $\max(1\text{E}-6, 100 \times \text{GTOL threshold})$. The $1\text{E}-6$ ensures that the switch is performed even if you set the GTOL threshold to zero.

The algorithm of Gill et al. (1983) that computes the finite-difference intervals h_j can be very expensive in the number of function calls it uses. If this algorithm is required, it is performed twice, once before the optimization process starts and once after the optimization terminates.

Many applications need considerably more time for computing second-order derivatives than for computing first-order derivatives. In such cases, you should use a quasi-Newton or conjugate gradient technique.

If you specify a vector, c , of nc nonlinear constraints with the “*nlc*” module but you do not specify the “*jacnlc*” module, the first-order formulas can be used to compute finite-difference approximations of the $nc \times n$ Jacobian matrix of the nonlinear constraints.

$$(\nabla c_i) = \left(\frac{\partial c_i}{\partial x_j} \right), \quad i = 1, \dots, nc, \quad j = 1, \dots, n$$

You can specify the number of accurate digits in the constraint evaluations with *par*[9]. This specification also defines the step sizes h_j , $j = 1, \dots, n$.

NOTE: If you are not able to specify analytic derivatives and if the finite-difference approximations provided by the subroutines are not good enough to solve your optimization problem, you might be able to implement better finite-difference approximations with the “*grd*,” “*hes*,” “*jac*,” and “*jacnlc*” module arguments.

Parameter Constraints

You can specify constraints in the following ways:

- The matrix input argument “*bld*” enables you to specify boundary and general linear constraints.
- The IML module input argument “*nld*” enables you to specify general constraints, particularly nonlinear constraints.

Specifying the BLC Matrix

The input argument “*bld*” specifies an $n_1 \times n_2$ constraint matrix, where n_1 is two more than the number of linear constraints, and n_2 is given by

$$n_2 = \begin{cases} n & \text{if } 1 \leq n_1 \leq 2 \\ n + 2 & \text{if } n_1 > 2 \end{cases}$$

The first two rows define lower and upper bounds for the n parameters, and the remaining $c = n_1 - 2$ rows define general linear equality and inequality constraints. Missing values in the first row (lower bounds) substitute for the largest negative floating point value, and missing values in the second row (upper bounds)

substitute for the largest positive floating point value. Columns $n + 1$ and $n + 2$ of the first two rows are not used.

The following c rows of the “*bld*” argument specify c linear equality or inequality constraints:

$$\sum_{j=1}^n a_{ij} x_j \quad (\leq \mid = \mid \geq) \quad b_i, \quad i = 1, \dots, c$$

Each of these c rows contains the coefficients a_{ij} in the first n columns. Column $n + 1$ specifies the kind of constraint, as follows:

- $bld[n + 1] = 0$ indicates an equality constraint.
- $bld[n + 1] = 1$ indicates a \geq inequality constraint.
- $bld[n + 1] = -1$ indicates a \leq inequality constraint.

Column $n + 2$ specifies the right-hand side, b_i . A missing value in any of these rows corresponds to a value of zero.

For example, suppose you have a problem with the following constraints on x_1, x_2, x_3, x_4 :

$$\begin{array}{rcl} 2 & \leq & x_1 \leq 100 \\ & & x_2 \leq 40 \\ 0 & \leq & x_4 \end{array}$$

$$\begin{array}{rcllcl} 4x_1 & + & 3x_2 & - & x_3 & \leq & 30 \\ & & x_2 & & & + & 6x_4 \geq 17 \\ x_1 & - & x_2 & & & = & 8 \end{array}$$

The following statements specify the matrix CON, which can be used as the “*bld*” argument to specify the preceding constraints:

```
proc iml;
  con = { 2   .   .   0   .   . ,
          100 40   .   .   .   . ,
           4   3  -1   .  -1  30 ,
           .   1   .   6   1  17 ,
           1  -1   .   .   0   8  };;
```

Specifying the NLC and JACNLC Modules

The input argument “*nld*” specifies an IML module that returns a vector, c , of length nc , with the values, c_i , of the nc linear or nonlinear constraints

$$\begin{array}{ll} c_i(x) & = 0, \quad i = 1, \dots, nec \\ c_i(x) & \geq 0, \quad i = nec + 1, \dots, nc \end{array}$$

for a given input parameter point x .

NOTE: You must specify the number of equality constraints, nec , and the total number of constraints, nc , returned by the “*nlc*” module to allocate memory for the return vector. You can do this with the *opt*[11] and *opt*[10] arguments, respectively.

For example, consider the problem of minimizing the objective function $f(x_1, x_2) = x_1 x_2$ in the interior of the unit circle, $x_1^2 + x_2^2 \leq 1$. The constraint can also be written as $c_1(x) = 1 - x_1^2 - x_2^2 \geq 0$. The following statements specify modules for the objective and constraint functions and call the NLPNMS subroutine to solve the minimization problem:

```
proc iml;
  start F_UC2D(x);
    f = x[1] * x[2];
    return(f);
  finish F_UC2D;

  start C_UC2D(x);
    c = 1. - x * x`;
    return(c);
  finish C_UC2D;

  x = j(1,2,1.);
  optn= j(1,10,.); optn[2]= 3; optn[10]= 1;
  CALL NLPNMS(rc,xres,"F_UC2D",x,optn) nlc="C_UC2D";
```

To avoid typing multiple commas, you can specify the “*nlc*” input argument with a keyword, as in the preceding code. The number of elements of the return vector is specified by *OPTN*[10] = 1. There is a missing value in *OPTN*[11], so the subroutine assumes there are zero equality constraints.

The NLPQN algorithm uses the $nc \times n$ Jacobian matrix of first-order derivatives

$$(\nabla_x c_i(x)) = \left(\frac{\partial c_i}{\partial x_j} \right), \quad i = 1, \dots, nc, \quad j = 1, \dots, n$$

of the nc equality and inequality constraints, c_i , for each point passed during the iteration. You can use the “*jacnlc*” argument to specify an IML module that returns the Jacobian matrix **JC**. If you specify the “*nlc*” module without using the “*jacnlc*” argument, the subroutine uses finite-difference approximations of the first-order derivatives of the constraints.

NOTE: The COBYLA algorithm in the NLPNMS subroutine and the NLPQN subroutine are the only optimization techniques that enable you to specify nonlinear constraints with the “*nlc*” input argument.

Options Vector

The options vector, represented by the “*opt*” argument, enables you to specify a variety of options, such as the amount of printed output or particular update or line-search techniques. Table 14.2 gives a summary of the available options.

Table 14.2 Summary of the Elements of the Options Vector

Index	Description
1	specifies minimization, maximization, or the number of least squares functions
2	specifies the amount of printed output
3	NLPDD, NLPLM, NLPNRA, NLPNRR, NLPTR: specifies the scaling of the Hessian matrix (HESCAL)
4	NLPCG, NLPDD, NLPHQN, NLPQN: specifies the update technique (UPDATE)
5	NLPCG, NLPHQN, NLPNRA, NLPQN (with no nonlinear constraints): specifies the line-search technique (LIS)
6	NLPHQN: specifies version of hybrid algorithm (VERSION) NLPQN with nonlinear constraints: specifies version of μ update
7	NLPDD, NLPHQN, NLPQN: specifies initial Hessian matrix (INHES- SIAN)
8	Finite-Difference Derivatives: specifies type of differences and how to compute the difference interval
9	NLPNRA: specifies the number of rows returned by the sparse Hessian module
10	NLPNMS, NLPQN: specifies the total number of constraints returned by the “ <i>nlc</i> ” module
11	NLPNMS, NLPQN: specifies the number of equality constraints returned by the “ <i>nlc</i> ” module

The following list contains detailed explanations of the elements of the options vector:

- **opt[1]**

indicates whether the problem is minimization or maximization. The default, $opt[1] = 0$, specifies a minimization problem, and $opt[1] = 1$ specifies a maximization problem. For least squares problems, $opt[1] = m$ specifies the number of functions or observations, which is the number of values returned by the “*fun*” module. This information is necessary to allocate memory for the return vector of the “*fun*” module.

- **opt[2]**

specifies the amount of output printed by the subroutine. The higher the value of $opt[2]$, the more printed output is produced. The following table indicates the specific items printed for each value.

Value of <i>opt</i> [2]	Printed Output
0	No printed output is produced. This is the default.
1	The summaries for optimization start and termination are produced, as well as the iteration history.
2	The initial and final parameter estimates are also printed.
3	The values of the termination criteria and other control parameters are also printed.
4	The parameter vector, x , is also printed after each iteration.
5	The gradient vector, g , is also printed after each iteration.

- **opt[3]**

selects a scaling for the Hessian matrix, \mathbf{G} . This option is relevant only for the NLPDD, NLPLM, NLPNRA, NLPNRR, and NLPTR subroutines. If $\text{opt}[3] \neq 0$, the first iteration and each restart iteration set the diagonal scaling matrix $\mathbf{D}^{(0)} = \text{diag}(d_i^{(0)})$, where

$$d_i^{(0)} = \sqrt{\max(|G_{i,i}^{(0)}|, \epsilon)}$$

and $G_{i,i}^{(0)}$ are the diagonal elements of the Hessian matrix, and ϵ is the machine precision. The diagonal scaling matrix $\mathbf{D}^{(0)} = \text{diag}(d_i^{(0)})$ is updated as indicated in the following table.

Value of <i>opt</i> [3]	Scaling Update
0	No scaling is done.
1	Moré (1978) scaling update: $d_i^{(k+1)} = \max\left(d_i^{(k)}, \sqrt{\max(G_{i,i}^{(k)} , \epsilon)}\right)$
2	Dennis, Gay, and Welsch (1981) scaling update: $d_i^{(k+1)} = \max\left(0.6 * d_i^{(k)}, \sqrt{\max(G_{i,i}^{(k)} , \epsilon)}\right)$
3	d_i is reset in each iteration: $d_i^{(k+1)} = \sqrt{\max(G_{i,i}^{(k)} , \epsilon)}$

For the NLPDD, NLPNRA, NLPNRR, and NLPTR subroutines, the default is $\text{opt}[3] = 0$; for the NLPLM subroutine, the default is $\text{opt}[3] = 1$.

- **opt[4]**

defines the update technique for (dual) quasi-Newton and conjugate gradient techniques. This option applies to the NLPCG, NLPDD, NLPHQN, and NLPQN subroutines. For the NLPCG subroutine, the following update techniques are available.

Value of <i>opt</i> [4]	Update Method for NLPCG
1	automatic restart method of Powell (1977) and Beale (1972). This is the default.
2	Fletcher-Reeves update (Fletcher 1987)
3	Polak-Ribiere update (Fletcher 1987)
4	conjugate-descent update of Fletcher (1987)

For the unconstrained or linearly constrained NLPQN subroutine, the following update techniques are available.

Value of <i>opt</i> [4]	Update Method for NLPQN
1	dual Broyden, Fletcher, Goldfarb, and Shanno (DBFGS) update of the Cholesky factor of the Hessian matrix. This is the default.
2	dual Davidon, Fletcher, and Powell (DDFP) update of the Cholesky factor of the Hessian matrix
3	original Broyden, Fletcher, Goldfarb, and Shanno (BFGS) update of the inverse Hessian matrix
4	original Davidon, Fletcher, and Powell (DFP) update of the inverse Hessian matrix

For the NLPQN subroutine used with the “*nlc*” module and for the NLPDD and NLPHQN subroutines, only the first two update techniques in the second table are available.

- **opt[5]**

defines the line-search technique for the unconstrained or linearly constrained NLPQN subroutine, as well as the NLPCG, NLPHQN, and NLPNRA subroutines. Refer to Fletcher (1987) for an introduction to line-search techniques. The following table describes the available techniques.

Value of <i>opt</i> [5]	Line-Search Method
1	This method needs the same number of function and gradient calls for cubic interpolation and cubic extrapolation; it is similar to a method used by the Harwell subroutine library.
2	This method needs more function than gradient calls for quadratic and cubic interpolation and cubic extrapolation; it is implemented as shown in Fletcher (1987) and can be modified to exact line search with the <i>par</i> [6] argument (see the section “ Control Parameters Vector ” on page 367). This is the default for the NLPCG, NLPNRA, and NLPQN subroutines.
3	This method needs the same number of function and gradient calls for cubic interpolation and cubic extrapolation; it is implemented as shown in Fletcher (1987) and can be modified to exact line search with the <i>par</i> [6] argument.
4	This method needs the same number of function and gradient calls for stepwise extrapolation and cubic interpolation.
5	This method is a modified version of the <i>opt</i> [5]=4 method.
6	This method is the golden section line search of Polak (1971), which uses only function values for linear approximation.
7	This method is the bisection line search of Polak (1971), which uses only function values for linear approximation.
8	This method is the Armijo line-search technique of Polak (1971), which uses only function values for linear approximation.

For the NLPHQN least squares subroutine, the default is a special line-search method that is based on an algorithm developed by Lindström and Wedin (1984). Although it needs more memory, this method sometimes works better with large least squares problems.

- **opt[6]**

is used only for the NLPHQN subroutine and the NLPQN subroutine with nonlinear constraints.

In the NLPHQN subroutine, it defines the criterion for the decision of the hybrid algorithm to step in a Gauss-Newton or a quasi-Newton search direction. You can specify one of the three criteria that correspond to the methods of Fletcher and Xu (1987). The methods are HY1 (*opt*[6]=1), HY2 (*opt*[6]=2), and HY3 (*opt*[6]=3), and the default is HY2.

In the NLPQN subroutine with nonlinear constraints, it defines the version of the algorithm used to update the vector μ of the Lagrange multipliers. The default is *opt*[6]=2, which specifies the approach of Powell (1982a) and Powell (1982b). You can specify the approach of Powell (1978a) with *opt*[6]=1.

- **opt[7]**

defines the type of start matrix, $G^{(0)}$, used for the Hessian approximation. This option applies only to

the NLPDD, NLPHQN, and NLPQN subroutines. If $opt[7]=0$, which is the default, the quasi-Newton algorithm starts with a multiple of the identity matrix where the scalar factor depends on $par[10]$; otherwise, it starts with the Hessian matrix computed at the starting point $x^{(0)}$.

- **opt[8]**

defines the type of finite-difference approximation used to compute first- or second-order derivatives and whether the finite-difference intervals, h , should be computed by using an algorithm of Gill et al. (1983). The value of $opt[8]$ is a two-digit integer, ij .

If $opt[8]$ is missing or $j = 0$, the fast but not very precise forward difference formulas are used; if $j \neq 0$, the numerically more expensive central-difference formulas are used.

If $opt[8]$ is missing or $i \neq 1, 2$, or 3 , the finite-difference intervals h are based only on the information of $par[8]$ or $par[9]$, which specifies the number of accurate digits to use in evaluating the objective function and nonlinear constraints, respectively. If $i = 1, 2$, or 3 , the intervals are computed with an algorithm by Gill et al. (1983). For $i = 1$, the interval is based on the behavior of the objective function; for $i = 2$, the interval is based on the behavior of the nonlinear constraint functions; and for $i = 3$, the interval is based on the behavior of both the objective function and the nonlinear constraint functions.

The algorithm of Gill et al. (1983) that computes the finite-difference intervals h_j can be very expensive in the number of function calls it uses. If this algorithm is required, it is performed twice, once before the optimization process starts and once after the optimization terminates. See the section “Finite-Difference Approximations of Derivatives” on page 352 for details.

- **opt[9]**

indicates that the Hessian module “*hes*” returns a sparse definition of the Hessian, in the form of an $nn \times 3$ matrix instead of the default dense $n \times n$ matrix. If $opt[9]$ is zero or missing, the Hessian module must return a dense $n \times n$ matrix. If you specify $opt[9] = nn$, the module must return a sparse $nn \times 3$ table. See the section “Objective Function and Derivatives” on page 347 for more details. This option applies only to the NLPNRA algorithm. If the dense specification contains a large proportion of analytical zero derivatives, the sparse specification can save memory and computer time.

- **opt[10]**

specifies the total number of nonlinear constraints returned by the “*nlc*” module. If you specify nc nonlinear constraints with the “*nlc*” argument module, you must specify $opt[10] = nc$ to allocate memory for the return vector.

- **opt[11]**

specifies the number of nonlinear equality constraints returned by the “*nlc*” module. If the first nec constraints are equality constraints, you must specify $opt[11] = nec$. The default value is $opt[11] = 0$.

Termination Criteria

The input argument tc specifies a vector of bounds that correspond to a set of termination criteria that are tested in each iteration. If you do not specify an IML module with the “*ptit*” argument, these bounds

determine when the optimization process stops.

If you specify the “*ptit*” argument, the “*tc*” argument is ignored. The module specified by the “*ptit*” argument replaces the subroutine that is used by default to test the termination criteria. The module is called in each iteration with the current location, x , and the value, f , of the objective function at x . The module must give a return code, rc , that decides whether the optimization process is to be continued or terminated. As long as the module returns $rc = 0$, the optimization process continues. When the module returns $rc \neq 0$, the optimization process stops.

If you use the tc vector, the optimization techniques stop the iteration process when at least one of the corresponding set of termination criteria are satisfied. Table 14.3 and Table 14.4 indicate the criterion associated with each element of the tc vector. There is a default for each criterion, and if you specify a missing value for the corresponding element of the tc vector, the default value is used. You can avoid termination with respect to the ABSFTOL, ABSGTOL, ABSXTOL, FTOL, FTOL2, GTOL, GTOL2, and XTOL criteria by specifying a value of zero for the corresponding element of the tc vector.

Table 14.3 Termination Criteria for the NLPNMS Subroutine

Index	Description
1	maximum number of iterations (MAXIT)
2	maximum number of function calls (MAXFU)
3	absolute function criterion (ABSTOL)
4	relative function criterion (FTOL)
5	relative function criterion (FTOL2)
6	absolute function criterion (ABSFTOL)
7	FSIZE value used in FTOL criterion
8	relative parameter criterion (XTOL)
9	absolute parameter criterion (ABSXTOL)
9	size of final trust-region radius ρ (COBYLA algorithm)
10	XSIZE value used in XTOL criterion

Table 14.4 Termination Criteria for Other Subroutines

Index	Description
1	maximum number of iterations (MAXIT)
2	maximum number of function calls (MAXFU)
3	absolute function criterion (ABSTOL)
4	relative gradient criterion (GTOL)
5	relative gradient criterion (GTOL2)
6	absolute gradient criterion (ABSGTOL)
7	relative function criterion (FTOL)
8	predicted function reduction criterion (FTOL2)
9	absolute function criterion (ABSFTOL)
10	FSIZE value used in GTOL and FTOL criterion
11	relative parameter criterion (XTOL)
12	absolute parameter criterion (ABSXTOL)
13	XSIZE value used in XTOL criterion

Criteria Used by All Techniques

The following list indicates the termination criteria that are used with all the optimization techniques:

- **tc[1]**
specifies the maximum number of iterations in the optimization process (MAXIT). The default values are

NLPNMS:	MAXIT=1000
NLPCG:	MAXIT=400
Others:	MAXIT=200
- **tc[2]**
specifies the maximum number of function calls in the optimization process (MAXFU). The default values are

NLPNMS:	MAXFU=3000
NLPCG:	MAXFU=1000
Others:	MAXFU=500
- **tc[3]**
specifies the absolute function convergence criterion (ABSTOL). For minimization, termination requires $f^{(k)} = f(x^{(k)}) \leq ABSTOL$, while for maximization, termination requires $f^{(k)} = f(x^{(k)}) \geq ABSTOL$. The default values are the negative and positive square roots of the largest double precision value, for minimization and maximization, respectively.

These criteria are useful when you want to divide a time-consuming optimization problem into a series of smaller problems.

Termination Criteria for NLPNMS

Since the Nelder-Mead simplex algorithm does not use derivatives, no termination criteria are available that are based on the gradient of the objective function.

When the NLPNMS subroutine implements Powell's COBYLA algorithm, it uses only one criterion other than the three used by all the optimization techniques. The COBYLA algorithm is a trust-region method that sequentially reduces the radius, ρ , of a spheric trust region from the start radius, ρ_{beg} , which is controlled with the *par[2]* argument, to the final radius, ρ_{end} , which is controlled with the *tc[9]* argument. The default value for *tc[9]* is $\rho_{end} = 1\text{E}-4$. Convergence to small values of ρ_{end} can take many calls of the function and constraint modules and might result in numerical problems.

In addition to the criteria used by all techniques, the original Nelder-Mead simplex algorithm uses several other termination criteria, which are described in the following list:

- **tc[4]**
specifies the relative function convergence criterion (FTOL). Termination requires a small relative difference between the function values of the vertices in the simplex with the largest and smallest function values.

$$\frac{|f_{hi}^{(k)} - f_{lo}^{(k)}|}{\max(|f_{hi}^{(k)}|, FSIZE)} \leq FTOL$$

where $FSIZE$ is defined by $tc[7]$. The default value is $tc[4] = 10^{-FDIGITS}$, where $FDIGITS$ is controlled by the $par[8]$ argument. The $par[8]$ argument has a default value of $\log_{10}(\epsilon)$, where ϵ is the machine precision. Hence, the default value for $FTOL$ is ϵ .

- **tc[5]**
specifies another relative function convergence criterion (FTOL2). Termination requires a small standard deviation of the function values of the $n + 1$ simplex vertices $x_0^{(k)}, \dots, x_n^{(k)}$.

$$\sqrt{\frac{1}{n+1} \sum_l (f(x_l^{(k)}) - \bar{f}(x^{(k)}))^2} \leq FTOL2$$

where $\bar{f}(x^{(k)}) = \frac{1}{n+1} \sum_l f(x_l^{(k)})$. If there are a active boundary constraints at $x^{(k)}$, the mean and standard deviation are computed only for the $n + 1 - a$ unconstrained vertices. The default is $tc[5] = 1E-6$.

- **tc[6]**
specifies the absolute function convergence criterion (ABSFTOL). Termination requires a small absolute difference between the function values of the vertices in the simplex with the largest and smallest function values.

$$|f_{hi}^{(k)} - f_{lo}^{(k)}| \leq ABSFTOL$$

The default is $tc[6] = 0$.

- **tc[7]**
specifies the $FSIZE$ value used in the FTOL termination criterion. The default is $tc[7] = 0$.

- **tc[8]**
specifies the relative parameter convergence criterion (XTOL). Termination requires a small relative parameter difference between the vertices with the largest and smallest function values.

$$\frac{\max_j |x_j^{lo} - x_j^{hi}|}{\max(|x_j^{lo}|, |x_j^{hi}|, XSIZE)} \leq XTOL$$

The default is $tc[8] = 1E-8$.

- **tc[9]**
specifies the absolute parameter convergence criterion (ABSXTOL). Termination requires either a small length, $\alpha^{(k)}$, of the vertices of a restart simplex or a small simplex size, $\delta^{(k)}$.

$$\begin{aligned} \alpha^{(k)} &\leq ABSXTOL \\ \delta^{(k)} &\leq ABSXTOL \end{aligned}$$

where $\delta^{(k)}$ is defined as the L1 distance of the simplex vertex with the smallest function value, $y^{(k)}$, to the other n simplex points, $x_l^{(k)} \neq y$.

$$\delta^{(k)} = \sum_{x_l \neq y} \|x_l^{(k)} - y^{(k)}\|_1$$

The default is $tc[9] = 1E-8$.

- **tc[10]**

specifies the XSIZE value used in the XTOL termination criterion. The default is $tc[10] = 0$.

Termination Criteria for Unconstrained and Linearly Constrained Techniques

- **tc[4]**

specifies the relative gradient convergence criterion (GTOL). For all techniques except the NLPCG subroutine, termination requires that the normalized predicted function reduction is small.

$$\frac{g(x^{(k)})^T [G^{(k)}]^{-1} g(x^{(k)})}{\max(|f(x^{(k)})|, FSIZE)} \leq GTOL$$

where $FSIZE$ is defined by $tc[10]$. For the NLPCG technique (where a reliable Hessian estimate is not available),

$$\frac{\|g(x^{(k)})\|_2^2 \|s(x^{(k)})\|_2}{\|g(x^{(k)}) - g(x^{(k-1)})\|_2 \max(|f(x^{(k)})|, FSIZE)} \leq GTOL$$

is used. The default is $tc[4] = 1E-8$.

- **tc[5]**

specifies another relative gradient convergence criterion (GTOL2). This criterion is used only by the NLPLM subroutine.

$$\max_j \frac{|g_j(x^{(k)})|}{\sqrt{f(x^{(k)}) G_{j,j}^{(k)}}} \leq GTOL2$$

The default is $tc[5]=0$.

- **tc[6]**

specifies the absolute gradient convergence criterion (ABSGTOL). Termination requires that the maximum absolute gradient element be small.

$$\max_j |g_j(x^{(k)})| \leq ABSGTOL$$

The default is $tc[6] = 1E-5$.

- **tc[7]**

specifies the relative function convergence criterion (FTOL). Termination requires a small relative change of the function value in consecutive iterations.

$$\frac{|f(x^{(k)}) - f(x^{(k-1)})|}{\max(|f(x^{(k-1)})|, FSIZE)} \leq FTOL$$

where $FSIZE$ is defined by $tc[10]$. The default is $tc[7] = 10^{-\text{FDIGITS}}$, where FDIGITS is controlled by the $par[8]$ argument. The $par[8]$ argument has a default value of $\log_{10}(\epsilon)$, where ϵ is the machine precision. Hence, the default for $FTOL$ is ϵ .

- **tc[8]**

specifies another function convergence criterion (FTOL2). For least squares problems, termination requires a small predicted reduction of the objective function, $df^{(k)} \approx f(x^{(k)}) - f(x^{(k)} + s^{(k)})$. The predicted reduction is computed by approximating the objective function by the first two terms of the Taylor series and substituting the Newton step, $s^{(k)} = -G^{(k)-1}g^{(k)}$, as follows:

$$\begin{aligned} df^{(k)} &= -g^{(k)T}s^{(k)} - \frac{1}{2}s^{(k)T}G^{(k)}s^{(k)} \\ &= -\frac{1}{2}s^{(k)T}g^{(k)} \\ &\leq FTOL2 \end{aligned}$$

The FTOL2 criterion is the unscaled version of the GTOL criterion. The default is $tc[8]=0$.

- **tc[9]**

specifies the absolute function convergence criterion (ABSFTOL). Termination requires a small change of the function value in consecutive iterations.

$$|f(x^{(k-1)}) - f(x^{(k)})| \leq ABSFTOL$$

The default is $tc[9]=0$.

- **tc[10]**

specifies the FSIZE value used in the GTOL and FTOL termination criteria. The default is $tc[10]=0$.

- **tc[11]**

specifies the relative parameter convergence criterion (XTOL). Termination requires a small relative parameter change in consecutive iterations.

$$\frac{\max_j |x_j^{(k)} - x_j^{(k-1)}|}{\max(|x_j^{(k)}|, |x_j^{(k-1)}|, XSIZE)} \leq XTOL$$

The default is $tc[11]=0$.

- **tc[12]**

specifies the absolute parameter convergence criterion (ABSXTOL). Termination requires a small Euclidean distance between parameter vectors in consecutive iterations.

$$\|x^{(k)} - x^{(k-1)}\|_2 \leq ABSXTOL$$

The default is $tc[12]=0$.

- **tc[13]**

specifies the XSIZE value used in the XTOL termination criterion. The default is $tc[13]=0$.

Termination Criteria for Nonlinearly Constrained Techniques

The only algorithm available for nonlinearly constrained optimization other than the NLPNMS subroutine is the NLPQN subroutine, when you specify the “*nlc*” module argument. This method, unlike the other optimization methods, does not monotonically reduce the value of the objective function or some kind of merit function that combines objective and constraint functions. Instead, the algorithm uses the watchdog technique with backtracking of Chamberlain et al. (1982). Therefore, no termination criteria are implemented that are based on the values x or f in consecutive iterations. In addition to the criteria used by all optimization techniques, there are three other termination criteria available; these are based on the Lagrange function

$$L(x, \lambda) = f(x) - \sum_{i=1}^m \lambda_i c_i(x)$$

and its gradient

$$\nabla_x L(x, \lambda) = g(x) - \sum_{i=1}^m \lambda_i \nabla_x c_i(x)$$

where m denotes the total number of constraints, $g = g(x)$ is the gradient of the objective function, and λ is the vector of Lagrange multipliers. The Kuhn-Tucker conditions require that the gradient of the Lagrange function is zero at the optimal point (x^*, λ^*) , as follows:

$$\nabla_x L(x^*, \lambda^*) = 0$$

- **tc[4]**

specifies the GTOL criterion, which requires that the normalized predicted function reduction be small.

$$\frac{|g(x^{(k)})^T s(x^{(k)})| + \sum_{i=1}^m |\lambda_i c_i(x^{(k)})|}{\max(|f(x^{(k)})|, FSIZE)} \leq GTOL$$

where $FSIZE$ is defined by the *tc*[10] argument. The default is *tc*[4] = 1E–8.

- **tc[6]**

specifies the ABSGTOL criterion, which requires that the maximum absolute gradient element of the Lagrange function be small.

$$\max_j |\{\nabla_x L(x^{(k)}, \lambda^{(k)})\}_j| \leq ABSGTOL$$

The default is *tc*[6] = 1E–5.

- **tc[8]**

specifies the FTOL2 criterion, which requires that the predicted function reduction be small.

$$|g(x^{(k)})^T s(x^{(k)})| + \sum_{i=1}^m |\lambda_i c_i| \leq FTOL2$$

The default is *tc*[8] = 1E–6. This is the criterion used by the programs VMCWD and VF02AD of Powell (1982b).

Control Parameters Vector

For all optimization and least squares subroutines, the input argument *par* specifies a vector of parameters that control the optimization process. For the NLPFDD and NLPFEA subroutines, the *par* argument is defined differently. For each element of the *par* vector there exists a default value, and if you specify a missing value, the default is used. Table 14.5 summarizes the uses of the *par* argument for the optimization and least squares subroutines.

Table 14.5 Summary of the Control Parameters Vector

Index	Description
1	specifies the singularity criterion (SINGULAR)
2	specifies the initial step length or trust-region radius
3	specifies the range for active (violated) constraints (LCEPS)
4	specifies the Lagrange multiplier threshold for constraints (LCDEACT)
5	specifies a criterion to determine linear dependence of constraints (LCS-ING)
6	specifies the required accuracy of the line-search algorithms (LSPRECI-SION)
7	reduces the line-search step size in successive iterations (DAMPSTEP)
8	specifies the number of accurate digits used in evaluating the objective function (FDIGITS)
9	specifies the number of accurate digits used in evaluating the nonlinear constraints (CDIGITS)
10	specifies a scalar factor for the diagonal of the initial Hessian (DIAHES)

- **par[1]**
specifies the singularity criterion for the decomposition of the Hessian matrix (SINGULAR). The value must be between zero and one, and the default is $par[1] = 1E-8$.
- **par[2]**
specifies different features depending on the subroutine in which it is used. In the NLPNMS subroutine, it defines the size of the start simplex. For the original Nelder-Mead simplex algorithm, the default value is $par[2] = 1$; for the COBYLA algorithm, the default is $par[2] = 0.5$. In the NLPCG, NLPQN, and NLPHQN subroutines, the *par[2]* argument specifies an upper bound for the initial step length for the line search during the first five iterations. The default initial step length is $par[2] = 1$. In the NLPTR, NLPDD, and NLPLM subroutines, the *par[2]* argument specifies a factor for the initial trust-region radius, Δ . For highly nonlinear functions, the default step length or trust-region radius can result in arithmetic overflows. In that case, you can specify stepwise decreasing values of *par[2]*, such as $par[2]=1E-1$, $par[2]=1E-2$, $par[2]=1E-4$, until the subroutine starts to iterate successfully.
- **par[3]**
specifies the range (LCEPS) for active and violated linear constraints. The *i*th constraint is considered

an active constraint if the point $x^{(k)}$ satisfies the condition

$$\left| \sum_{j=1}^n a_{ij} x_j^{(k)} - b_i \right| \leq LCEPS(|b_i| + 1)$$

where $LCEPS$ is the value of $par[3]$ and a_{ij} and b_i are defined as in the section “[Parameter Constraints](#)” on page 354. Otherwise, the constraint i is either an inactive inequality or a violated inequality or equality constraint. The default is $par[3] = 1E-8$. During the optimization process, the introduction of rounding errors can force the subroutine to increase the value of $par[3]$ by a power of 10, but the value never becomes larger than $1E-3$.

- **par[4]**

specifies a threshold (LCDEACT) for the Lagrange multiplier that decides whether an active inequality constraint must remain active or can be deactivated. For maximization, $par[4]$ must be positive, and for minimization, $par[4]$ must be negative. The default is

$$par[4] = \pm \min \left(0.01, \max \left(0.1 \times ABSGTOL, 0.001 \times gmax^{(k)} \right) \right)$$

where the positive value is for maximization and the negative value is for minimization. $ABSGTOL$ is the value of the absolute gradient criterion, and $gmax^{(k)}$ is the maximum absolute element of the gradient, $g^{(k)}$, or the projected gradient, $Z^T g^{(k)}$.

- **par[5]**

specifies a criterion (LCSING) used in the update of the QR decomposition that decides whether an active constraint is linearly dependent on a set of other active constraints. The default is $par[5] = 1E-8$. As the value of $par[5]$ increases, more active constraints are recognized as being linearly dependent. If the value of $par[5]$ is larger than 0.1, it is reset to 0.1, and if it is negative, it is reset to zero.

- **par[6]**

specifies the degree of accuracy (LSPRECISION) that should be obtained by the second or third line-search algorithm. This argument can be used with the NLPCG, NLPHQN, and NLPNRA algorithms and with the NLPQN algorithm if the “*nlc*” argument is specified. Usually, an imprecise line search is computationally inexpensive and successful, but for more difficult optimization problems, a more precise and time consuming line search can be necessary. Refer to Fletcher (1987) for details. If you have numerical problems, you should decrease the value of the $par[6]$ argument to obtain a more precise line search. The default values are given in the following table.

Subroutine	Update Method	Default value
NLPCG	All	$par[6] = 0.1$
NLPHQN	DBFGS	$par[6] = 0.1$
NLPHQN	DDFP	$par[6] = 0.06$
NLPNRA	No update	$par[6] = 0.9$
Nlpqn	BFGS, DBFGS	$par[6] = 0.4$
NLPQN	DFP, DDFP	$par[6] = 0.06$

- **par[7]**

specifies a scalar factor (DAMPSTEP) that can be used to reduce the step size in each of the first five iterations. In each of these iterations, the starting step size, $\alpha^{(0)}$, can be no larger than the value of $par[7]$ times the step size obtained by the line-search algorithm in the previous iteration. If $par[7]$

is missing or if $par[7]=0$, which is the default, the starting step size in iteration t is computed as a function of the function change from the former iteration, $f^{(t-1)} - f^{(t)}$. If the computed value is outside the interval $[0.1, 10.0]$, it is moved to the next endpoint. You can further restrict the starting step size in the first five iterations with the $par[2]$ argument.

- **par[8]**
specifies the number of accurate digits (FDIGITS) used to evaluate the objective function. The default is $-\log_{10}(\epsilon)$, where ϵ is the machine precision, and fractional values are permitted. This value is used to compute the step size h for finite-difference derivatives and the default value for the FTOL termination criterion.
- **par[9]**
specifies the number of accurate digits (CDIGITS) used to evaluate the nonlinear constraint functions of the “*nlc*” module. The default is $-\log_{10}(\epsilon)$, where ϵ is the machine precision, and fractional values are permitted. The value is used to compute the step size h for finite-difference derivatives. If first-order derivatives are specified by the “*jacnlc*” module, the $par[9]$ argument is ignored.
- **par[10]**
specifies a scalar factor (DIAHES) for the diagonal of the initial Hessian approximation. This argument is available in the NLPDD, NLPQN, and NLPQN subroutines. If the $opt[7]$ argument is not specified, the initial Hessian approximation is a multiple of the identity matrix determined by the magnitude of the initial gradient $g(x^{(0)})$. The value of the $par[10]$ argument is used to specify $par[10] \times \mathbf{I}$ for the initial Hessian in the quasi-Newton algorithm.

Printing the Optimization History

Each optimization and least squares subroutine prints the optimization history, as long as $opt[2] \geq 1$ and you do not specify the “*ptit*” module argument. You can use this output to check for possible convergence problems. If you specify the “*ptit*” argument, you can enter a print command inside the module, which is called at each iteration.

The amount of information printed depends on the $opt[2]$ argument. See the section “[Options Vector](#)” on page 356.

The output consists of three main parts:

- **Optimization Start Output**

The following information about the initial state of the optimization can be printed:

- the number of constraints that are active at the starting point, or, more precisely, the number of constraints that are currently members of the working set. If this number is followed by a plus sign (+), there are more active constraints, at least one of which is temporarily released from the working set due to negative Lagrange multipliers.
- the value of the objective function at the starting point
- the value of the largest absolute (projected) gradient element
- the initial trust-region radius for the NLPTR and NLPLM subroutines

- **General Iteration History**

In general, the iteration history consists of one line of printed output for each iteration, with the exception of the Nelder-Mead simplex method. The NLPNMS subroutine prints a line only after several internal iterations because some of the termination tests are time-consuming compared to the simplex operations and because the subroutine typically uses many iterations.

The iteration history always includes the following columns:

- *iter* is the iteration number.
- *nrest* is the number of iteration restarts.
- *nfun* is the number of function calls.
- *act* is the number of active constraints.
- *optcrit* is the value of the optimization criterion.
- *difcrit* is the difference between adjacent function values.
- *maxgrad* is the maximum of the absolute (projected) gradient components.

An apostrophe trailing the number of active constraints indicates that at least one of the active constraints was released from the active set due to a significant Lagrange multiplier.

Some subroutines print additional information at each iteration; for details see the entry that corresponds to each subroutine in the section “Nonlinear Optimization and Related Subroutines” on page 823.

- **Optimization Result Output**

The output ends with the following information about the optimization result:

- the number of constraints that are active at the final point, or more precisely, the number of constraints that are currently members of the working set. When this number is followed by a plus sign (+), there are more active constraints, at least one of which is temporarily released from the working set due to negative Lagrange multipliers.
- the value of the objective function at the final point
- the value of the largest absolute (projected) gradient element

Nonlinear Optimization Examples

Example 14.1: Chemical Equilibrium

The following example is used in many test libraries for nonlinear programming. It appeared originally in Bracken and McCormick (1968).

The problem is to determine the composition of a mixture of various chemicals that satisfy the mixture’s chemical equilibrium state. The second law of thermodynamics implies that at a constant temperature and

pressure, a mixture of chemicals satisfies its chemical equilibrium state when the free energy of the mixture is reduced to a minimum. Therefore, the composition of the chemicals satisfying its chemical equilibrium state can be found by minimizing the free energy of the mixture.

The following notation is used in this problem:

- m number of chemical elements in the mixture
- n number of compounds in the mixture
- x_j number of moles for compound j , $j = 1, \dots, n$
- s total number of moles in the mixture, $s = \sum_{j=1}^n x_j$
- a_{ij} number of atoms of element i in a molecule of compound j
- b_i atomic weight of element i in the mixture $i = 1, \dots, m$

The constraints for the mixture are as follows. Each of the compounds must have a nonnegative number of moles.

$$x_j \geq 0, \quad j = 1, \dots, n$$

There is a mass balance relationship for each element. Each relation is given by a linear equality constraint.

$$\sum_{j=1}^n a_{ij} x_j = b_i, \quad i = 1, \dots, m$$

The objective function is the total free energy of the mixture.

$$f(x) = \sum_{j=1}^n x_j \left[c_j + \ln \left(\frac{x_j}{s} \right) \right]$$

where

$$c_j = \left(\frac{F^0}{RT} \right)_j + \ln(P)$$

and $(F^0/RT)_j$ is the model standard free energy function for the j th compound. The value of $(F^0/RT)_j$ is found in existing tables. P is the total pressure in atmospheres.

The problem is to determine the parameters x_j that minimize the objective function $f(x)$ subject to the nonnegativity and linear balance constraints. To illustrate this, consider the following situation. Determine the equilibrium composition of compound $\frac{1}{2}N_2H_4 + \frac{1}{2}O_2$ at temperature $T = 3500^\circ K$ and pressure $P = 750$ psi. The following table gives a summary of the information necessary to solve the problem.

j	Compound	$(F^0/RT)_j$	c_j	a_{ij}		
				$i=1$	$i=2$	$i=3$
				H	N	O
1	H	-10.021	-6.089	1		
2	H_2	-21.096	-17.164	2		
3	H_2O	-37.986	-34.054	2		1
4	N	-9.846	-5.914		1	
5	N_2	-28.653	-24.721		2	
6	NH	-18.918	-14.986	1	1	
7	NO	-28.032	-24.100		1	1
8	O	-14.640	-10.708			1
9	O_2	-30.594	-26.662			2
10	OH	-26.111	-22.179	1		1

The following statements solve the minimization problem:

```
proc iml;
  c = { -6.089 -17.164 -34.054 -5.914 -24.721
        -14.986 -24.100 -10.708 -26.662 -22.179 };
  start F_BRACK(x) global(c);
    s = x[+];
    f = sum(x # (c + log(x / s)));
    return(f);
  finish F_BRACK;

  con = { . . . . . . . . . . . . ,
          . . . . . . . . . . . . ,
          1. 2. 2. . . 1. . . . 1. 0. 2. ,
          . . . 1. 2. 1. 1. . . . 0. 1. ,
          . . 1. . . . 1. 1. 2. 1. 0. 1. };
  con[1,1:10] = 1.e-6;

  x0 = j(1,10, .1);
  optn = {0 3};

  title 'NLPTR subroutine: No Derivatives';
  call nlpnr(xres,rc,"F_BRACK",x0,optn,con);
```

The `F_BRACK` module specifies the objective function, $f(x)$. The matrix `CON` specifies the constraints. The first row gives the lower bound for each parameter, and to prevent the evaluation of the $\log(x)$ function for values of x that are too small, the lower bounds are set here to $1\text{E}-6$. The following three rows contain the three linear equality constraints.

The starting point, which must be given to specify the number of parameters, is represented by `X0`. The first element of the `OPTN` vector specifies a minimization problem, and the second element specifies the amount of printed output.

The `CALL NLPTR` statement runs trust-region minimization. In this case, since no analytic derivatives are specified, the `F_BRACK` module is used to generate finite-difference approximations for the gradient vector and Hessian matrix.

The output is shown in the following figures. The iteration history does not show any problems.

Optimization Start			
Active Constraints	3	Objective Function	-45.05516448
Max Abs Gradient	4.4710303342	Radius	1
Element			

Iter	Rest arts	Func Calls	Act Con	Objective Function	Obj Fun Change	Max Abs Gradient Element	Lambda	Trust Region Radius
1	0	2	3'	-47.33413	2.2790	4.3611	2.456	1.000
2	0	3	3'	-47.70050	0.3664	7.0045	0.909	0.418
3	0	4	3	-47.73117	0.0307	5.3051	0	0.359
4	0	5	3	-47.73426	0.00310	3.7015	0	0.118
5	0	6	3	-47.73982	0.00555	2.3054	0	0.0169
6	0	7	3	-47.74846	0.00864	1.3029	90.133	0.00476
7	0	9	3	-47.75796	0.00950	0.5073	0	0.0134
8	0	10	3	-47.76094	0.00297	0.0988	0	0.0124
9	0	11	3	-47.76109	0.000155	0.00447	0	0.0111
10	0	12	3	-47.76109	3.386E-7	9.328E-6	0	0.00332

Optimization Results

Iterations	10	Function Calls	13
Hessian Calls	11	Active Constraints	3
Objective Function	-47.76109086	Max Abs Gradient Element	6.6122907E-6
Lambda	0	Actual Over Pred Change	0
Radius	0.0033211642		

The output lists the optimal parameters with the gradient.

Optimization Results		
Parameter Estimates		
N Parameter	Estimate	Gradient Objective Function
1 X1	0.040668	-9.785055
2 X2	0.147730	-19.570111
3 X3	0.783153	-34.792170
4 X4	0.001414	-12.968921
5 X5	0.485247	-25.937842
6 X6	0.000693	-22.753976
7 X7	0.027399	-28.190991
8 X8	0.017947	-15.222060
9 X9	0.037314	-30.444120
10 X10	0.096871	-25.007114

The three equality constraints are satisfied at the solution.

Linear Constraints Evaluated at Solution									
1	ACT	-3.192E-16	=	-2.0000	+	1.0000	* X1	+	2.0000
2	ACT	3.8164E-17	=	-1.0000	+	1.0000	* X4	+	2.0000
3	ACT	-2.637E-16	=	-1.0000	+	1.0000	* X3	+	1.0000

The Lagrange multipliers and the projected gradient are also printed. The elements of the projected gradient must be small to satisfy a first-order optimality condition.

First Order Lagrange Multipliers			
Active Constraint			Lagrange Multiplier
Linear EC	[1]		-9.785055
Linear EC	[2]		-12.968922
Linear EC	[3]		-15.222061
Projected Gradient			
Free Dimension		Projected Gradient	
1		0.000000142	
2		-0.000000548	
3		-0.000000472	
4		-0.000006612	
5		-0.000004683	
6		-0.000004373	
7		-0.000001815	

Example 14.2: Network Flow and Delay

The following example is taken from the user's guide of the GINO program (Liebman et al. 1986). A simple network of five roads (arcs) can be illustrated by a path diagram.

The five roads connect four intersections illustrated by numbered nodes. Each minute, F vehicles enter and leave the network. The parameter x_{ij} refers to the flow from node i to node j . The requirement that traffic

that flows into each intersection j must also flow out is described by the linear equality constraint

$$\sum_i x_{ij} = \sum_i x_{ji} \quad , \quad j = 1, \dots, n$$

In general, roads also have an upper limit on the number of vehicles that can be handled per minute. These limits, denoted c_{ij} , can be enforced by boundary constraints:

$$0 \leq x_{ij} \leq c_{ij}$$

The goal in this problem is to maximize the flow, which is equivalent to maximizing the objective function $f(x)$, where $f(x)$ is

$$f(x) = x_{24} + x_{34}$$

The boundary constraints are

$$\begin{aligned} 0 \leq x_{12}, x_{32}, x_{34} &\leq 10 \\ 0 \leq x_{13}, x_{24} &\leq 30 \end{aligned}$$

and the flow constraints are

$$\begin{aligned} x_{13} &= x_{32} + x_{34} \\ x_{24} &= x_{12} + x_{32} \\ x_{12} + x_{13} &= x_{24} + x_{34} \end{aligned}$$

The three linear equality constraints are linearly dependent. One of them is deleted automatically by the optimization subroutine. The following notation is used in this example:

$$X1 = x_{12}, \quad X2 = x_{13}, \quad X3 = x_{32}, \quad X4 = x_{24}, \quad X5 = x_{34}$$

Even though the NLPCG subroutine is used, any other optimization subroutine would also solve this small problem. The following code finds the maximum flow:

```
proc iml;
  title 'Maximum Flow Through a Network';
  start MAXFLOW(x);
    f = x[4] + x[5];
    return(f);
  finish MAXFLOW;

  con = { 0.  0.  0.  0.  0.  .  . ,
          10. 30. 10. 30. 10.  .  . ,
          0.  1. -1.  0. -1.  0.  0. ,
          1.  0.  1. -1.  0.  0.  0. ,
          1.  1.  0. -1. -1.  0.  0. };
  x = j(1,5, 1.);
  optn = {1 3};
  call nlpcg(xres,rc,"MAXFLOW",x,optn,con);
```

The optimal solution is shown in the following output.

Optimization Results			
Parameter Estimates			
N Parameter	Estimate	Gradient Objective Function	Active Bound Constraint
1 X1	10.000000	0	Upper BC
2 X2	10.000000	0	
3 X3	10.000000	1.000000	Upper BC
4 X4	20.000000	1.000000	
5 X5	-1.11022E-16	0	Lower BC

Finding the maximum flow through a network is equivalent to solving a simple linear optimization problem, and for large problems, the LP procedure or the NETFLOW procedure of the SAS/OR product can be used. On the other hand, finding a traffic pattern that minimizes the total delay to move F vehicles per minute from node 1 to node 4 includes nonlinearities that need nonlinear optimization techniques. As traffic volume increases, speed decreases. Let t_{ij} be the travel time on arc (i, j) and assume that the following formulas describe the travel time as decreasing functions of the amount of traffic:

$$t_{12} = 5 + 0.1x_{12}/(1 - x_{12}/10)$$

$$t_{13} = x_{13}/(1 - x_{13}/30)$$

$$t_{32} = 1 + x_{32}/(1 - x_{32}/10)$$

$$t_{24} = x_{24}/(1 - x_{24}/30)$$

$$t_{34} = 5 + x_{34}/(1 - x_{34}/10)$$

These formulas use the road capacities (upper bounds), and you can assume that $F = 5$ vehicles per minute have to be moved through the network. The objective is now to minimize

$$f = f(x) = t_{12}x_{12} + t_{13}x_{13} + t_{32}x_{32} + t_{24}x_{24} + t_{34}x_{34}$$

The constraints are

$$0 \leq x_{12}, x_{32}, x_{34} \leq 10$$

$$0 \leq x_{13}, x_{24} \leq 30$$

$$x_{13} = x_{32} + x_{34}$$

$$x_{24} = x_{12} + x_{32}$$

$$x_{24} + x_{34} = F = 5$$

In the following code, the NLPNRR subroutine is used to solve the minimization problem:


```

proc iml;
  title 'Minimize Total Delay in Network';
  start MINDEL(x);
    t12 = 5. + .1 * x[1] / (1. - x[1] / 10.);
    t13 = x[2] / (1. - x[2] / 30.);
    t32 = 1. + x[3] / (1. - x[3] / 10.);
    t24 = x[4] / (1. - x[4] / 30.);
    t34 = 5. + .1 * x[5] / (1. - x[5] / 10.);
    f = t12*x[1] + t13*x[2] + t32*x[3] + t24*x[4] + t34*x[5];
    return(f);
  finish MINDEL;

  con = { 0. 0. 0. 0. 0. . . ,
          10. 30. 10. 30. 10. . . ,
          0. 1. -1. 0. -1. 0. 0. ,
          1. 0. 1. -1. 0. 0. 0. ,
          0. 0. 0. 1. 1. 0. 5. };

  x = j(1,5, 1.);
  optn = {0 3};
  call nlpnrr(xres,rc,"MINDEL",x,optn,con);

```

The optimal solution is shown in the following output.

Optimization Results			
Parameter Estimates			
N Parameter	Estimate	Gradient Objective Function	Active Bound Constraint
1 X1	2.500001	5.777778	
2 X2	2.499999	5.702478	
3 X3	-5.55112E-17	1.000000	Lower BC
4 X4	2.500001	5.702481	
5 X5	2.499999	5.777778	

The active constraints and corresponding Lagrange multiplier estimates (costs) are shown in the following output.

Linear Constraints Evaluated at Solution					
1 ACT	-4.441E-16	=	0	+	1.0000 * X2
					- 1.0000
					* X3
					- 1.0000 * X5
2 ACT	4.4409E-16	=	0	+	1.0000 * X1
					+ 1.0000
					* X3
					- 1.0000 * X4
3 ACT	4.4409E-16	=	-5.0000	+	1.0000 * X4
					+ 1.0000
					* X5

First Order Lagrange Multipliers		
Active Constraint		Lagrange Multiplier
Lower BC	X3	0.924702
Linear EC	[1]	5.702479
Linear EC	[2]	5.777777
Linear EC	[3]	11.480257

Example 14.3: Compartmental Analysis

Numerical Considerations

An important class of nonlinear models involves a dynamic description of the response rather than an explicit description. These models arise often in chemical kinetics, pharmacokinetics, and ecological compartmental modeling. Two examples are presented in this section. Refer to Bates and Watts (1988) for a more general introduction to the topic.

In this class of problems, function evaluations, as well as gradient evaluations, are not done in full precision. Evaluating a function involves the numerical solution of a differential equation with some prescribed precision. Therefore, two choices exist for evaluating first- and second-order derivatives:

- differential equation approach
- finite-difference approach

In the differential equation approach, the components of the Hessian and the gradient are written as a solution of a system of differential equations that can be solved simultaneously with the original system. However, the size of a system of differential equations, n , would suddenly increase to $n^2 + 2n$. This huge increase makes the finite difference approach an easier one.

With the finite-difference approach, a very delicate balance of all the precision requirements of every routine must exist. In the examples that follow, notice the relative levels of precision that are imposed on different modules. Since finite differences are used to compute the first- and second-order derivatives, it is incorrect to set the precision of the ODE solver at a coarse level because that would render the numerical estimation of the finite differences worthless.

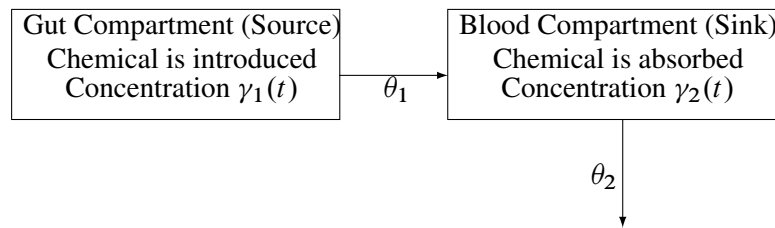
A coarse computation of the solution of the differential equation cannot be accompanied by very fine computation of the finite-difference estimates of the gradient and the Hessian. That is, you cannot set the precision of the differential equation solver to be $1\text{E}-4$ and perform the finite difference estimation with a precision of $1\text{E}-10$.

In addition, this precision must be well-balanced with the termination criteria imposed on the optimization process.

In general, if the precision of the function evaluation is $O(\epsilon)$, the gradient should be computed by finite differences $O(\sqrt{\epsilon})$, and the Hessian should be computed with finite differences $O(\epsilon^{\frac{1}{3}})$.¹

Diffusion of Tetracycline

Consider the concentration of tetracycline hydrochloride in blood serum. The tetracycline is administered to a subject orally, and the concentration of the tetracycline in the serum is measured. The biological system to be modeled consists of two compartments: a gut compartment in which tetracycline is injected and a blood compartment that absorbs the tetracycline from the gut compartment for delivery to the body. Let $\gamma_1(t)$ and $\gamma_2(t)$ be the concentrations at time t in the gut and the serum, respectively. Let θ_1 and θ_2 be the transfer parameters. The model is depicted as follows.



The rates of flow of the drug are described by the following pair of ordinary differential equations:

$$\begin{aligned}\frac{d\gamma_1(t)}{dt} &= -\theta_1\gamma_1(t) \\ \frac{d\gamma_2(t)}{dt} &= \theta_1\gamma_1(t) - \theta_2\gamma_2(t)\end{aligned}$$

The initial concentration of the tetracycline in the gut is unknown, and while the concentration in the blood can be measured at all times, initially it is assumed to be zero. Therefore, for the differential equation, the initial conditions are given by

$$\begin{aligned}\gamma_1(0) &= \theta_3 \\ \gamma_2(0) &= 0\end{aligned}$$

Also, a nonnegativity constraint is imposed on the parameters θ_1 , θ_2 , and θ_3 , although for numerical purposes, you might need to use a small value instead of zero for these bounds (such as 1E−7).

¹In Release 6.09 and in later releases, you can specify the step size h in the finite-difference formulas.

Suppose y_i is the observed serum concentration at time t_i . The parameters are estimated by minimizing the sum of squares of the differences between the observed and predicted serum concentrations:

$$\sum_i (y_i - \gamma_2(t_i))^2$$

The following IML program illustrates how to combine the NLPDD subroutine and the ODE subroutine to estimate the parameters $(\theta_1, \theta_2, \theta_3)$ of this model. The input data are the measurement time and the concentration of the tetracycline in the blood. For more information about the ODE call, see the section “ODE Call” on page 857.

```
data tetra;
    input t c @@;
    datalines;
    1 0.7    2 1.2    3 1.4    4 1.4    6 1.1
    8 0.8   10 0.6   12 0.5   16 0.3
;

proc iml;
    use tetra;
    read all into tetra;
    start f(theta) global(thmtrx,t,h,tetra,eps);
        thmtrx = ( -theta[1] || 0 )      //
                  (  theta[1] || -theta[2] );
        c = theta[3]//0 ;
        t = 0 // tetra[,1];
        call ode( r1, "der",c , t, h) j="jac" eps=eps;
        f = ssq((r1[2,])`-tetra[,2]);
        return(f);
    finish;

    start der(t,x) global(thmtrx);
        y = thmtrx*x;
        return(y);
    finish;

    start jac(t,x) global(thmtrx);
        y = thmtrx;
        return(y);
    finish;

    h      = {1.e-14 1. 1.e-5};
    opt     = {0 2 0 1 };
    tc      = repeat(.,1,12);
    tc[1]   = 100;
    tc[7]   = 1.e-8;
    par     = { 1.e-13 . 1.e-10 . . . . };
    con     = j(1,3,0.);
    itheta  = { .1 .3 10};
    eps     = 1.e-11;

    call nlpdd(rc,rx,"f",itheta) blc=con opt=opt tc=tc par=par;
```

The output from the optimization process is shown in [Output 14.3.1](#).

Output 14.3.1 Printed Output for Tetracycline Diffusion Problem

Optimization Start			
Parameter Estimates			
		Gradient	Lower
		Objective	Bound
N Parameter	Estimate	Function	Constraint
1 X1	0.100000	76.484452	0
2 X2	0.300000	-48.149258	0
3 X3	10.000000	1.675423	0
Optimization Start			
Parameter Estimates			
		Upper	
		Bound	
N Parameter		Constraint	
1 X1		.	
2 X2		.	
3 X3		.	
Value of Objective Function = 4.1469872322			
Double Dogleg Optimization			
Dual Broyden - Fletcher - Goldfarb - Shanno Update (DBFGS)			
Without Parameter Scaling			
Gradient Computed by Finite Differences			
Parameter Estimates		3	
Lower Bounds		3	
Upper Bounds		0	
Optimization Start			
Active Constraints	0	Objective Function	4.1469872322
Max Abs Gradient	76.484451645	Radius	1
Element			

Output 14.3.1 *continued*

Iter	Rest arts	Func Calls	Act Con	Objective Function	Obj Fun Change	Max Abs Gradient Element	Lambda	Slope Search Direc
1	0	5	0	3.11868	1.0283	124.2	67.146	-8.014
2	0	6	0	0.89559	2.2231	14.1614	1.885	-5.015
3	0	7	0	0.32352	0.5721	3.7162	1.187	-0.787
4	0	8	0	0.14619	0.1773	2.6684	0	-0.123
5	0	9	0	0.07462	0.0716	2.3061	0	-0.0571
6	0	10	0	0.06549	0.00913	1.5874	0	-0.0075
7	0	11	0	0.06416	0.00132	1.0928	0	-0.0010
8	0	12	0	0.06334	0.000823	0.5649	0	-0.0006
9	0	13	0	0.06288	0.000464	0.1213	1.024	-0.0004
10	0	14	0	0.06279	0.000092	0.0195	0.321	-0.0001
11	0	15	0	0.06276	0.000024	0.0240	0	-199E-7
12	0	16	0	0.06275	0.000015	0.0195	0	-875E-8
13	0	17	0	0.06269	0.000055	0.0281	0.323	-366E-7
14	0	18	0	0.06248	0.000209	0.0474	0.283	-0.0001
15	0	19	0	0.06190	0.000579	0.1213	0.704	-0.0006
16	0	20	0	0.06135	0.000552	0.1844	0.314	-0.0004
17	0	21	0	0.05956	0.00179	0.3314	0.217	-0.0012
18	0	22	0	0.05460	0.00496	0.9879	0	-0.0036
19	0	23	0	0.04999	0.00461	1.4575	0	-0.0029
20	0	24	0	0.04402	0.00597	1.8484	0	-0.0067
21	0	25	0	0.04007	0.00395	0.1421	0	-0.0053
22	0	26	0	0.03865	0.00142	0.3127	0	-0.0008
23	0	27	0	0.03755	0.00110	0.8395	0	-0.0019
24	0	28	0	0.03649	0.00106	0.2732	0	-0.0010
25	0	29	0	0.03603	0.000464	0.1380	0	-0.0003
26	0	30	0	0.03580	0.000226	0.1191	0.669	-0.0003
27	0	31	0	0.03571	0.000090	0.0103	0	-581E-7
28	0	32	0	0.03565	0.000056	0.00786	0	-334E-7
29	0	34	0	0.03565	4.888E-6	0.00967	1.752	-486E-7
30	0	35	0	0.03565	6.841E-7	0.000493	0	-244E-7
31	0	36	0	0.03565	2.417E-7	0.00270	0	-57E-9
32	0	42	0	0.03565	1.842E-9	0.00179	2.431	-13E-9
33	0	49	0	0.03565	1.08E-11	0.00212	786.7	-35E-12

Optimization Results

Iterations	33	Function Calls	50
Gradient Calls	35	Active Constraints	0
Objective Function	0.0356478102	Max Abs Gradient Element	0.0021167366
Slope of Search Direction	-3.52366E-11	Radius	1

GCONV convergence criterion satisfied.

NOTE: At least one element of the (projected) gradient is greater than 1e-3.

Output 14.3.1 *continued*

Optimization Results		
Parameter Estimates		
N Parameter	Estimate	Gradient Objective Function
1 X1	0.182491	0.002117
2 X2	0.435865	-0.000501
3 X3	6.018219	0.000046711
Value of Objective Function = 0.0356478102		

The differential equation model is linear, and in fact, it can be solved by using an eigenvalue decomposition (this is not always feasible without complex arithmetic). Alternately, the availability and the simplicity of the closed form representation of the solution enable you to replace the solution produced by the ODE routine with the simpler and faster analytical solution. Closed forms are not expected to be easily available for nonlinear systems of differential equations, which is why the preceding solution was introduced.

The closed form of the solution requires a change to the function $f(\cdot)$. The functions needed as arguments of the ODE routine, namely the *der* and *jac* modules, can be removed. Here is the revised code:

```
start f(th) global(theta,tetra);
    theta = th;
    vv    = v(tetra[,1]);
    error = ssq(vv-tetra[,2]);
    return(error);
finish;

start v(t) global(theta);
    v = theta[3]*theta[1]/(theta[2]-theta[1])*
        (exp(-theta[1]*t)-exp(-theta[2]*t));
    return(v);
finish;

call nlpdd(rc,rx,"f",itheta) blc=con opt=opt tc=tc par=par;
```

The parameter estimates, which are shown in [Output 14.3.2](#), are close to those obtained by the first solution.

Output 14.3.2 Second Set of Parameter Estimates for Tetracycline Diffusion

Optimization Results		
Parameter Estimates		
N Parameter	Estimate	Gradient Objective Function
1 X1	0.183024	0.000000111
2 X2	0.434484	-0.000000115
3 X3	5.995273	9.3860868E-9

Because of the nature of the closed form of the solution, you might want to add an additional constraint to guarantee that $\theta_2 \neq \theta_1$ at any time during the optimization. This prevents a possible division by 0 or a value near 0 in the execution of the $v(\cdot)$ function. For example, you might add the constraint

$$\theta_2 - \theta_1 \geq 10^{-7}$$

Chemical Kinetics of Pyrolysis of Oil Shale

Pyrolysis is a chemical change effected by the action of heat, and this example considers the pyrolysis of oil shale described in Ziegel and Gorman (1980). Oil shale contains organic material that is bonded to the rock. To extract oil from the rock, heat is applied, and the organic material is decomposed into oil, bitumen, and other byproducts. The model is given by

$$\begin{aligned}\frac{d\gamma_1(t)}{dt} &= -(\theta_1 + \theta_4)\gamma_1(t)\iota(t, \theta_5) \\ \frac{d\gamma_2(t)}{dt} &= [\theta_1\gamma_1(t) - (\theta_2 + \theta_3)\gamma_2(t)]\iota(t, \theta_5) \\ \frac{d\gamma_3(t)}{dt} &= [\theta_4\gamma_1(t) + \theta_2\gamma_2(t)]\iota(t, \theta_5)\end{aligned}$$

with the initial conditions

$$\gamma_1(t) = 100, \quad \gamma_2(t) = 0, \quad \gamma_3(t) = 0$$

A dead time is assumed to exist in the process. That is, no change occurs up to time θ_5 . This is controlled by the indicator function $\iota(t, \theta_5)$, which is given by

$$\iota(t, \theta_5) = \begin{cases} 0 & \text{if } t < \theta_5 \\ 1 & \text{if } t \geq \theta_5 \end{cases}$$

where $\theta_5 \geq 0$. Only one of the cases in Ziegel and Gorman (1980) is analyzed in this report, but the others can be handled in a similar manner. The following IML program illustrates how to combine the NLPQN subroutine and the ODE subroutine to estimate the parameters θ_i in this model:

```
data oil ( drop=temp);
  input temp time bitumen oil;
  datalines;
673    5      0.      0.
673    7      2.2     0.
673   10     11.5     0.7
673   15     13.7     7.2
673   20     15.1    11.5
673   25     17.3    15.8
673   30     17.3    20.9
673   40     20.1    26.6
673   50     20.1    32.4
673   60     22.3    38.1
673   80     20.9    43.2
673  100     11.5    49.6
```



```

673    120      6.5    51.8
673    150      3.6    54.7
;

proc iml;
    use oil;
    read all into a;

    /*****
    /* The INS function inserts a value given by FROM into a vector */
    /* given by INTO, sorts the result, and posts the global matrix */
    /* that can be used to delete the effects of the point FROM.    */
    *****/
    start ins(from,into) global(permm);
        in    = into // from;
        x      = i(nrow(in));
        permm = inv(x[rank(in),]);
        return(permm*in);
    finish;

    start der(t,x) global(thmtrx,thet);
        y      = thmtrx*x;
        if ( t <= thet[5] ) then y = 0*y;
        return(y);
    finish;

    start jac(t,x) global(thmtrx,thet);
        y      = thmtrx;
        if ( t <= thet[5] ) then y = 0*y;
        return(y);
    finish;

    start f(theta) global(thmtrx,thet,time,h,a,eps,permm);
        thet = theta;
        thmtrx = (- (theta[1]+theta[4]) || 0 || 0 )//
                 (theta[1] || - (theta[2]+theta[3]) || 0 )//
                 (theta[4] || theta[2] || 0 );
        t = ins( theta[5],time);
        c = { 100, 0, 0};
        call ode( r1, "der",c , t , h) j="jac" eps=eps;

    /* send the intermediate value to the last column */
        r = (c || r1) * permm;
        m = r[2:3, (2:nrow(time))];
        mm = m` - a[,2:3];
        call qr(q,r,piv,lindep,mm);
        v = det(r);
        return(abs(v));
    finish;

    opt = {0 2 0 1 };
    tc = repeat(.,1,12);
    tc[1] = 100;
    tc[7] = 1.e-7;

```

```

par = { 1.e-13 . 1.e-10 . . . .};
con = j(1,5,0.);
h = {1.e-14 1. 1.e-5};
time = (0 // a[,1]);
eps = 1.e-5;
itheta = { 1.e-3 1.e-3 1.e-3 1.e-3 1.};

call nlpqn(rc,rx,"f",itheta) blc=con opt=opt tc=tc par=par;

```

The parameter estimates are shown in [Output 14.3.3](#).

Output 14.3.3 Parameter Estimates for Oil Shale Pyrolysis

Optimization Results			Gradient
Parameter Estimates			Objective
N	Parameter	Estimate	Function
1	X1	0.023086	1282509
2	X2	0.008127	696102
3	X3	0.013701	722960
4	X4	0.011014	592104
5	X5	1.000012	-8123.799232

Again, compare the solution using the approximation produced by the ODE subroutine to the solution obtained through the closed form of the given differential equation. Impose the following additional constraint to avoid a possible division by 0 when evaluating the function:

$$\theta_2 + \theta_3 - \theta_1 - \theta_4 \geq 10^{-7}$$

The closed form of the solution requires a change in the function $f(\cdot)$. The functions needed as arguments of the ODE routine, namely the `der` and `jac` modules, can be removed. Here is the revised code:

```

start f(thet) global(time,a);
do i = 1 to nrow(time);
  t = time[i];
  v1 = 100;
  if ( t >= thet[5] ) then
    v1 = 100*ev(t,thet[1],thet[4],thet[5]);
  v2 = 0;
  if ( t >= thet[5] ) then
    v2 = 100*thet[1]/(thet[2]+thet[3]-thet[1]-thet[4]) *
      (ev(t,thet[1],thet[4],thet[5]) -
        ev(t,thet[2],thet[3],thet[5]));
  v3 = 0;
  if ( t >= thet[5] ) then
    v3 = 100*thet[4]/(thet[1]+thet[4]) *
      (1. - ev(t,thet[1],thet[4],thet[5])) +
      100*thet[1]*thet[2]/(thet[2]+thet[3]-thet[1]-thet[4]) * (

```

```

        (1.-ev(t,thet[1],thet[4],thet[5]))/(thet[1]+thet[4]) -
        (1.-ev(t,thet[2],thet[3],thet[5]))/(thet[2]+thet[3])    );
    y = y // (v1 || v2 || v3);
end;
mm = y[,2:3]-a[,2:3];
call qr(q,r,piv,lindep,mm);
v = det(r);
return(abs(v));
finish;

start ev(t,a,b,c);
    return(exp(-(a+b)*(t-c)));
finish;

con      = { 0.   0.   0.   0.   .   .   . ,
             .   .   .   .   .   .   . ,
             -1   1   1   -1   .   1  1.e-7 };
time     = a[,1];
par      = { 1.e-13 . 1.e-10 . . . . };
itheta   = { 1.e-3 1.e-3 1.e-2 1.e-3 1. };

call nlpqn(rc,rx,"f",itheta)  blc=con opt=opt tc=tc par=par;

```

The parameter estimates are shown in [Output 14.3.4](#).

Output 14.3.4 Second Set of Parameter Estimates for Oil Shale Pyrolysis

Optimization Results		
Parameter Estimates		
N Parameter	Estimate	Gradient Objective Function
1 X1	0.017178	-0.030690
2 X2	0.008912	0.070424
3 X3	0.020007	-0.010621
4 X4	0.010494	0.206102
5 X5	7.771458	-0.000062272

Example 14.4: MLEs for Two-Parameter Weibull Distribution

This example considers a data set given in Lawless (1982). The data are the number of days it took rats painted with a carcinogen to develop carcinoma. The last two observations are censored. Maximum likelihood estimates (MLEs) and confidence intervals for the parameters of the Weibull distribution are computed. In the following code, the data set is given in the vector `CARCIN`, and the variables `P` and `M` give the total number of observations and the number of uncensored observations. The set D represents the indices of the observations.

```

proc iml;
  carcin = { 143  164  188  188  190  192  206
            209  213  216  220  227  230  234
            246  265  304  216  244 };
  p = ncol(carcin); m = p - 2;

```

The three-parameter Weibull distribution uses three parameters: a scale parameter, a shape parameter, and a location parameter. This example computes MLEs and corresponding 95% confidence intervals for the scale parameter, σ , and the shape parameter, c , for a constant value of the location parameter, $\theta = 0$. The program can be generalized to estimate all three parameters. Note that Lawless (1982) denotes σ , c , and θ by α , β , and μ , respectively.

The observed likelihood function of the three-parameter Weibull distribution is

$$L(\theta, \sigma, c) = \frac{c^m}{\sigma^m} \prod_{i \in D} \left(\frac{t_i - \theta}{\sigma} \right)^{c-1} \prod_{i=1}^p \exp \left\{ - \left(\frac{t_i - \theta}{\sigma} \right)^c \right\}$$

The log likelihood, $\ell(\theta, \sigma, c) = \log L(\theta, \sigma, c)$, is

$$\ell(\theta, \sigma, c) = m \log c - mc \log \sigma + (c-1) \sum_{i \in D} \log(t_i - \theta) - \sum_{i=1}^p \left(\frac{t_i - \theta}{\sigma} \right)^c$$

The log-likelihood function, $\ell(\theta, \sigma, c)$, for $\theta = 0$ is the objective function to be maximized to obtain the MLEs $(\hat{\sigma}, \hat{c})$. The following statements define the function:

```

start f_weib2(x) global(carcin,thet);
  /* x[1]=sigma and x[2]=c */
  p = ncol(carcin); m = p - 2;
  sum1 = 0.; sum2 = 0.;
  do i = 1 to p;
    temp = carcin[i] - thet;
    if i <= m then sum1 = sum1 + log(temp);
    sum2 = sum2 + (temp / x[1])##x[2];
  end;
  f = m*log(x[2]) - m*x[2]*log(x[1]) + (x[2]-1)*sum1 - sum2;
  return(f);
finish f_weib2;

```

The derivatives of ℓ with respect to the parameters θ , σ , and c are given in Lawless (1982). The following code specifies a gradient module, which computes $\partial \ell / \partial \sigma$ and $\partial \ell / \partial c$:

```

start g_weib2(x) global(carcin,thet);
  /* x[1]=sigma and x[2]=c */
  p = ncol(carcin); m = p - 2;
  g = j(1,2,0.);
  sum1 = 0.; sum2 = 0.; sum3 = 0.;
  do i = 1 to p;
    temp = carcin[i] - thet;
    if i <= m then sum1 = sum1 + log(temp);

```

```

    sum2 = sum2 + (temp / x[1])##x[2];
    sum3 = sum3 + ((temp / x[1])##x[2]) * (log(temp / x[1]));
end;
g[1] = -m * x[2] / x[1] + sum2 * x[2] / x[1];
g[2] = m / x[2] - m * log(x[1]) + sum1 - sum3;
return(g);
finish g_weib2;

```

The MLEs are computed by maximizing the objective function with the trust-region algorithm in the NLPTR subroutine. The following code specifies starting values for the two parameters, $c = \sigma = 0.5$, and to avoid infeasible values during the optimization process, it imposes lower bounds of $c, \sigma \geq 10^{-6}$. The optimal parameter values are saved in the variable XOPT, and the optimal objective function value is saved in the variable FOPT.

```

n = 2; thet = 0.;
x0 = j(1,n,.5);
optn = {1 2};
con = { 1.e-6 1.e-6 ,
        .      .      };
call nlpnr(rc,xres,"f_weib2",x0,optn,con,,,,,"g_weib2");
/*--- Save result in xopt, fopt ---*/
xopt = xres`; fopt = f_weib2(xopt);

```

The results shown in [Output 14.4.1](#) are the same as those given in Lawless (1982).

Output 14.4.1 Parameter Estimates for Carcinogen Data

Optimization Results Parameter Estimates		
N Parameter	Estimate	Gradient Objective Function
1 X1	234.318611	1.3363926E-9
2 X2	6.083147	-7.851053E-9

The following code computes confidence intervals based on the asymptotic normal distribution. These are compared with the profile-likelihood-based confidence intervals computed in the next example. The diagonal of the inverse Hessian (as calculated by the NLPFDD subroutine) is used to calculate the standard error.

```

call nlpfdd(f,g,hess2,"f_weib2",xopt,,,"g_weib2");
hin2 = inv(hess2);
/* quantile of normal distribution */
prob = .05;
noqua = probit(1. - prob/2);
stderr = sqrt(abs(vecdiag(hin2)));
xlb = xopt - noqua * stderr;
xub = xopt + noqua * stderr;

```

```
print "Normal Distribution Confidence Interval";
print xlb xopt xub;
```

Output 14.4.2 Confidence Interval Based on Normal Distribution

Normal Distribution Confidence Interval				
xlb		xopt	xub	
215.41298	234.31861	6.0831471	253.22425	
3.9894574			8.1768368	

Example 14.5: Profile-Likelihood-Based Confidence Intervals

This example calculates confidence intervals based on the profile likelihood for the parameters estimated in the previous example. The following introduction on profile-likelihood methods is based on the paper of Venzon and Moolgavkar (1988).

Let $\hat{\theta}$ be the maximum likelihood estimate (MLE) of a parameter vector $\theta_0 \in \mathcal{R}^n$ and let $\ell(\theta)$ be the log-likelihood function defined for parameter values $\theta \in \Theta \subset \mathcal{R}^n$.

The profile-likelihood method reduces $\ell(\theta)$ to a function of a single parameter of interest, $\beta = \theta_j$, where $\theta = (\theta_1, \dots, \theta_j, \dots, \theta_n)'$, by treating the others as nuisance parameters and maximizing over them. The profile likelihood for β is defined as

$$\tilde{\ell}_j(\beta) = \max_{\theta \in \Theta_j(\beta)} \ell(\theta)$$

where $\Theta_j(\beta) = \{\theta \in \Theta : \theta_j = \beta\}$. Define the complementary parameter set $\omega = (\theta_1, \dots, \theta_{j-1}, \theta_{j+1}, \dots, \theta_n)'$ and $\hat{\omega}(\beta)$ as the optimizer of $\tilde{\ell}_j(\beta)$ for each value of β . Of course, the maximum of function $\tilde{\ell}_j(\beta)$ is located at $\beta = \hat{\theta}_j$. The profile-likelihood-based confidence interval for parameter θ_j is defined as

$$\{\beta : \ell(\hat{\theta}) - \tilde{\ell}_j(\beta) \leq \frac{1}{2}q_1(1 - \alpha)\}$$

where $q_1(1 - \alpha)$ is the $(1 - \alpha)$ th quantile of the χ^2 distribution with one degree of freedom. The points (β_l, β_u) are the endpoints of the profile-likelihood-based confidence interval for parameter $\beta = \theta_j$. The points β_l and β_u can be computed as the solutions of a system of n nonlinear equations $f_i(x)$ in n parameters, where $x = (\beta, \omega)$:

$$\begin{bmatrix} \ell(\theta) - \ell^* \\ \frac{\partial \ell}{\partial \omega}(\theta) \end{bmatrix} = 0$$

where ℓ^* is the constant threshold $\ell^* = \ell(\hat{\theta}) - \frac{1}{2}q_1(1 - \alpha)$. The first of these n equations defines the locations β_l and β_u where the function $\ell(\theta)$ cuts ℓ^* , and the remaining $n - 1$ equations define the optimality of the $n - 1$ parameters in ω . Jointly, the n equations define the locations β_l and β_u where the function $\tilde{\ell}_j(\beta)$

cuts the constant threshold ℓ^* , which is given by the roots of $\tilde{\ell}_j(\beta) - \ell^*$. Assuming that the two solutions $\{\beta_l, \beta_u\}$ exist (they do not if the quantile $q_1(1 - \alpha)$ is too large), this system of n nonlinear equations can be solved by minimizing the sum of squares of the n functions $f_i(\beta, \omega)$:

$$F = \frac{1}{2} \sum_{i=1}^n f_i^2(\beta, \omega)$$

For a solution of the system of n nonlinear equations to exist, the minimum value of the convex function F must be zero.

The following code defines the module for the system of $n = 2$ nonlinear equations to be solved:

```
start f_plwei2(x) global(carcin, ipar, lstar);
  /* x[1]=sigma, x[2]=c */
  like = f_weib2(x);
  grad = g_weib2(x);
  grad[ipar] = like - lstar;
  return(grad);
finish f_plwei2;
```

The following code implements the Levenberg-Marquardt algorithm with the NLPLM subroutine to solve the system of two equations for the left and right endpoints of the interval. The starting point is the optimizer $(\hat{\sigma}, \hat{c})$, as computed in the previous example, moved toward the left or right endpoint of the interval by an initial step (refer to Venzon and Moolgavkar (1988)). This forces the algorithm to approach the specified endpoint.

```
/* quantile of chi**2 distribution */
chqua = cinv(1-prob,1); lstar = fopt - .5 * chqua;
optn = {2 0};
do ipar = 1 to 2;
/* Compute initial step: */
/* Choose (alfa,delt) to go in right direction */
/* Venzon & Moolgavkar (1988), p.89 */
  if ipar=1 then ind = 2; else ind = 1;
  delt = - inv(hes2[ind,ind]) * hes2[ind,ipar];
  alfa = - (hes2[ipar,ipar] - delt` * hes2[ind,ipar]);
  if alfa > 0 then alfa = .5 * sqrt(chqua / alfa);
  else do;
    print "Bad alpha";
    alfa = .1 * xopt[ipar];
  end;
  if ipar=1 then delt = 1 || delt;
  else delt = delt || 1;

/* Get upper end of interval */
  x0 = xopt + (alfa * delt);
/* set lower bound to optimal value */
  con2 = con; con2[1,ipar] = xopt[ipar];
  call nlplm(rc,xres,"f_plwei2",x0,optn,con2);
  f = f_plwei2(xres); s = ssq(f);
  if (s < 1.e-6) then xub[ipar] = xres[ipar];
```

```

        else xub[ipar] = .;

/* Get lower end of interval */
    x0 = xopt - (alfa * delt)`;
/* reset lower bound and set upper bound to optimal value */
    con2[1,ipar] = con[1,ipar]; con2[2,ipar] = xopt[ipar];
    call nlpplm(rc,xres,"f_plwei2",x0,optn,con2);
    f = f_plwei2(xres); s = ssq(f);
    if (s < 1.e-6) then xlb[ipar] = xres[ipar];
        else xlb[ipar] = .;
end;
print "Profile-Likelihood Confidence Interval";
print xlb xopt xub;

```

The results, shown in [Output 14.5.1](#), are close to the results shown in [Output 14.4.2](#).

Output 14.5.1 Confidence Interval Based on Profile Likelihood

Profile-Likelihood Confidence Interval		
xlbl	xopt2	xub
215.1963	234.31861	255.2157
4.1344126	6.0831471	8.3063797

Example 14.6: Survival Curve for Interval Censored Data

In some studies, subjects are assessed only periodically for outcomes or responses of interest. In such situations, the occurrence times of these events are not observed directly; instead they are known to have occurred within some time interval. The times of occurrence of these events are said to be *interval censored*. A first step in the analysis of these interval censored data is the estimation of the distribution of the event occurrence times.

In a study with n subjects, denote the raw interval censored observations by $\{(L_i, R_i] : 1 \leq i \leq n\}$. For the i th subject, the event occurrence time T_i lies in $(L_i, R_i]$, where L_i is the last assessment time at which there was no evidence of the event, and R_i is the earliest time when a positive assessment was noted (if it was observed at all). If the event does not occur before the end of the study, R_i is given a value larger than any assessment time recorded in the data.

A set of nonoverlapping time intervals $I_j = (q_j, p_j]$, $1 \leq j \leq m$, is generated over which the survival curve $S(t) = \Pr[T > t]$ is estimated. Refer to Peto (1973) and Turnbull (1976) for details. Assuming the independence of T_i and $(L_i, R_i]$, and also independence across subjects, the likelihood of the data $\{T_i \in (L_i, R_i], 1 \leq i \leq n\}$ can be constructed in terms of the pseudo-parameters $\theta_j = \Pr[T_i \in I_j], 1 \leq i \leq m$. The conditional likelihood of $\theta = (\theta_1, \dots, \theta_m)$ is

$$L(\theta) = \prod_{i=1}^n \left(\sum_{j=1}^m x_{ij} \theta_j \right)$$

where x_{ij} is 1 or 0 according to whether I_j is a subset of $(L_i, R_i]$. The maximum likelihood estimates, $\hat{\theta}_j, 1 \leq j \leq m$, yield an estimator $\hat{S}(t)$ of the survival function $S(t)$, which is given by

$$\hat{S}(t) = \begin{cases} 1 & t \leq q_1 \\ \sum_{i=j+1}^m \hat{\theta}_i & p_j \leq t \leq q_{j+1}, 1 \leq j \leq m-1 \\ 0 & t \geq p_m \end{cases}$$

$\hat{S}(t)$ remains undefined in the intervals (q_j, p_j) where the function can decrease in an arbitrary way. The asymptotic covariance matrix of $\hat{\theta}$ is obtained by inverting the estimated matrix of second partial derivatives of the negative log likelihood (Peto 1973), (Turnbull 1976). You can then compute the standard errors of the survival function estimators by the delta method and approximate the confidence intervals for survival function by using normal distribution theory.

The following code estimates the survival curve for interval censored data. As an illustration, consider an experiment to study the onset of a special kind of palpable tumor in mice. Forty mice exposed to a carcinogen were palpated for the tumor every two weeks. The times to the onset of the tumor are interval censored data. These data are contained in the data set CARCIN. The variable L represents the last time the tumor was not yet detected, and the variable R represents the first time the tumor was palpated. Three mice died tumor free, and one mouse was tumor free by the end of the 48-week experiment. The times to tumor for these four mice were considered right censored, and they were given an R value of 50 weeks.

```
data carcin;
  input id l r @@;
  datalines;
  1 20 22    11 30 32    21 22 24    31 34 36
  2 22 24    12 32 34    22 22 24    32 34 36
  3 26 28    13 32 34    23 28 30    33 36 38
  4 26 28    14 32 34    24 28 30    34 38 40
  5 26 28    15 34 36    25 32 34    35 38 40
  6 26 28    16 36 38    26 32 34    36 42 44
  7 28 30    17 42 44    27 32 34    37 42 44
  8 28 30    18 30 50    28 32 34    38 46 48
  9 30 32    19 34 50    29 32 34    39 28 50
  10 30 32   20 20 22    30 32 34    40 48 50
  ;

proc iml;
  use carcin;
  read all var{l r};
  nobs= nrow(l);
  /*****
  construct the nonoverlapping intervals (Q,P) and
  determine the number of pseudo-parameters (NPARM)
  *****/
  pp= unique(r); npp= ncol(pp);
  qq= unique(l); nqq= ncol(qq);
  q= j(1,npp, .);
  do;
    do i= 1 to npp;
      do j= 1 to nqq;
```

```

        if ( qq[j] < pp[i] ) then q[i]= qq[j];
    end;
    if q[i] = qq[nqq] then goto lab1;
end;
lab1:
end;

if i > npp then nq= npp;
else          nq= i;
q= unique(q[1:nq]);
nparm= ncol(q);
p= j(1,nparm, .);
do i= 1 to nparm;
    do j= npp to 1 by -1;
        if ( pp[j] > q[i] ) then p[i]= pp[j];
    end;
end;

/*****
    generate the X-matrix for the likelihood
    *****/
_x= j(nobs, nparm, 0);
do j= 1 to nparm;
    _x[,j]= choose(1 <= q[j] & p[j] <= r, 1, 0);
end;

/*****
    log-likelihood function (LL)
    *****/
start LL(theta) global(_x,nparm);
    xlt= log(_x * theta`);
    f= xlt[+];
    return(f);
finish LL;

/*****
    gradient vector (GRAD)
    *****/
start GRAD(theta) global(_x,nparm);
    g= j(1,nparm,0);
    tmp= _x # (1 / (_x * theta`));
    g= tmp[+,];
    return(g);
finish GRAD;

/*****
    estimate the pseudo-parameters using quasi-newton technique
    *****/
/* options */
optn= {1 2};

/* constraints */
con= j(3, nparm + 2, .);
con[1, 1:nparm]= 1.e-6;

```

```

con[2:3, 1:nparm]= 1;
con[3,nparm + 1]=0;
con[3,nparm + 2]=1;

/* initial estimates */
x0= j(1, nparm, 1/nparm);

/* call the optimization routine */
call nlpqn(rc,rx,"LL",x0,optn,con,,,"GRAD");

/*****
  survival function estimate (SDF)
  *****/
tmp1= cusum(rx[nparm:1]);
sdf= tmp1[nparm-1:1];

/*****
  covariance matrix of the first nparm-1 pseudo-parameters (SIGMA2)
  *****/
mm= nparm - 1;
_x= _x - _x[nparm] * (j(1, mm, 1) || {0});
h= j(mm, mm, 0);
ixtheta= 1 / (_x * ((rx[,1:mm]) || {1}))`;
if _zfreq then
  do i= 1 to nob;
    rowtmp= ixtheta[i] # _x[i,1:mm];
    h= h + (_freq[i] # (rowtmp` * rowtmp));
  end;
else do i= 1 to nob;
  rowtmp= ixtheta[i] # _x[i,1:mm];
  h= h + (rowtmp` * rowtmp);
end;
sigma2= inv(h);

/*****
  standard errors of the estimated survival curve (SIGMA3)
  *****/
sigma3= j(mm, 1, 0);
tmp1= sigma3;
do i= 1 to mm;
  tmp1[i]= 1;
  sigma3[i]= sqrt(tmp1` * sigma2 * tmp1);
end;

/*****
  95% confidence limits for the survival curve (LCL,UCL)
  *****/
/* confidence limits */
tmp1= probit(.975);
*print tmp1;
tmp1= tmp1 * sigma3;
lcl= choose(sdf > tmp1, sdf - tmp1, 0);
ucl= sdf + tmp1;
ucl= choose( ucl > 1., 1., ucl);

```

```

/*****
  print estimates of pseudo-parameters
  *****/
reset center noname;
q= q`;
p= p`;
theta= rx`;
print , "Parameter Estimates", , q[colname={q}] p[colname={p}]
      theta[colname={theta} format=12.7],;

/*****
  print survival curve estimates and confidence limits
  *****/
left= {0} // p;
right= q // p[nparm];
sdf= {1} // sdf // {0};
lcl= {.} // lcl //{.};
ucl= {.} // ucl //{.};
print , "Survival Curve Estimates and 95% Confidence Intervals", ,
      left[colname={left}] right[colname={right}]
      sdf[colname={estimate} format=12.4]
      lcl[colname={lower} format=12.4]
      ucl[colname={upper} format=12.4];

```

The iteration history produced by the NLPQN subroutine is shown in [Output 14.6.1](#).

Output 14.6.1 Iteration History for the NLPQN Subroutine

Parameter Estimates	12
Lower Bounds	12
Upper Bounds	12
Linear Constraints	1

Optimization Start

Active Constraints	1	Objective Function	-93.3278404
Max Abs Gradient	65.361558529		
Element			

						Max Abs		Slope
	Rest	Func	Act	Objective	Obj Fun	Gradient	Step	Search
Iter	arts	Calls	Con	Function	Change	Element	Size	Direc
1	0	3	1	-88.51201	4.8158	16.6594	0.0256	-305.2
2	0	4	1	-87.42665	1.0854	10.8769	1.000	-2.157
3	0	5	1	-87.27408	0.1526	5.4965	1.000	-0.366
4	0	7	1	-87.17314	0.1009	2.2856	2.000	-0.113
5	0	8	1	-87.16611	0.00703	0.3444	1.000	-0.0149
6	0	10	1	-87.16582	0.000287	0.0522	1.001	-0.0006
7	0	12	1	-87.16581	9.128E-6	0.00691	1.133	-161E-7
8	0	14	1	-87.16581	1.712E-7	0.00101	1.128	-303E-9

Output 14.6.1 *continued*

Optimization Results			
Iterations	8	Function Calls	15
Gradient Calls	11	Active Constraints	1
Objective Function	-87.16581343	Max Abs Gradient	0.0010060788
		Element	
Slope of Search	-3.033154E-7		
Direction			
GCONV convergence criterion satisfied.			

The estimates of the pseudo-parameter for the nonoverlapping intervals are shown in [Output 14.6.2](#).

Output 14.6.2 Estimates for the Probability of Event Occurrence

Parameter Estimates		
Q	P	THETA
20	22	0.0499997
22	24	0.0749988
26	28	0.0999978
28	30	0.1033349
30	32	0.0806014
32	34	0.2418023
34	36	0.0873152
36	38	0.0582119
38	40	0.0582119
42	44	0.0873152
46	48	0.0291055
48	50	0.0291055

The survival curve estimates and confidence intervals are displayed in [Output 14.6.3](#).

Output 14.6.3 Survival Estimates and Confidence Intervals

Survival Curve Estimates and 95% Confidence Intervals

Output 14.6.3 *continued*

LEFT	RIGHT	ESTIMATE	LOWER	UPPER
0	20	1.0000	.	.
22	22	0.9500	0.8825	1.0000
24	26	0.8750	0.7725	0.9775
28	28	0.7750	0.6456	0.9044
30	30	0.6717	0.5252	0.8182
32	32	0.5911	0.4363	0.7458
34	34	0.3493	0.1973	0.5013
36	36	0.2619	0.1194	0.4045
38	38	0.2037	0.0720	0.3355
40	42	0.1455	0.0293	0.2617
44	46	0.0582	0.0000	0.1361
48	48	0.0291	0.0000	0.0852
50	50	0.0000	.	.

In this program, the quasi-Newton technique is used to maximize the likelihood function. You can replace the quasi-Newton routine by other optimization routines, such as the NLPNRR subroutine, which performs Newton-Raphson ridge optimization, or the NLPCG subroutine, which performs conjugate gradient optimization. Depending on the number of parameters and the number of observations, these optimization routines do not perform equally well. For survival curve estimation, the quasi-Newton technique seems to work fairly well since the number of parameters to be estimated is usually not too large.

Example 14.7: A Two-Equation Maximum Likelihood Problem

The following example and notation are taken from Bard (1974). A two-equation model is used to fit U.S. production data for the years 1909–1949, where z_1 is capital input, z_2 is labor input, z_3 is real output, z_4 is time in years (with 1929 as the origin), and z_5 is the ratio of price of capital services to wage scale. The data can be entered by using the following statements:

```
proc iml;
  z={ 1.33135 0.64629 0.4026 -20 0.24447,
      1.39235 0.66302 0.4084 -19 0.23454,
      1.41640 0.65272 0.4223 -18 0.23206,
      1.48773 0.67318 0.4389 -17 0.22291,
      1.51015 0.67720 0.4605 -16 0.22487,
      1.43385 0.65175 0.4445 -15 0.21879,
      1.48188 0.65570 0.4387 -14 0.23203,
      1.67115 0.71417 0.4999 -13 0.23828,
      1.71327 0.77524 0.5264 -12 0.26571,
      1.76412 0.79465 0.5793 -11 0.23410,
      1.76869 0.71607 0.5492 -10 0.22181,
      1.80776 0.70068 0.5052 -9 0.18157,
      1.54947 0.60764 0.4679 -8 0.22931,
      1.66933 0.67041 0.5283 -7 0.20595,
      1.93377 0.74091 0.5994 -6 0.19472,
      1.95460 0.71336 0.5964 -5 0.17981,
```

```

2.11198 0.75159 0.6554 -4 0.18010,
2.26266 0.78838 0.6851 -3 0.16933,
2.33228 0.79600 0.6933 -2 0.16279,
2.43980 0.80788 0.7061 -1 0.16906,
2.58714 0.84547 0.7567 0 0.16239,
2.54865 0.77232 0.6796 1 0.16103,
2.26042 0.67880 0.6136 2 0.14456,
1.91974 0.58529 0.5145 3 0.20079,
1.80000 0.58065 0.5046 4 0.18307,
1.86020 0.62007 0.5711 5 0.18352,
1.88201 0.65575 0.6184 6 0.18847,
1.97018 0.72433 0.7113 7 0.20415,
2.08232 0.76838 0.7461 8 0.18847,
1.94062 0.69806 0.6981 9 0.17800,
1.98646 0.74679 0.7722 10 0.19979,
2.07987 0.79083 0.8557 11 0.21115,
2.28232 0.88462 0.9925 12 0.23453,
2.52779 0.95750 1.0877 13 0.20937,
2.62747 1.00285 1.1834 14 0.19843,
2.61235 0.99329 1.2565 15 0.18898,
2.52320 0.94857 1.2293 16 0.17203,
2.44632 0.97853 1.1889 17 0.18140,
2.56478 1.02591 1.2249 18 0.19431,
2.64588 1.03760 1.2669 19 0.19492,
2.69105 0.99669 1.2708 20 0.17912 };

```

The two-equation model in five parameters c_1, \dots, c_5 is

$$\begin{aligned}
 g_1 &= c_1 10^{c_2 z_4} [c_5 z_1^{-c_4} + (1 - c_5) z_2^{-c_4}]^{-c_3/c_4} - z_3 = 0 \\
 g_2 &= \left[\frac{c_5}{1 - c_5} \right] \left(\frac{z_1}{z_2} \right)^{-1 - c_4} - z_5 = 0
 \end{aligned}$$

where the variables z_1 and z_2 are considered dependent (endogenous) and the variables z_3 , z_4 , and z_5 are considered independent (exogenous).

Differentiation of the two equations g_1 and g_2 with respect to the endogenous variables z_1 and z_2 yields the Jacobian matrix $\partial g_i / \partial z_j$ for $i = 1, 2$ and $j = 1, 2$, where i corresponds to rows (equations) and j corresponds to endogenous variables (refer to Bard (1974)). You must consider parameter sets for which the elements of the Jacobian and the logarithm of the determinant cannot be computed. In such cases, the function module must return a missing value. Here is the code:

```

start fiml(pr) global(z);
  c1 = pr[1]; c2 = pr[2]; c3 = pr[3]; c4 = pr[4]; c5 = pr[5];
  /* 1. Compute Jacobian */
  lndet = 0 ;
  do t= 1 to 41;
    j11 = (-c3/c4) * c1 * 10 ##(c2 * z[t,4]) * (-c4) * c5 *
          z[t,1]##(-c4-1) * (c5 * z[t,1]##(-c4) + (1-c5) *

```

```

        z[t,2]##(-c4))##(-c3/c4 -1);
j12 = (-c3/c4) * (-c4) * c1 * 10 ##(c2 * z[t,4]) * (1-c5) *
      z[t,2]##(-c4-1) * (c5 * z[t,1]##(-c4) + (1-c5) *
      z[t,2]##(-c4))##(-c3/c4 -1);
j21 = (-1-c4)*(c5/(1-c5))*z[t,1]##(-2-c4)/ (z[t,2]##(-1-c4));
j22 = (1+c4)*(c5/(1-c5))*z[t,1]##(-1-c4)/ (z[t,2]##(-c4));

j = (j11 || j12 ) // (j21 || j22) ;
if any(j = .) then detj = 0.;
  else detj = det(j);
if abs(detj) < 1.e-30 then do;
  print t detj j;
  return(.);
end;
lndet = lndet + log(abs(detj));
end;

```

Assuming that the residuals of the two equations are normally distributed, the likelihood is then computed as in Bard (1974). The following code computes the logarithm of the likelihood function:

```

/* 2. Compute Sigma */
sb = j(2,2,0.);
do t= 1 to 41;
  eq_g1 = c1 * 10##(c2 * z[t,4]) * (c5*z[t,1]##(-c4)
    + (1-c5)*z[t,2]##(-c4))##(-c3/c4) - z[t,3];
  eq_g2 = (c5/(1-c5)) * (z[t,1] / z[t,2])##(-1-c4) - z[t,5];
  resid = eq_g1 // eq_g2;
  sb = sb + resid * resid`;
end;
sb = sb / 41;
/* 3. Compute log L */
const = 41. * (log(2 * 3.1415) + 1.);
lnds = 0.5 * 41 * log(det(sb));
logl = const - lndet + lnds;
return(logl);
finish fiml;

```

There are potential problems in computing the power and log functions for an unrestricted parameter set. As a result, optimization algorithms that use line search fail more often than algorithms that restrict the search area. For that reason, the NLPDD subroutine is used in the following code to maximize the log-likelihood function:

```

pr = j(1,5,0.001);
optn = {0 2};
tc = {. . . 0};
call nlpdd(rc, xr,"fiml", pr, optn,,tc);
print "Start" pr, "RC=" rc, "Opt Par" xr;

```

Part of the iteration history is shown in [Output 14.7.1](#).

The results are very close to those reported by Bard (1974). Bard also reports different approaches to the same problem that can lead to very different MLEs.

Output 14.7.2 Parameter Estimates

Optimization Results		
Parameter Estimates		
N	Parameter	Estimate
1	X1	0.583884
2	X2	0.005882
3	X3	1.362817
4	X4	0.475091
5	X5	0.447072
		Gradient Objective Function
		0.000028901
		0.000656
		0.000008072
		-0.000023275
		0.000153

Example 14.8: Time-Optimal Heat Conduction

The following example illustrates a nontrivial application of the NLPQN algorithm that requires nonlinear constraints, which are specified by the *nlc* module. The example is listed as problem 91 in Hock and Schittkowski (1981). The problem describes a time-optimal heating process minimizing the simple objective function

$$f(x) = \sum_{j=1}^n x_j^2$$

subjected to a rather difficult inequality constraint:

$$c(x) = 10^{-4} - h(x) \geq 0$$

where $h(x)$ is defined as

$$\begin{aligned}
 h(x) &= \int_0^1 \left(\sum_{i=1}^{30} \alpha_i(s) \rho_i(x) - k_0(s) \right)^2 ds \\
 \alpha_i(s) &= \mu_i^2 A_i \cos(\mu_i s) \\
 \rho_i(x) &= -\mu_i^2 \left[\exp \left(-\mu_i^2 \sum_{j=1}^n x_j^2 \right) - 2 \exp \left(-\mu_i^2 \sum_{j=2}^n x_j^2 \right) + \cdots \right. \\
 &\quad \left. + (-1)^{n-1} 2 \exp(-\mu_i^2 x_n^2) + (-1)^n \right] \\
 k_0(s) &= 0.5(1 - s^2) \\
 A_i &= \frac{2 \sin \mu_i}{\mu_i + \sin \mu_i \cos \mu_i}, \\
 \mu &= (\mu_1, \dots, \mu_{30})', \text{ where } \mu_i \tan(\mu_i) = 1
 \end{aligned}$$

The gradient of the objective function f , $g(x) = 2x$, is easily supplied to the NLPQN subroutine. However, the analytical derivatives of the constraint are not used; instead, finite-difference derivatives are computed.

In the following code, the vector MU represents the first 30 positive values μ_i that satisfy $\mu_i \tan(\mu_i) = 1$:

```
proc iml;
  mu = { 8.6033358901938E-01 ,    3.4256184594817E+00 ,
        6.4372981791719E+00 ,    9.5293344053619E+00 ,
        1.2645287223856E+01 ,    1.5771284874815E+01 ,
        1.8902409956860E+01 ,    2.2036496727938E+01 ,
        2.5172446326646E+01 ,    2.8309642854452E+01 ,
        3.1447714637546E+01 ,    3.4586424215288E+01 ,
        3.7725612827776E+01 ,    4.0865170330488E+01 ,
        4.4005017920830E+01 ,    4.7145097736761E+01 ,
        5.0285366337773E+01 ,    5.3425790477394E+01 ,
        5.6566344279821E+01 ,    5.9707007305335E+01 ,
        6.2847763194454E+01 ,    6.5988598698490E+01 ,
        6.9129502973895E+01 ,    7.2270467060309E+01 ,
        7.5411483488848E+01 ,    7.8552545984243E+01 ,
        8.1693649235601E+01 ,    8.4834788718042E+01 ,
        8.7975960552493E+01 ,    9.1117161394464E+01 };;
```

The vector $A = (A_1, \dots, A_{30})'$ depends only on μ and is computed only once, before the optimization starts, as follows:

```
nmu = nrow(mu);
a = j(1,nmu,0.);
do i = 1 to nmu;
  a[i] = 2*sin(mu[i]) / (mu[i] + sin(mu[i])*cos(mu[i]));
end;
```

The constraint is implemented with the QUAD subroutine, which performs numerical integration of scalar functions in one dimension. The subroutine calls the module `fquad` that supplies the integrand for $h(x)$. For details about the QUAD call, see the section “QUAD Call” on page 896. Here is the code:

```
/* This is the integrand used in h(x) */
start fquad(s) global(mu,rho);
  z = (rho * cos(s*mu) - 0.5*(1. - s##2))##2;
  return(z);
finish;

/* Obtain nonlinear constraint h(x) */
start h(x) global(n,nmu,mu,a,rho);
  xx = x##2;
  do i= n-1 to 1 by -1;
    xx[i] = xx[i+1] + xx[i];
  end;
  rho = j(1,nmu,0.);
  do i=1 to nmu;
    mu2 = mu[i]##2;
```

```

    sum = 0; t1n = -1.;
    do j=2 to n;
        t1n = -t1n;
        sum = sum + t1n * exp(-mu2*xx[j]);
    end;
    sum = -2*sum + exp(-mu2*xx[1]) + t1n;
    rho[i] = -a[i] * sum;
end;
aint = do(0,1,.5);
call quad(z,"fquad",aint) eps=1.e-10;
v = sum(z);
return(v);
finish;

```

The modules for the objective function, its gradient, and the constraint $c(x) \geq 0$ are given in the following code:

```

/* Define modules for NLPQN call: f, g, and c */
start F_HS88(x);
    f = x * x`;
    return(f);
finish F_HS88;

start G_HS88(x);
    g = 2 * x;
    return(g);
finish G_HS88;

start C_HS88(x);
    c = 1.e-4 - h(x);
    return(c);
finish C_HS88;

```

The number of constraints returned by the “nlc” module is defined by $opt[10] = 1$. The ABSGTOL termination criterion (maximum absolute value of the gradient of the Lagrange function) is set by $tc[6] = 1E-4$. Here is the code:

```

print 'Hock & Schittkowski Problem #91 (1981) n=5, INSTEP=1';
opt = j(1,10,.);
opt[2]=3;
opt[10]=1;
tc = j(1,12,.);
tc[6]=1.e-4;
x0 = {.5 .5 .5 .5 .5};
n = ncol(x0);
call nlpqn(rc,rx,"F_HS88",x0,opt,,tc) grd="G_HS88" nlc="C_HS88";

```

Part of the iteration history and the parameter estimates are shown in [Output 14.8.1](#).

Output 14.8.1 Iteration History and Parameter Estimates

Parameter Estimates		5	
Nonlinear Constraints		1	
Optimization Start			
Objective Function		1.25	Maximum Constraint Violation
Maximum Gradient of the Lagran Func		1.1433393264	0.0952775105
		Maximum	Maximum
		Con-	Grad
		straint	Element
		Predicted	of the
		Function	Lagran
		Reduction	Func
Iter	Rest arts	Func Calls	Objective Function
			Violation
			Step Size
1	0	3	0.81165
2	0	4	0.18232
3*	0	5	0.34576
4	0	6	0.77689
5	0	7	0.54995
6	0	9	0.55322
7	0	10	0.75884
8	0	12	0.76720
9	0	13	0.94843
10	0	15	0.95661
11	0	16	1.11201
12	0	18	1.14603
13	0	20	1.19821
14	0	22	1.22804
15	0	23	1.31506
16	0	25	1.31759
17	0	26	1.35547
18	0	27	1.36136
19	0	28	1.36221
20	0	29	1.36266
21	0	30	1.36266
22	0	31	1.36266
			0.0869
			0.1175
			0.0690
			0.0132
			0.0239
			0.0212
			0.00828
			0.00681
			0.00237
			0.00207
			0.000690
			0.000494
			0.2810
			0.1991
			0.2292
			0.0697
			0.0876
			0.0133
			0.00259
			0.000902
			2.063E-6
			1.031E-6
			2.044E-6
Optimization Results			
Iterations		22	Function Calls
Gradient Calls		24	Active Constraints
Objective Function		1.3626578338	Maximum Constraint Violation
Maximum Projected Gradient		3.2132973E-6	Value Lagrange Function
Maximum Gradient of the Lagran Func		2.957267E-6	Slope of Search Direction
			1.3626568149
			-2.043849E-6

Output 14.8.1 *continued*

Optimization Results			
Parameter Estimates			
N Parameter	Estimate	Gradient Objective Function	Gradient Lagrange Function
1 X1	0.860193	1.720386	0.000001798
2 X2	6.0264249E-8	0.000000121	0.000000341
3 X3	0.643607	1.287214	-0.000000306
4 X4	-0.456614	-0.913228	0.000002957
5 X5	-7.390521E-9	-1.478104E-8	-1.478104E-8

Problems 88 to 92 of Hock and Schittkowski (1981) specify the same optimization problem for $n = 2$ to $n = 6$. You can solve any of these problems with the preceding code by submitting a vector of length n as the initial estimate, x_0 .

References

- Abramowitz, M. and Stegun, I. A. (1972), *Handbook of Mathematical Functions*, New York: Dover Publications.
- Al-Baali, M. and Fletcher, R. (1985), "Variational Methods for Nonlinear Least Squares," *Journal of the Operations Research Society*, 36, 405–421.
- Al-Baali, M. and Fletcher, R. (1986), "An Efficient Line Search for Nonlinear Least Squares," *Journal of Optimization Theory and Applications*, 48, 359–377.
- Anderson, B. D. and Moore, J. B. (1979), *Optimal Filtering*, New Jersey: Prentice-Hall.
- Bard, Y. (1974), *Nonlinear Parameter Estimation*, New York: Academic Press.
- Bates, D. M. and Watts, D. G. (1988), *Nonlinear Regression Analysis and Its Applications*, John Wiley & Sons.
- Beale, E. M. L. (1972), "A Derivation of Conjugate Gradients," in F. A. Lootsma, ed., *Numerical Methods for Nonlinear Optimization*, London: Academic Press.
- Betts, J. T. (1977), "An Accelerated Multiplier Method for Nonlinear Programming," *Journal of Optimization Theory and Applications*, 21, 137–174.
- Bracken, J. and McCormick, G. P. (1968), *Selected Applications of Nonlinear Programming*, New York: John Wiley & Sons.
- Chamberlain, R. M., Powell, M. J. D., Lemarechal, C., and Pedersen, H. C. (1982), "The Watchdog Technique for Forcing Convergence in Algorithms for Constrained Optimization," *Mathematical Programming*, 16, 1–17.

- De Jong, P. (1988), "The Likelihood for a State Space Model," *Biometrika*.
- Dennis, J. E., Gay, D. M., and Welsch, R. E. (1981), "An Adaptive Nonlinear Least-Squares Algorithm," *ACM Transactions on Mathematical Software*, 7, 348–368.
- Dennis, J. E. and Mei, H. H. W. (1979), "Two New Unconstrained Optimization Algorithms Which Use Function and Gradient Values," *Journal of Optimization Theory Applications*, 28, 453–482.
- Dennis, J. E. and Schnabel, R. B. (1983), *Numerical Methods for Unconstrained Optimization and Nonlinear Equations*, Englewood, NJ: Prentice-Hall.
- Eskow, E. and Schnabel, R. B. (1991), "Algorithm 695: Software for a New Modified Cholesky Factorization," *ACM Transactions on Mathematical Software*, 17, 306–312.
- Fletcher, R. (1987), *Practical Methods of Optimization*, Second Edition, Chichester, UK: John Wiley & Sons.
- Fletcher, R. and Powell, M. J. D. (1963), "A Rapidly Convergent Descent Method for Minimization," *Computer Journal*, 6, 163–168.
- Fletcher, R. and Xu, C. (1987), "Hybrid Methods for Nonlinear Least Squares," *Journal of Numerical Analysis*, 7, 371–389.
- Gay, D. M. (1983), "Subroutines for Unconstrained Minimization," *ACM Transactions on Mathematical Software*, 9, 503–524.
- George, J. A. and Liu, J. W. (1981), *Computer Solutions of Large Sparse Positive Definite Systems*, Englewood Cliffs, NJ: Prentice-Hall.
- Gill, E. P., Murray, W., Saunders, M. A., and Wright, M. H. (1983), "Computing Forward-Difference Intervals for Numerical Optimization," *SIAM J. Sci. Stat. Comput.*, 4, 310–321.
- Gill, E. P., Murray, W., Saunders, M. A., and Wright, M. H. (1984), "Procedures for Optimization Problems with a Mixture of Bounds and General Linear Constraints," *ACM Transactions on Mathematical Software*, 10, 282–298.
- Gill, E. P., Murray, W., and Wright, M. H. (1981), *Practical Optimization*, New York: Academic Press.
- Goldfeld, S. M., Quandt, R. E., and Trotter, H. F. (1966), "Maximisation by Quadratic Hill-Climbing," *Econometrica*, 34, 541–551.
- Hartmann, W. (1991), *The NLP Procedure: Extended User's Guide*, Releases 6.08 and 6.10, Cary, NC: SAS Institute Inc.
- Hock, W. and Schittkowski, K. (1981), "Test Examples for Nonlinear Programming Codes," *Lecture Notes in Economics and Mathematical Systems* 187.
- Jennrich, R. I. and Sampson, P. F. (1968), "Application of Stepwise Regression to Nonlinear Estimation," *Technometrics*, 10, 63–72.
- Lawless, J. F. (1982), *Statistical Methods and Methods for Lifetime Data*, New York: John Wiley & Sons.
- Liebman, J., Lasdon, L., Schrage, L., and Waren, A. (1986), *Modeling and Optimization with GINO*, California: The Scientific Press.

- Lindström, P. and Wedin, P. A. (1984), "A New Line-Search Algorithm for Nonlinear Least-Squares Problems," *Mathematical Programming*, 29, 268–296.
- Lütkepohl, H. (1991), *Introduction to Multiple Time Series Analysis*, Berlin: Springer-Verlag.
- Moré, J. J. (1978), "The Levenberg-Marquardt Algorithm: Implementation and Theory," in G. A. Watson, ed., *Lecture Notes in Mathematics*, volume 30, 105–116, Berlin-Heidelberg-New York: Springer-Verlag.
- Moré, J. J., Garbow, B. S., and Hillstom, K. E. (1981), "Testing Unconstrained Optimization Software," *ACM Transactions on Mathematical Software*, 7, 17–41.
- Moré, J. J. and Sorensen, D. C. (1983), "Computing a Trust-Region Step," *SIAM Journal on Scientific and Statistical Computing*, 4, 553–572.
- Moré, J. J. and Wright, S. J. (1993), *Optimization Software Guide*, Philadelphia: SIAM.
- Murtagh, B. A. and Saunders, M. A. (1983), *MINOS 5.0 User's Guide*, Technical Report SOL 83-20, Stanford University.
- Nelder, J. A. and Mead, R. (1965), "A Simplex Method for Function Minimization," *Computer Journal*, 7, 308–313.
- Peto, R. (1973), "Experimental Survival Curves for Interval-Censored Data," *Applied Statistics*, 22, 86–91.
- Polak, E. (1971), *Computational Methods in Optimization*, New York - San Francisco - London: Academic Press.
- Powell, M. J. D. (1977), "Restart Procedures for the Conjugate Gradient Method," *Mathematical Programming*, 12, 241–254.
- Powell, M. J. D. (1978a), "Algorithms for Nonlinear Constraints That Use Lagrangian Functions," *Mathematical Programming*, 14, 224–248.
- Powell, M. J. D. (1978b), "A Fast Algorithm for Nonlinearly Constrained Optimization Calculations," in G. A. Watson, ed., *Lecture Notes in Mathematics*, volume 630, 144–175, Berlin-Heidelberg-New York: Springer-Verlag.
- Powell, M. J. D. (1982a), "Extensions to Subroutine VF02AD," in R. F. Drenick and F. Kozin, eds., *Systems Modeling and Optimization, Lecture Notes in Control and Information Sciences*, volume 38, 529–538, Berlin-Heidelberg-New York: Springer-Verlag.
- Powell, M. J. D. (1982b), "VMCWD: A Fortran Subroutine for Constrained Optimization," *DAMTP 1982/NA4*, Cambridge, England.
- Powell, M. J. D. (1992), "A Direct Search Optimization Method That Models the Objective and Constraint Functions by Linear Interpolation," *DAMTP/NA5*, Cambridge, England.
- Rosenbrock, H. H. (1960), "An Automatic Method for Finding the Greatest or Least Value of a Function," *Computer Journal*, 3, 175–184.
- Schittkowski, K. (1978), "An Adaptive Precision Method for the Numerical Solution of Constrained Optimization Problems Applied to a Time-Optimal Heating Process," *Proceedings of the 8th IFIP Conference on Optimization Techniques*.

- Schittkowski, K. (1987), *More Test Examples for Nonlinear Programming Codes*, volume 282 of *Lecture Notes in Economics and Mathematical Systems*, Berlin-Heidelberg-New York: Springer-Verlag.
- Schittkowski, K. and Stoer, J. (1979), “A Factorization Method for the Solution of Constrained Linear Least Squares Problems Allowing Subsequent Data Changes,” *Numerische Mathematik*, 31, 431–463.
- Turnbull, B. W. (1976), “The Empirical Distribution Function with Arbitrarily Grouped, Censored and Truncated Data,” *Journal of the Royal Statistical Society, Series B*, 38, 290–295.
- Venzon, D. J. and Moolgavkar, S. H. (1988), “A Method for Computing Profile-Likelihood Based Confidence Intervals,” *Applied Statistics*, 37, 87–94.
- Wedin, P. A. and Lindström, P. (1987), *Methods and Software for Nonlinear Least Squares Problems*, University of Umea, Report No. UMINF 133.87.
- Ziegel, E. R. and Gorman, J. W. (1980), “Kinetic Modelling with Multipurpose Data,” *Technometrics*, 27, 352–357.

Chapter 15

Graphics Examples

Contents

Overview	411
An Introductory Graph	412
Details	413
Graphics Segments	413
Segment Attributes	414
Coordinate Systems	414
Windows and Viewports	417
Clipping Your Graphs	425
Common Arguments	426
Graphics Examples	427
Example 15.1: Scatter Plot Matrix	428
Example 15.2: Train Schedule	435
Example 15.3: Fisher's Iris Data	437

Overview

SAS/IML software provides you with a powerful set of graphics commands, called graphics *primitives*, from which to create customized displays. Basic drawing statements include the [GDRAW subroutine](#), which draws a line, the [GPOINT subroutine](#), which plots points, and the [GPOLY subroutine](#), which draws a polygon. With each drawing statement, you can associate a set of attributes such as color or line style.

In this chapter you learn about

- plotting simple two-dimensional plots
- naming and saving a graph
- changing attributes such as color and line style
- specifying the location and scale of your graph
- adding axes and text

SAS/IML graphics commands depend on the libraries and device drivers distributed with SAS/GRAPH software, and they do not work unless you have SAS/GRAPH software.

An Introductory Graph

Suppose that you have data for ACME Corporation's stock price and you want a simple $\text{PRICE} \times \text{DAY}$ graph to see the overall trend of the stock's price. The data are as follows.

Day	Price
0	43.75
5	48.00
10	59.75
15	75.5
20	59.75
25	71.50
30	70.575
35	61.125
40	79.50
45	72.375
50	67.00
55	54.125
60	58.750
65	43.625
70	47.125
75	45.50

To graph a scatter plot of these points, enter the following statements. These statements generate [Figure 15.1](#).

```
proc iml;                                /* invoke IML      */
  call gstart;                            /* start graphics  */
  xbox={0 100 100 0};
  ybox={0 0 100 100};
  day=do(0,75,5);                        /* initialize day  */
  price={43.75,48,59.75,75.5,            /* initialize price */
         59.75,71.5,70.575,
         61.125,79.5,72.375,67,
         54.125,58.75,43.625,
         47.125,45.50};
  call gopen;                             /* start new graph */
  call gpoly(xbox,ybox);                  /* draw a box around plot */
  call gpoint(day,price);                 /* plot the points  */
  call gshow;                             /* display the graph */
```

Figure 15.1 Scatter plot

Note that the `GSTART` statement initializes the graphics session. It usually needs to be called only once. Next, you enter the data matrices. Then you open a graphics segment (that is, begin a new graph) with the `GOPEN` command. The `GPOINT` command draws the scatter plot of points of `DAY` versus `PRICE`. The `GSHOW` command displays the graph.

Notice also that, for this example, the x coordinate of the data is `DAY` and that $0 \leq \text{DAY} \leq 100$. The y coordinate is `PRICE`, which ranges from $0 \leq \text{PRICE} \leq 100$. For this example, the ranges are this way because the IML default ranges are from 0 to 100 on both the x and y axes. Later on you learn how to change the default ranges for the axes with the `GWINDOW` statement so that you can handle data with any range of values.

Of course, this graph is quite simple. By the end of this chapter, you will know how to add axes and titles, scale axes, and connect the points with lines.

Details

Graphics Segments

A graph is saved in what is called a graphics segment. A *graphics segment* is simply a collection of primitives and their associated attributes that creates a graph.

Each time you create a new segment, it is named and stored in a SAS graphics catalog called WORK.GSEG. If you want to store your graphics segments in a permanent SAS catalog, do this with options to the GSTART call. You can name the segments yourself in the GOPEN statement, or you can let the IML procedure automatically generate a segment name. In this way, graphics segments that are used several times can be included in subsequent graphs by using the GINCLUDE command with the segment name. You can also manage and replay a segment by using the GREPLAY procedure as well as replay it in another IML session by using the GSHOW command.

To name a segment, include the name as an argument to the GOPEN statement. For example, to begin a new segment and name it STOCK1, use the following statement:

```
call gopen("stock1");
```

For more information about SAS catalogs and graphics, refer to the chapter on graphics in *SAS/GRAPH Software: Reference*.

Segment Attributes

A set of attributes is initialized for each graphics segment. These attributes are color, line style, line thickness, fill pattern, font, character height, and aspect ratio. You can change any of these attributes for a graphics segment by using the GSET command. Some IML graphics commands take optional attribute arguments. The values of these arguments affect only the graphics output associated with the call.

The IML graphics subsystem uses the same conventions that SAS/GRAPH software uses in setting the default attributes. It also uses the options set in the GOPTIONS statement when applicable. The SAS/IML default values for the GSET command are given by their corresponding GOPTIONS default values. To change the default, you need to issue a GOPTIONS statement. The GOPTIONS statement can also be used to set graphics options not available through the GSET command (for example, the ROTATE option).

For more information about GOPTIONS, refer to the chapter on the GOPTIONS statement in *SAS/GRAPH Software: Reference*.

Coordinate Systems

Each IML graph is associated with two independent cartesian coordinate systems, a *world coordinate System* and a *normalized coordinate system*.

Understanding World Coordinates

The *world coordinate system* is the coordinate system defined by your data. Because these coordinates help define objects in the data's two-dimensional world, these are referred to as *world coordinates*. For example, suppose that you have a data set that contains heights and weights and that you are interested in plotting height versus weight. Your data induces a world coordinate system in which each point (x, y) represents

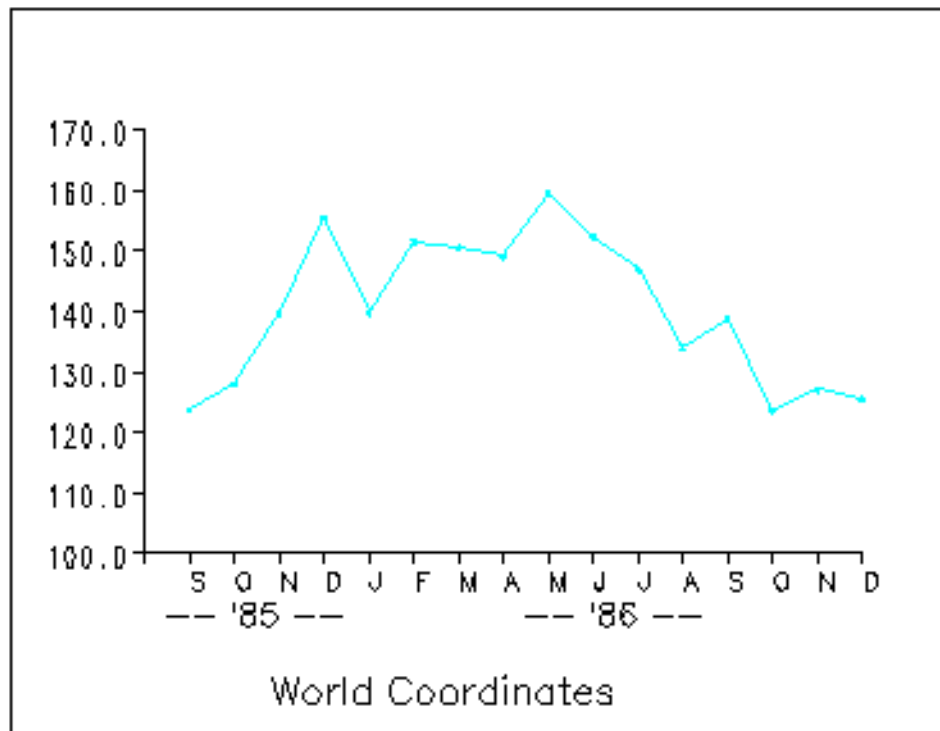
a pair of data values (*height,weight*). The world could be defined by the observed ranges of heights and weights, or it could be enlarged to include a range of all reasonable values for heights and weights.

Now consider a more realistic example of the stock price data for ACME Corporation. Suppose that the stock price data were actually the year-end prices of ACME stock for the years 1971 through 1986, as follows:

YEAR	PRICE
71	123.75
72	128.00
73	139.75
74	155.50
75	139.75
76	151.50
77	150.375
78	149.125
79	159.50
80	152.375
81	147.00
82	134.125
83	138.75
84	123.625
85	127.125
86	125.500

The actual range of YEAR is from 71 to 86, and the range of PRICE is from \$123.625 to \$159.50. These are the ranges in world coordinate space for the stock data. Of course, you could say that the range for PRICE could start at \$0 and range upwards to, for example, \$200. Or, if you were interested only in prices during the 80's, you could say the range for PRICE is from \$123.625 to \$152.375. As you see, it all depends on how you want to define your world.

Figure 15.2 shows a graph of the stock data with the world defined as the actual data given. The corners of the rectangle give the actual boundaries for this data.

Figure 15.2 World Coordinates

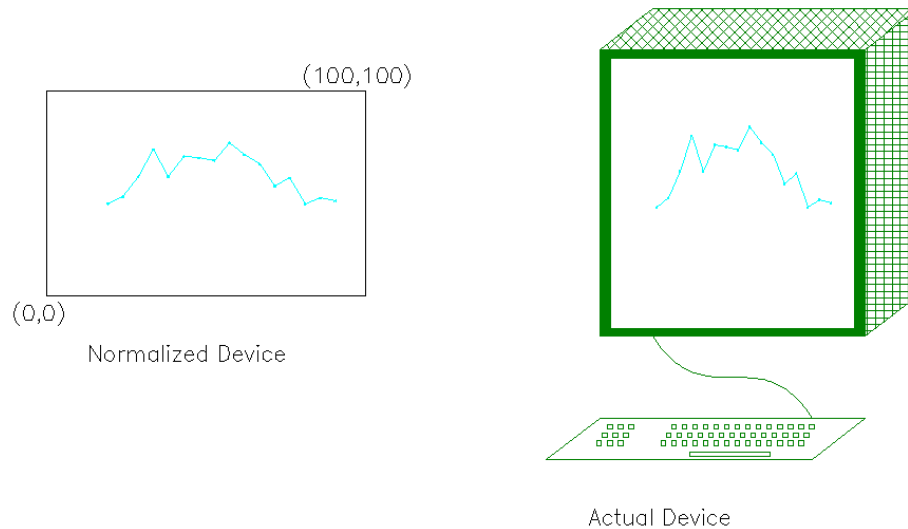
Understanding Normalized Coordinates

The *normalized coordinate system* is defined relative to your display device, usually a monitor or plotter. It is always defined with points varying between (0,0) and (100,100), where (0,0) refers to the lower-left corner and (100,100) refers to the upper-right corner.

In summary,

- the world coordinate system is defined relative to your data
- the normalized coordinate system is defined relative to the display device

Figure 15.3 shows the ACME stock data in terms of normalized coordinates. There is a natural mathematical relationship between each point in world and normalized coordinates. The normalized device coordinate system is mapped to the device display area so that (0,0), the lower-left corner, corresponds to (71, 123.625) in world coordinates, and (100,100), the upper-right corner, corresponds to (86,159.5) in world coordinates.

Figure 15.3 Normalized Coordinates

Windows and Viewports

A *window* defines a rectangular area in world coordinates. You define a window with a `GWINDOW` statement. You can define the window to be larger than, the same size as, or smaller than the actual range of data values, depending on whether you want to show all of the data or only part of the data.

A *viewport* defines in normalized coordinates a rectangular area on the display device where the image of the data appears. You define a viewport with the `GPORT` command. You can have your graph take up the entire display device or show it in only a portion, say the upper-right part.

Mapping Windows to Viewports

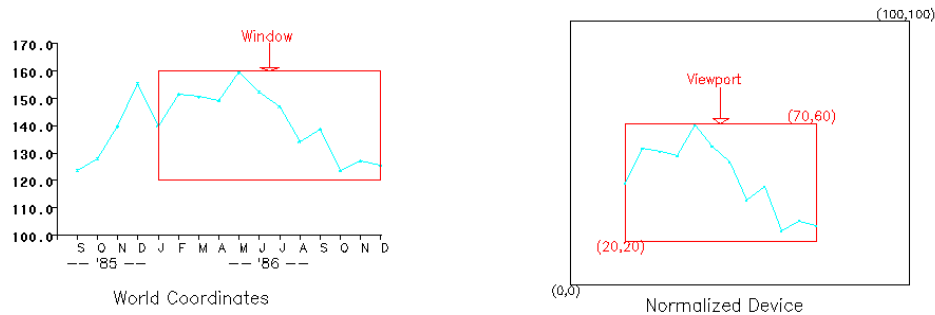
A *window* and a *viewport* are related by the linear transformation that maps the window onto the viewport. A line segment in the window is mapped to a line segment in the viewport such that the relative positions are preserved.

You do not have to display all of your data in a graph. In [Figure 15.4](#), the graph on the left displays all of the ACME stock data, and the graph on the right displays only a part of the data. Suppose that you wanted to graph only the last 10 years of the stock data—say, from 1977 to 1986. You would want to define a window where the YEAR axis ranges from 77 to 86, while the PRICE axis could range from 120 to 160. [Figure 15.4](#) shows stock prices in a window defined for data from 1977 to 1986 along the horizontal direction and from 120 to 160 along the vertical direction. The window is mapped to a viewport defined by the points (20,20) and (70,60). The appropriate `GPORT` and `GWINDOW` specifications are as follows:

```
call gwindow({77 120, 86 160});
call gport({20 20, 70 60});
```

The window, in effect, defines the portion of the graph that is to be displayed in world coordinates, and the viewport specifies the area on the device on which the image is to appear.

Figure 15.4 Window to Viewport Mapping



Understanding Windows

Because the default world coordinate system ranges from (0,0) to (100,100), you usually need to define a *window* in order to set the world coordinates that correspond to your data. A window specifies which part of the data in world coordinate space is to be shown. Sometimes you want all of the data shown; other times, you want to show only part of the data.

A window is defined by an array of four numbers, which define a rectangular area. You define this area by specifying the *world coordinates* of the lower-left and upper-right corners in the `GWINDOW` statement, which has the following general form:

CALL GWINDOW (*minimum-x minimum-y maximum-x maximum-y*) ;

The argument can be either a matrix or a literal. The order of the elements is important. The array of coordinates can be a 2×2 , 1×4 , or 4×1 *matrix*. These coordinates can be specified as matrix literals or as the name of a numeric matrix that contains the coordinates. If you do not define a window, the default is to assume both *x* and *y* range between 0 and 100.

In summary, a window

- defines the portion of the graph that appears in the viewport
- is a rectangular area
- is defined by an array of four numbers
- is defined in world coordinates
- scales the data relative to world coordinates

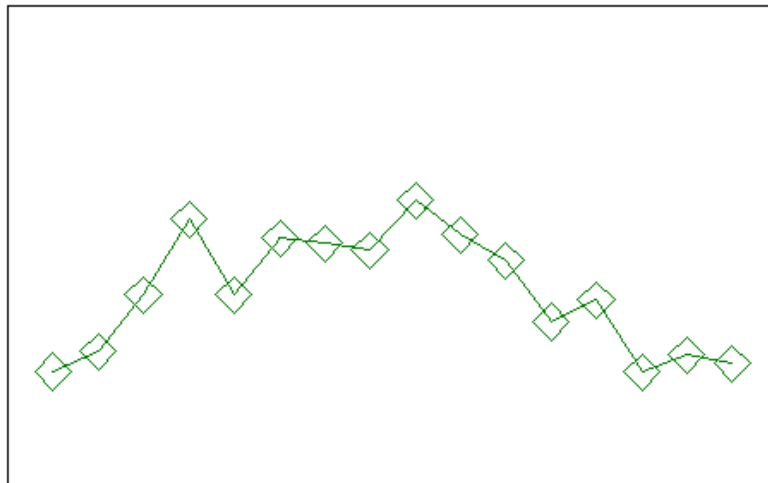
In the previous example, the variable `YEAR` ranges from 1971 to 1986, while `PRICE` ranges from 123.625 to 159.50. Because the data do not fit nicely into the default, you want to define a window that reflects the ranges of the variables `YEAR` and `PRICE`. To draw the graph of these data to scale, you can let the `YEAR` axis range from 70 to 87 and the `PRICE` axis range from 100 to 200. Use the following statements to draw the graph, shown in Figure 15.5.

```

call gstart;
xbox={0 100 100 0};
ybox={0 0 100 100};
call gopen("stocks1");          /* begin new graph STOCKS1 */
call gset("height", 2.0);
year=do(71,86,1);               /* initialize YEAR */
price={123.75 128.00 139.75      /* initialize PRICE */
       155.50 139.750 151.500
       150.375 149.125 159.500
       152.375 147.000 134.125
       138.750 123.625 127.125
       125.50};
call gwindow({70 100 87 200});  /* define window */
call gpoint(year,price,"diamond","green"); /* graph the points */
call gdraw(year,price,1,"green"); /* connect points */
call gshow;                     /* show the graph */

```

Figure 15.5 Stock Data



In the following example, you perform several steps that you did not do with the previous graph:

- You associate the name STOCKS1 with this graphics segment in the GOPEN command.
- You define a window that reflects the actual ranges of the data with a GWINDOW command.
- You associate a plotting symbol, the diamond, and the color green with the GPOINT command.
- You connect the points with line segments with the GDRAW command. The GDRAW command requests that the line segments be drawn in style 1 and be green.

Understanding Viewports

A *viewport* specifies a rectangular area on the display device where the graph appears. You define this area by specifying the *normalized* coordinates, the lower-left corner and the upper-right corner, in the GPORT statement, which has the following general form:

CALL GPORT (*minimum-x minimum-y maximum-x maximum-y*) ;

The argument can be either a matrix or a literal. Note that both *x* and *y* must range between 0 and 100. As with the GWINDOW specification, you can give the coordinates either as a matrix literal enclosed in braces or as the name of a numeric matrix that contains the coordinates. The array can be a 2×2 , 1×4 , or 4×1 matrix. If you do not define a viewport, the default is to span the entire display device.

In summary, a viewport

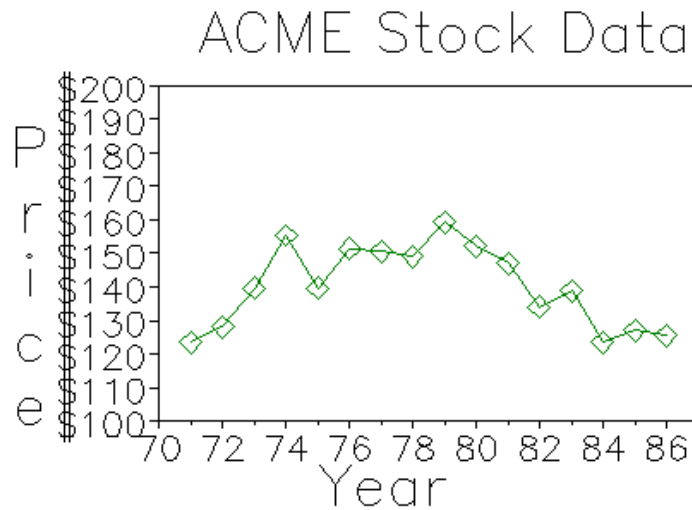
- specifies where the image appears on the display
- is a rectangular area
- is specified by an array of four numbers
- is defined in normalized coordinates
- scales the data relative to the shape of the viewport

To display the stock price data in a smaller area on the display device, you must define a viewport. While you are at it, add some text to the graph. You can use the graph that you created and named STOCKS1 in this new graph. The following statements create the graph shown in [Figure 15.6](#).

```

/* module centers text strings */
start gscenter(x,y,str);
  call gslen(len,str);           /* find string length */
  call gscript(x-len/2,y,str);   /* print text */
finish gscenter;

call gopen("stocks2");           /* open a new segment */
call gset("font","swiss");        /* set character font */
call gpoly(xbox,ybox);           /* draw a border */
call gwindow({70 100,87 200});   /* define a window */
call gport({15 15,85 85});       /* define a viewport */
call ginclude("stocks1");         /* include segment STOCKS1 */
call gxaxis({70 100},17,18, ,    /* draw x-axis */
  ,"2.",1.5);
call gyaxis({70 100},100,11, ,    /* draw y-axis */
  ,"dollar5.",1.5);
call gset("height",2.0);          /* set character height */
call gtext(77,89,"Year");         /* print horizontal text */
call gvtext(68,200,"Price");      /* print vertical text */
call gscenter(79,210,"ACME Stock Data"); /* print title */
call gshow;
```

Figure 15.6 Stock Data with Axes and Labels

The following list describes the statements that generated this graph:

- **GOPEN** begins a new graph and names it STOCKS2.
- **GPOLY** draws a box around the display area.
- **GWINDOW** defines the world coordinate space to be larger than the actual range of stock data values.
- **GPORT** defines a viewport. It causes the graph to appear in the center of the display, with a border around it for text. The lower-left corner has coordinates (15,15) and the upper-right corner has coordinates (85,85).
- **GINCLUDE** includes the graphics segment STOCKS1. This saves you from having to plot points you have already created.
- **GXAXIS** draws the x axis. It begins at the point (70,100) and is 17 units (years) long, divided with 18 tick marks. The axis tick marks are printed with the numeric 2.0 format, and they have a height of 1.5 units.
- **GYAXIS** draws the y axis. It also begins at (70,100) but is 100 units (dollars) long, divided with 11 tick marks. The axis tick marks are printed with the DOLLAR5.0 format and have a height of 1.5 units.
- **GSET** sets the text font to be Swiss and the height of the letters to be 2.0 units. The height of the characters has been increased because the viewport definition scales character sizes relative to the viewport.
- **GTEXT** prints horizontal text. It prints the text string **Year** beginning at the world coordinate point (77,89).

- GVTEXT prints vertical text. It prints the text string **Price** beginning at the world coordinate point (68,200).
- GSCENTER runs the module to print centered text strings.
- GSHOW displays the graph.

Changing Windows and Viewports

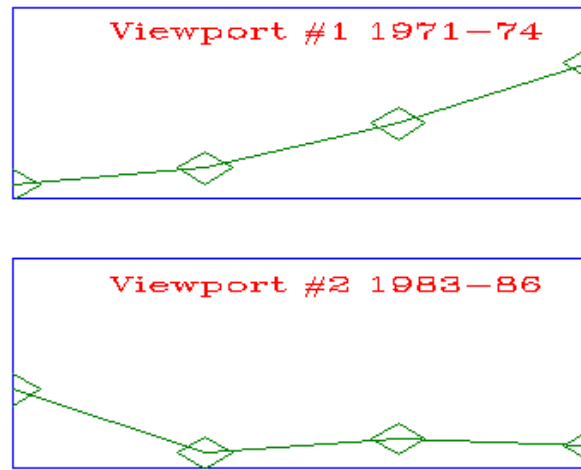
Windows and viewports can be changed for the graphics segment any time that the segment is active. Using the stock price example, you can first define a window for the data during the years 1971 to 1974 and map this to the viewport defined on the upper half of the normalized device; then you can redefine the window to enclose the data for 1983 to 1986 and map this to an area in the lower half of the normalized device. Notice how the shape of the viewport affects the shape of the curve. Changing the viewport can affect the height of any printed characters as well. In this case, you can modify the HEIGHT parameter.

The following statements generate the graph in [Figure 15.7](#):

```

/* figure 12.7 */
reset clip;                      /* clip outside viewport */
call gopen;                      /* open a new segment */
call gset("color","blue");
call gset("height",2.0);
call gwindow({71 120,74 175});    /* define a window */
call gport({20 55,80 90});        /* define a viewport */
call gpoly({71 74 74 71},{120 120 170 170}); /* draw a border */
call gscript(71.5,162,"Viewport #1 1971-74",, /* print text */
,3.0,"complex","red");
call gpoint(year,price,"diamond","green"); /* draw points */
call gdraw(year,price,1,"green");          /* connect points */
call gblkvpd;
call gwindow({83 120,86 170});    /* define new window */
call gport({20 10,80 45});        /* define new viewport */
call gpoly({83 86 86 83},{120 120 170 170}); /* draw border */
call gpoint(year,price,"diamond","green"); /* draw points */
call gdraw(year,price,1,"green");          /* connect points */
call gscript(83.5,162,"Viewport #2 1983-86",, /* print text */
,3.0,"complex","red");
call gshow;

```

Figure 15.7 Multiple Viewports

The RESET CLIP command is necessary because you are graphing only a part of the data in the window. You want to clip the data that falls outside of the window. See the section “Clipping Your Graphs” on page 425 for more about clipping. In this graph, you

- open a new segment (GOPEN)
- define the first window for the first four years’ data (GWINDOW)
- define a viewport in the upper part of the display device (GPORT)
- draw a box around the viewport (GPOLY)
- add text (GSCRIPT)
- graph the points and connect them (GPOINT and GDRAW)
- define the second window for the last four years (GWINDOW)
- define a viewport in the lower part of the display device (GPORT)
- draw a box around the viewport (GPOLY)
- graph the points and connect them (GPOINT and GDRAW)
- add text (GSCRIPT)
- display the graph (GSHOW)

Stacking Viewports

Viewports can be stacked; that is, a viewport can be defined relative to another viewport so that you have a viewport within a viewport.

A window or a viewport is changed globally through the IML graphics commands: the GWINDOW command for windows, and the GPORT, GPORTSTK, and GPORTPOP commands for viewports. When a window or viewport is defined, it persists across IML graphics commands until another window- or viewport-altering command is encountered. Stacking helps you define a viewport without losing the effect of a previously defined viewport. When a stacked viewport is *popped*, you are placed into the environment of the previous viewport.

Windows and viewports are associated with a particular segment; thus, they automatically become undefined when the segment is closed. A segment is closed whenever IML encounters a GCLOSE command or a GOPEN command. A window or a viewport can also be changed for a single graphics command. Either one can be passed as an argument to a graphics primitive, in which case any graphics output associated with the call is defined in the specified window or viewport. When a viewport is passed as an argument, it is stacked, or defined relative to the current viewport, and *popped* when the graphics command is complete.

For example, suppose you want to create a legend that shows the low and peak points of the data for the ACME stock graph. Use the following statements to create a graphics segment showing this information:

```
call gopen("legend");
call gset('height',5);    /* enlarged to accommodate viewport later */
call gset('font','swiss');
call gscript(5,75,"Stock Peak:  159.5 in 1979");
call gscript(5,65,"Stock Low:   123.6 in 1984");
call gclose;
```

Use the following statements to create a segment that highlights and labels the low and peak points of the data:

```
/* Highlight and label the low and peak points of the stock */
call gopen("labels");
call gwindow({70 100 87 200}); /* define window */
call gpoint(84,123.625,"circle","red",4) ;
call gtext(84,120,"LOW","red");
call gpoint(79,159.5,"circle","red",4);
call gtext(79,162,"PEAK","red");
call gclose;
```

Next, open a new graphics segment and include the STOCK1 segment created earlier in the chapter, placing the segment in the viewport {10 10 90 90}. Here is the code:

```
call gopen;
call gportstk ({10 10 90 90}); /* viewport for the plot itself */
call ginclude('stocks2');
```


To place the legend in the upper-right corner of this viewport, use the GPORTSTK command instead of the GPORT command to define the legend's viewport relative to the one used for the plot of the stock data, as follows:

```
call gportstk ({70 70 100 100}); /* viewport for the legend */
call ginclude("legend");
```

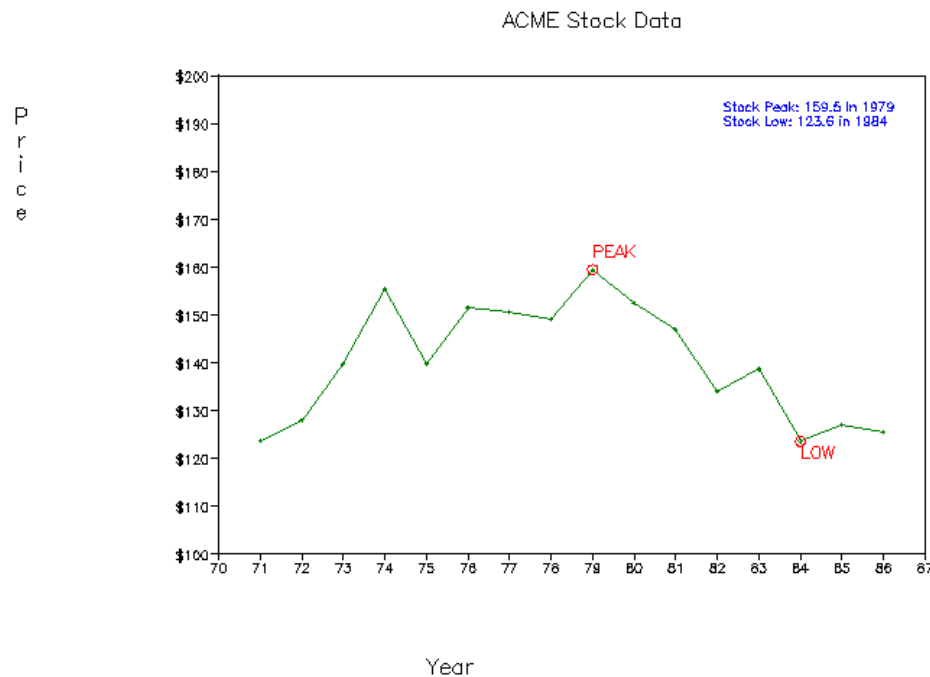
Now pop the legend's viewport to get back to the viewport of the plot itself and include the segment that labels and highlights the low and peak stock points. Here is the code:

```
call gportpop; /* viewport for the legend */
call ginclude ("labels");
```

Finally, display the graph, as follows:

```
call gshow;
```

Figure 15.8 Stacking Viewports



Clipping Your Graphs

The IML graphics subsystem does not automatically clip the output to the viewport. Thus, it is possible that data are graphed outside the defined viewport. This happens when there are data points lying outside the defined window. For instance, if you specify a window to be a subset of the world, then there will be data

lying outside the window and these points will be graphed outside the viewport. This is usually not what you want. To clean up such graphs, you either delete the points you do not want to graph or clip the graph.

There are two ways to clip a graph. You can use the RESET CLIP command, which clips outside a viewport. The CLIP option remains in effect until you submit a RESET NOCLIP command. You can also use the GBLKVP command, which clips either inside or outside a viewport. Use the GBLKVP command to define a blanking area in which nothing can be drawn until the blanking area is released. Use the GBLKVPD command to release the blanking area.

Common Arguments

IML graphics commands are available in the form of call subroutines. They generally take a set of required arguments followed by a set of optional arguments. All graphics primitives take *window* and *viewport* as optional arguments. Some IML graphics commands, like GPOINT or GPIE, accept implicit repetition factors in the argument lists. The GPOINT command places as many markers as there are well-defined (x, y) pairs. The GPIE command draws as many slices as there are well-defined pies. In those cases, some of the attribute matrices can have more than one element, which are used in order. If an attribute list is exhausted before the repetition factor is completed, the last element of the list is used as the attribute for the remaining primitives.

The arguments to the IML graphics commands are positional. Thus, to skip over an optional argument from the middle of a list, you must specify a comma to hold its place. For example, the following command omits the third argument from the argument list:

```
call gpoint(x,y, , "red");
```

The following list details the arguments commonly used in IML graphics commands:

<i>color</i>	is a character matrix or literal that names a valid color as specified in the GOPTIONS statement. The default color is the first color specified in the COLORS= list in the GOPTIONS statement. If no such list is given, IML uses the first default color for the graphics device. Note that <i>color</i> can be specified either as a quoted literal, such as "RED," a color number, such as 1, or the name of a matrix that contains a reference to a valid color. A color number <i>n</i> refers to the <i>n</i> th color in the color list. You can change the default color with the GSET command.
<i>font</i>	is a character matrix or quoted literal that specifies a valid font name. The default font is the hardware font, which can be changed by the GSET command unless a viewport is in effect.
<i>height</i>	is a numeric matrix or literal that specifies the character height. The unit of height is the <i>gunit</i> of the GOPTIONS statement, when specified; otherwise, the unit is a character cell. The default height is 1 <i>gunit</i> , which you can change by using the GSET command.
<i>pattern</i>	is a character matrix or quoted literal that specifies the pattern to fill the interior of a closed curve. You specify a pattern by a coded character string as documented in the V= option in the PATTERN statement (refer to the chapter on the PATTERN statement in <i>SAS/GRAPH Software: Reference</i>).

The default pattern set by the IML graphics subsystem is “E,” that is, empty. The default pattern can be changed by using the GSET command.

segment-name is a character matrix or quoted literal that specifies a valid SAS name used to identify a graphics segment. The *segment-name* is associated with the graphics segment opened with a GOPEN command. If you do not specify *segment-name*, IML generates default names. For example, to create a graphics segment called PLOTA, use the following statement:

```
call gopen("plota");
```

Graphics segments are not allowed to have the same name as an existing segment. If you try to create a second segment named PLOTA (that is, when the *replace flag* is turned off), then the second segment is named PLOTA1. The *replace flag* is set by the GOPEN command for the segment that is being created. To open a new segment named PLOTA and replace an existing segment with the same name, use the following statement:

```
call gopen("plota",1);
```

If you do not specify a *replace* argument to the GOPEN command, the default is set by the GSTART command for all subsequent segments that are created. By default, the GSTART command sets the *replace flag* to 0, so that new segments do not replace like-named segments.

style is a numeric matrix or literal that specifies an index that corresponds to the line style documented for the SYMBOL statement in the chapter on the SYMBOL statement in *SAS/GRAPH Software: Reference*. The IML graphics subsystem sets the default line style to be 1, a solid line. The default line style can be changed by using the GSET command.

symbol is a character matrix or quoted literal that specifies either a character string that corresponds to a symbol as defined for the V= option of the SYMBOL statement or specifies the corresponding identifying symbol number. STAR is the default symbol used by the IML graphics subsystem.

SAS/IML graphics commands are described in detail in [Chapter 23](#).

Refer also to *SAS/GRAPH Software: Reference* for additional information.

Graphics Examples

This section provides the details and code for three examples that involve SAS/IML graphics. The first example shows a 2×2 matrix of scatter plots and a 3×3 matrix of scatter plots. A matrix of scatter plots is useful when you have several variables that you want to investigate simultaneously rather than in pairs. The second example draws a grid for representing a train schedule, with arrival and departure dates on the horizontal axis and destinations along the vertical axis. The final example plots Fisher’s iris data. The following example shows how to plot several graphs on one page.

Example 15.1: Scatter Plot Matrix

With the viewport capability of the IML graphics subroutine, you can arrange several graphs on a page. In this example, multiple graphs are generated from three variables and are displayed in a scatterplot matrix. For each variable, one contour plot is generated with each of the other variables as the dependent variable. For the graphs on the main diagonal, a box-and-whiskers plot is generated for each variable.

This example takes advantage of user-defined IML modules:

BOXWSKR	computes median and quartiles.
GBXWSKR	draws box-and-whiskers plots.
CONTOUR	generates confidence ellipses assuming bivariate normal data.
GCONTOUR	draws the confidence ellipses for each pair of variables.
GSCATMAT	produces the $n \times n$ scatter plot matrix, where n is the number of variables.

The code for the five modules and a sample data set follow. The modules produce [Figure 15.1.1](#) and [Figure 15.1.2](#).

```

/* This program generates a data set and uses iml graphics      */
/* subsystem to draw a scatterplot matrix.                      */
/*                                                                */
data factory;
  input recno prod temp a defect mon;
  datalines;
    1  1.82675    71.124    1.12404    1.79845          2
    2  1.67179    70.9245   0.924523   1.05246          3
    3  2.22397    71.507    1.50696    2.36035          4
    4  2.39049    74.8912    4.89122    1.93917          5
    5  2.45503    73.5338    3.53382    2.0664          6
    6  1.68758    71.6764    1.67642    1.90495          7
    7  1.98233    72.4222    2.42221    1.65469          8
    8  1.17144    74.0884    4.08839    1.91366          9
    9  1.32697    71.7609    1.76087    1.21824         10
   10  1.86376    70.3978    0.397753   1.21775         11
   11  1.25541    74.888     4.88795    1.87875         12
   12  1.17617    73.3528    3.35277    1.15393          1
   13  2.38103    77.1762    7.17619    2.26703          2
   14  1.13669    73.0157    3.01566          1          3
   15  1.01569    70.4645    0.464485          1          4
   16  2.36641    74.1699    4.16991    1.73009          5
   17  2.27131    73.1005    3.10048    1.79657          6
   18  1.80597    72.6299    2.62986    1.8497          7
   19  2.41142    81.1973    11.1973     2.137          8
   20  1.69218    71.4521    1.45212    1.47894          9
   21  1.95271    74.8427     4.8427    1.93493         10
   22  1.28452    76.7901     6.79008    2.09208         11
   23  1.51663    83.4782    13.4782    1.81162         12
   24  1.34177    73.4237     3.42369    1.57054          1
   25  1.4309     70.7504    0.750369    1.22444          2
  
```

26	1.84851	72.9226	2.92256	2.04468	3
27	2.08114	78.4248	8.42476	1.78175	4
28	1.99175	71.0635	1.06346	1.25951	5
29	2.01235	72.2634	2.2634	1.36943	6
30	2.38742	74.2037	4.20372	1.82846	7
31	1.28055	71.2495	1.24953	1.8286	8
32	2.05698	76.0557	6.05571	2.03548	9
33	1.05429	77.721	7.72096	1.57831	10
34	2.15398	70.8861	0.886068	2.1353	11
35	2.46624	70.9682	0.968163	2.26856	12
36	1.4406	73.5243	3.52429	1.72608	1
37	1.71475	71.527	1.52703	1.72932	2
38	1.51423	78.5824	8.5824	1.97685	3
39	2.41538	73.7909	3.79093	2.07129	4
40	2.28402	71.131	1.13101	2.25293	5
41	1.70251	72.3616	2.36156	2.04926	6
42	1.19747	72.3894	2.3894	1	7
43	1.08089	71.1729	1.17288	1	8
44	2.21695	72.5905	2.59049	1.50915	9
45	1.52717	71.1402	1.14023	1.88717	10
46	1.5463	74.6696	4.66958	1.25725	11
47	2.34151	90	20	3.57864	12
48	1.10737	71.1989	1.19893	1.62447	1
49	2.2491	76.6415	6.64147	2.50868	2
50	1.76659	71.7038	1.70377	1.231	3
51	1.25174	76.9657	6.96572	1.99521	4
52	1.81153	73.0722	3.07225	2.15915	5
53	1.72942	71.9639	1.96392	1.86142	6
54	2.17748	78.1207	8.12068	2.54388	7
55	1.29186	77.0589	7.05886	1.82777	8
56	1.92399	72.6126	2.61256	1.32816	9
57	1.38008	70.8872	0.887228	1.37826	10
58	1.96143	73.8529	3.85289	1.87809	11
59	1.61795	74.6957	4.69565	1.65806	12
60	2.02756	75.7877	5.78773	1.72684	1
61	2.41378	75.9826	5.98255	2.76309	2
62	1.41413	71.3419	1.34194	1.75285	3
63	2.31185	72.5469	2.54685	2.27947	4
64	1.94336	71.5592	1.55922	1.96157	5
65	2.094	74.7338	4.73385	2.07885	6
66	1.19458	72.233	2.23301	1	7
67	2.13118	79.1225	9.1225	1.84193	8
68	1.48076	87.0511	17.0511	2.94927	9
69	1.98502	79.0913	9.09131	2.47104	10
70	2.25937	73.8232	3.82322	2.49798	12
71	1.18744	70.6821	0.682067	1.2848	1
72	1.20189	70.7053	0.705311	1.33293	2
73	1.69115	73.9781	3.9781	1.87517	3
74	1.0556	73.2146	3.21459	1	4
75	1.59936	71.4165	1.41653	1.29695	5
76	1.66044	70.7151	0.715145	1.22362	6
77	1.79167	74.8072	4.80722	1.86081	7
78	2.30484	71.5028	1.50285	1.60626	8
79	2.49073	71.5908	1.59084	1.80815	9

```

80  1.32729  70.9077  0.907698  1.12889      10
81  2.48874  83.0079  13.0079  2.59237      11
82  2.46786  84.1806  14.1806  3.35518      12
83  2.12407  73.5826  3.58261  1.98482       1
84  2.46982  76.6556  6.65559  2.48936       2
85  1.00777  70.2504  0.250364      1       3
86  1.93118  73.9276  3.92763  1.84407       4
87  1.00017  72.6359  2.63594  1.3882       5
88  1.90622   71.047   1.047   1.7595       6
89  2.43744   72.321  2.32097  1.67244       7
90  1.25712    90      20  2.63949       8
91  1.10811  71.8299  1.82987      1       9
92  2.25545  71.8849  1.8849  1.94247      10
93  2.47971  73.4697  3.4697  1.87842      11
94  1.93378  74.2952  4.2952  1.52478      12
95  2.17525  73.0547  3.05466  2.23563       1
96  2.18723  70.8299  0.829929  1.75177       2
97  1.69984  72.0026  2.00263  1.45564       3
98  1.12504  70.4229  0.422904  1.06042       4
99  2.41723  73.7324  3.73238  2.18307       5
;

proc iml;

  /*-- Load graphics --*/
  call gstart;

  /*-----*/
  /*-- Define modules --*/
  /*-----*/

  /*  Module : compute contours  */
  start contour(c,x,y,npoints,pvalues);

  /*  This routine computes contours for a scatter plot      */
  /*  c returns the contours as consecutive pairs of columns */
  /*  x and y are the x and y coordinates of the points      */
  /*  npoints is the number of points in a contour           */
  /*  pvalues is a column vector of contour probabilities     */
  /*  the number of contours is controlled by the ncol(pvalue) */

  xx=x||y;
  n=nrow(x);
  /* Correct for the mean */
  mean=xx[+,]/n;
  xx=xx-mean@j(n,1,1);

  /* Find principal axes of ellipses */
  xx=xx`*xx/n;
  call eigen(v,e,xx);

  /* Set contour levels */
  c=-2*log(1-pvalues);
  a=sqrt(c*v[1]); b=sqrt(c*v[2]);

```

```

/* Parameterize the ellipse by angle */
t=((1:npoints)-{1})#atan(1)#8/(npoints-1);
s=sin(t);
t=cos(t);
s=s` *a;
t=t` *b;

/* Form contour points */
s=((e*(shape(s,1)//shape(t,1))+mean`@j(1,npoints*ncol(c),1))`);
c=shape(s,npoints);

/* Returned as ncol pairs of columns for contours */
finish contour;

/*-- Module : draw contour curves --*/
start gcontour(t1, t2);
  run contour(t12, t1, t2, 30, {.5 .8 .9});
  window=(min(t12[, {1 3}], t1) || min(t12[, {2 4}], t2)) //
    (max(t12[, {1 3}], t1) || max(t12[, {2 4}], t2));
  call gwindow(window);
  call gdraw(t12[, 1], t12[, 2], , 'blue');
  call gdraw(t12[, 3], t12[, 4], , 'blue');
  call gdraw(t12[, 5], t12[, 6], , 'blue');
  call gpoint(t1, t2, , 'red');
finish gcontour;

/*-- Module : find median, quartiles for box and whisker plot --*/
start boxwhskr(x, u, q2, m, q1, l);
  rx=rank(x);
  s=x;
  s[rx,]=x;
  n=nrow(x);

/*-- Median --*/
  m=floor(((n+1)/2) || ((n+2)/2));
  m=(s[m,]) [+, ]/2;

/*-- Compute quartiles --*/
  q1=floor(((n+3)/4) || ((n+6)/4));
  q1=(s[q1,]) [+, ]/2;
  q2=ceil(((3*n+1)/4) || ((3*n-2)/4));
  q2=(s[q2,]) [+, ]/2;
  h=1.5*(q2-q1); /*-- step=1.5*(interquartile range) --*/
  u=q2+h;
  l=q1-h;
  u=(u>s) [+, ]; /*-- adjacent values -----*/
  u=s[u,];
  l=(l>s) [+, ];
  l=s[l+1,];

finish boxwhskr;

/*-- Box and Whisker plot --*/
start gbxwhskr(t, ht);

```

```

    run boxwhskr(t, up, q2,med, q1, lo);

/*---Adjust screen viewport and data window */
    y=min(t)//max(t);
    call gwindow({0, 100} || y);
    mid = 50;
    wlen = 20;

/*-- Add whiskers */
    wstart=mid-(wlen/2);
    from=(wstart||up)//(wstart||lo);
    to=((wstart//wstart)+wlen)||from[,2];

/*-- Add box */
    len=50;
    wstart=mid-(len/2);
    wstop=wstart+len;
    from=from//(wstart||q2)//(wstart||q1)//
        (wstart||q2)//(wstop||q2);
    to=to//(wstop||q2)//(wstop||q1)//
        (wstart||q1)//(wstop||q1);

/*---Add median line */
    from=from//(wstart||med);
    to=to//(wstop||med);

/*---Attach whiskers to box */
    from=from//(mid||up)//(mid||lo);
    to=to//(mid||q2)//(mid||q1);

/*-- Draw box and whiskers */
    call gdrawl(from, to,, 'red');

/*---Add minimum and maximum data points */
    call gpoint(mid, y ,3, 'red');

/*---Label min, max, and mean */
    y=med//y;
    s={'med' 'min' 'max'};
    call gset("font","swiss");
    call gset('height',13);
    call gscript(wstop+ht, y, char(y,5,2),,,,, 'blue');
    call gstrlen(len, s);
    call gscript(wstart-len-ht,y,s,,,, 'blue');
    call gset('height');
finish gbxwhskr;

/*-- Module : do scatter plot matrix --*/
start gscatmat(data, vname);
    call gopen('scatter');
    nv=ncol(vname);
    if (nv=1) then nv=nrow(vname);
    cellwid=int(90/nv);
    dist=0.1*cellwid;

```



```

width=cellwid-2*dist;
xstart=int((90 -cellwid * nv)/2) + 5;
xgrid=((0:nv)#cellwid + xstart)`;

/*-- Delineate cells --*/
cell1=xgrid;
cell1=cell1||(cell1[nv+1]//cell1[nv+1-(0:nv-1)]);
cell2=j(nv+1, 1, xstart);
cell2=cell1[,1]||cell2;
call gdrawl(cell1, cell2);
call gdrawl(cell1[, {2 1}], cell2[, {2 1}]);
xstart = xstart + dist; ystart = xgrid[nv] + dist;

/*-- Label variables ---*/
call gset("height", 5);
call gset("font","swiss");
call gstrlen(len, vname);
where=xgrid[1:nv] + (cellwid-len)/2;
call gscript(where, 0, vname) ;
len=len[nv-(0:nv-1)];
where=xgrid[1:nv] + (cellwid-len)/2;
call gscript(4,where, vname[nv - (0:nv-1)],90);

/*-- First viewport --*/
vp=(xstart || ystart)//((xstart || ystart) + width) ;

/* Since the characters are scaled to the viewport */
/* (which is inversely porportional to the */
/* number of variables), */
/* enlarge it proportional to the number of variables */

ht=2*nv;
call gset("height", ht);
do i=1 to nv;
  do j=1 to i;
    call gportstk(vp);
    if (i=j) then run gbxwhskr(data[,i], ht);
    else run gcontour(data[,j], data[,i]);
  /*-- onto the next viewport --*/
  vp[,1] = vp[,1] + cellwid;
  call gportpop;
  end;
  vp=(xstart // xstart + width) || (vp[,2] - cellwid);
end;
call gshow;
finish gscatmat;

/*-- Placement of text is based on the character height. */
/* The IML modules defined here assume percent as the unit of */
/* character height for device independent control. */
goptions gunit=pct;

use factory;
vname={prod, temp, defect};

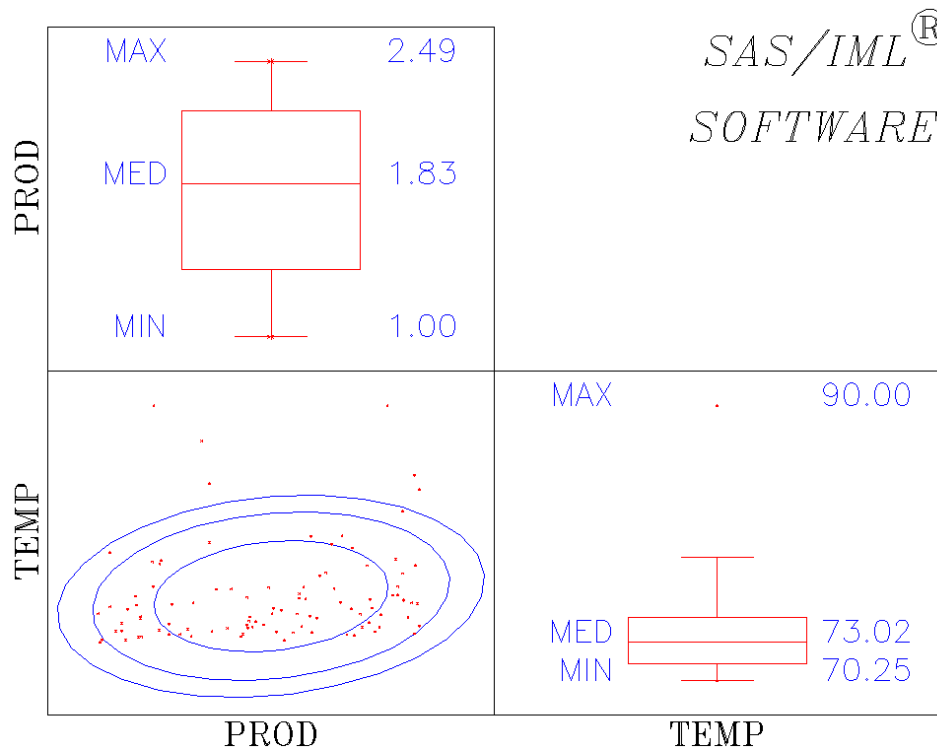
```

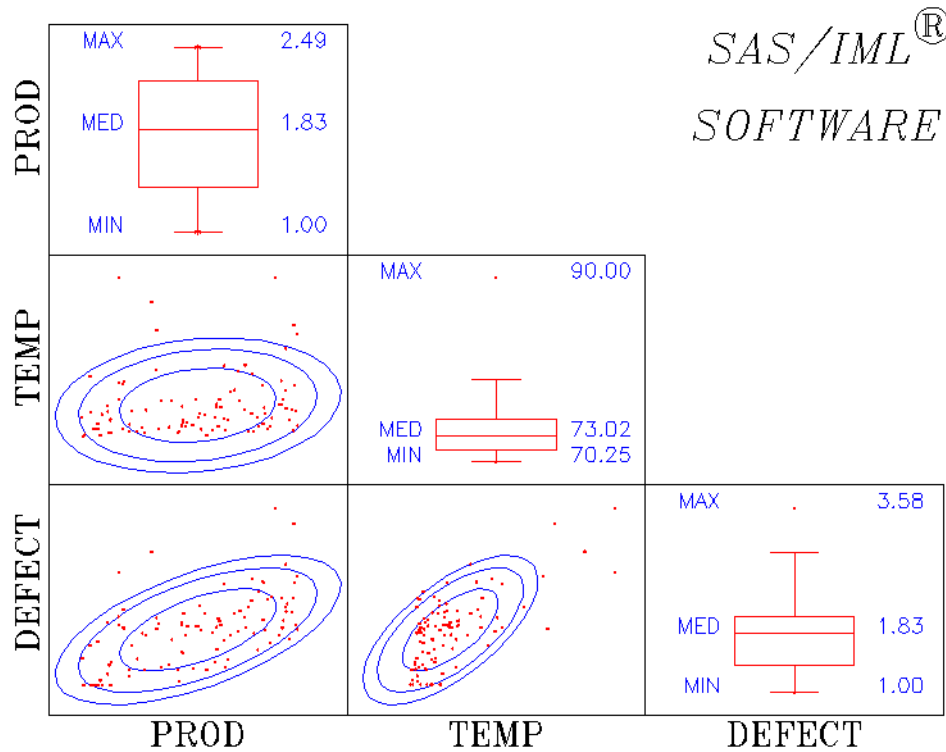
```

read all var vname into xyz;
run gscatmat(xyz, vname[1:2]);  /*-- 2 x 2 scatter plot matrix --*/
run gscatmat(xyz, vname);      /*-- 3 x 3 scatter plot matrix --*/
quit;

goptions gunit=cell;           /*-- reset back to default --*/

```

Output 15.1.1 2 × 2 Scatter Plot Matrix

Output 15.1.2 3 × 3 Scatter Plot Matrix

Example 15.2: Train Schedule

This example draws a grid on which the horizontal dimension gives the arrival/departure data and the vertical dimension gives the destination. The first section of the code defines the matrices used. The following section generates the graph. The following example code shows some applications of the GGRID, GDRAWL, GSTRLEN, and GSCRIPT subroutines. This code produces Figure 15.2.1.

```
proc iml;
/* Placement of text is based on the character height.      */
/* The graphics segment defined here assumes percent as the */
/* unit of character height for device independent control. */
goptions gunit=pct;

call gstart;
/* Define several necessary matrices */
cityloc={0 27 66 110 153 180}`;
cityname={"Paris" "Montereau" "Tonnerre" "Dijon" "Macon" "Lyons"};
timeloc=0:30;
timename=char(timeloc,2,0);
/* Define a data matrix */
schedule=
  /* origin dest start end      comment */
  { 1      2   11.0 12.5,    /* train 1 */
    2      3   12.6 14.9,
```

```

        3      4    15.5  18.1,
        4      5    18.2  20.6,
        5      6    20.7  22.3,
        6      5    22.6  24.0,
        5      4     0.1   2.3,
        4      3     2.5   4.5,
        3      2     4.6   6.8,
        2      1     6.9   8.5,
        1      2    19.2  20.5,    /* train 2 */
        2      3    20.6  22.7,
        3      4    22.8  25.0,
        4      5     1.0   3.3,
        5      6     3.4   4.5,
        6      5     6.9   8.5,
        5      4     8.6  11.2,
        4      3    11.6  13.9,
        3      2    14.1  16.2,
        2      1    16.3  18.0
    };

    xy1=schedule[,3]||cityloc[schedule[,1]];
    xy2=schedule[,4]||cityloc[schedule[,2]];

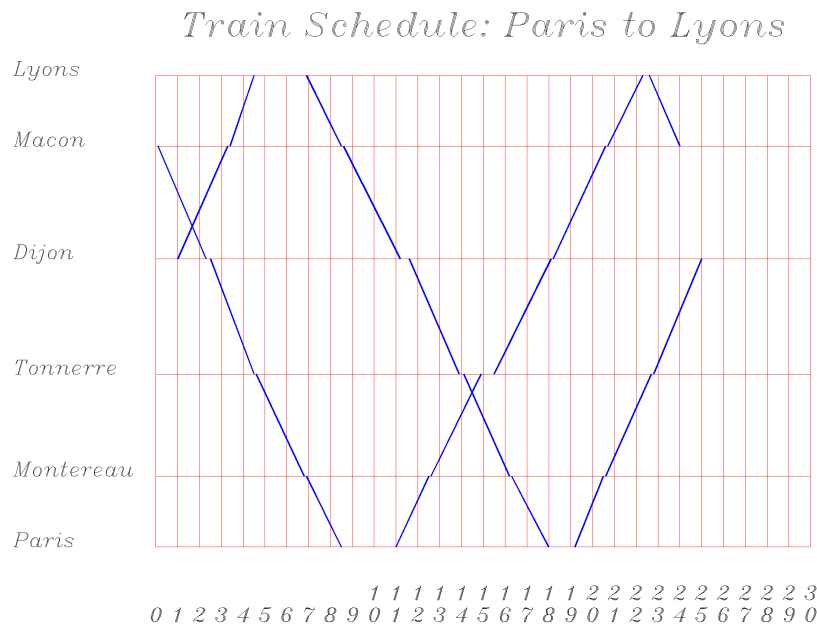
    call gopen;
    call gwindow({-8 -35, 36 240});
    call ggrid(timeloc,cityloc,1,"red");
    call gdrawl(xy1,xy2,, "blue");

    /*-- center title -- */
    s = "Train Schedule: Paris to Lyons";
    call gstrlen(m, s,5,"titalic");
    call gscript(15-m/2,185,s,,,5,"titalic");

    /*-- find max graphics text length of cityname --*/
    call gset("height",3);
    call gset("font","italic");
    call gstrlen(len, cityname);
    m = max(len) +1.0
    call gscript(-m, cityloc,cityname);
    call gscript(timeloc - .5,-12,timename,-90,90);
    call gshow;

quit;
goptions gunit=cell;                /*-- reset back to default --*/

```

Output 15.2.1 Train Schedule**Example 15.3: Fisher's Iris Data**

This example generates four scatter plots and prints them on a single page. Scatter plots of sepal length versus petal length, sepal width versus petal width, sepal length versus sepal width, and petal length versus petal width are generated. The following code produces [Figure 15.3.1](#).

```
data iris;
  title 'Fisher (1936) Iris Data';
  input sepallen sepalwid petallen petalwid spec_no @@;
  if spec_no=1 then species='setosa    ';
  if spec_no=2 then species='versicolor';
  if spec_no=3 then species='virginica ';
  label sepallen='sepal length in mm.'
        sepalwid='sepal width  in mm.'
        petallen='petal length in mm.'
        petalwid='petal width  in mm.';
  datalines;

50 33 14 02 1 64 28 56 22 3 65 28 46 15 2
67 31 56 24 3 63 28 51 15 3 46 34 14 03 1
69 31 51 23 3 62 22 45 15 2 59 32 48 18 2
46 36 10 02 1 61 30 46 14 2 60 27 51 16 2
65 30 52 20 3 56 25 39 11 2 65 30 55 18 3
58 27 51 19 3 68 32 59 23 3 51 33 17 05 1
57 28 45 13 2 62 34 54 23 3 77 38 67 22 3
```

```

63 33 47 16 2 67 33 57 25 3 76 30 66 21 3
49 25 45 17 3 55 35 13 02 1 67 30 52 23 3
70 32 47 14 2 64 32 45 15 2 61 28 40 13 2
48 31 16 02 1 59 30 51 18 3 55 24 38 11 2
63 25 50 19 3 64 32 53 23 3 52 34 14 02 1
49 36 14 01 1 54 30 45 15 2 79 38 64 20 3
44 32 13 02 1 67 33 57 21 3 50 35 16 06 1
58 26 40 12 2 44 30 13 02 1 77 28 67 20 3
63 27 49 18 3 47 32 16 02 1 55 26 44 12 2
50 23 33 10 2 72 32 60 18 3 48 30 14 03 1
51 38 16 02 1 61 30 49 18 3 48 34 19 02 1
50 30 16 02 1 50 32 12 02 1 61 26 56 14 3
64 28 56 21 3 43 30 11 01 1 58 40 12 02 1
51 38 19 04 1 67 31 44 14 2 62 28 48 18 3
49 30 14 02 1 51 35 14 02 1 56 30 45 15 2
58 27 41 10 2 50 34 16 04 1 46 32 14 02 1
60 29 45 15 2 57 26 35 10 2 57 44 15 04 1
50 36 14 02 1 77 30 61 23 3 63 34 56 24 3
58 27 51 19 3 57 29 42 13 2 72 30 58 16 3
54 34 15 04 1 52 41 15 01 1 71 30 59 21 3
64 31 55 18 3 60 30 48 18 3 63 29 56 18 3
49 24 33 10 2 56 27 42 13 2 57 30 42 12 2
55 42 14 02 1 49 31 15 02 1 77 26 69 23 3
60 22 50 15 3 54 39 17 04 1 66 29 46 13 2
52 27 39 14 2 60 34 45 16 2 50 34 15 02 1
44 29 14 02 1 50 20 35 10 2 55 24 37 10 2
58 27 39 12 2 47 32 13 02 1 46 31 15 02 1
69 32 57 23 3 62 29 43 13 2 74 28 61 19 3
59 30 42 15 2 51 34 15 02 1 50 35 13 03 1
56 28 49 20 3 60 22 40 10 2 73 29 63 18 3
67 25 58 18 3 49 31 15 01 1 67 31 47 15 2
63 23 44 13 2 54 37 15 02 1 56 30 41 13 2
63 25 49 15 2 61 28 47 12 2 64 29 43 13 2
51 25 30 11 2 57 28 41 13 2 65 30 58 22 3
69 31 54 21 3 54 39 13 04 1 51 35 14 03 1
72 36 61 25 3 65 32 51 20 3 61 29 47 14 2
56 29 36 13 2 69 31 49 15 2 64 27 53 19 3
68 30 55 21 3 55 25 40 13 2 48 34 16 02 1
48 30 14 01 1 45 23 13 03 1 57 25 50 20 3
57 38 17 03 1 51 38 15 03 1 55 23 40 13 2
66 30 44 14 2 68 28 48 14 2 54 34 17 02 1
51 37 15 04 1 52 35 15 02 1 58 28 51 24 3
67 30 50 17 2 63 33 60 25 3 53 37 15 02 1
;

proc iml;

use iris; read all;

/*----- */
/* Create 5 graphs, PETAL, SEPAL, SPWID, SPLEN, and ALL4 */
/* After the graphs are created, to see any one, type */
/* CALL GSHOW("name"); */
/* where name is the name of any one of the 5 graphs */

```

```

/* ----- */

call gstart;                      /*-- always start with GSTART --*/

/*-- Spec_no is used as marker index, change 3 to 4 */
/*-- 1 is + , 2 is x, 3 is *, 4 is a square -----*/
do i=1 to 150;
  if (spec_no[i] = 3) then spec_no[i] = 4;
end;

/*-- Creates 4 x-y plots stored in 4 different segments */

/*-- Creates a segment called petal, petallen by petalwid --*/
call gopen("petal");
wp = { -10 -5, 90 30};
call gwindow(wp);
call gxaxis({0 0}, 75, 6,,, '5.1');
call gyaxis({0 0}, 25, 5,,, '5.1');
call gpoint(petallen, petalwid, spec_no, 'blue');
labs = "Petallen vs Petalwid";
call gstrlen(len, labs,2, 'swiss');
call gscript(40-len/2,-4,labs,,,2,'swiss');

/*-- Creates a segment called sepal, sepallen by sepalwid --*/
call gopen("sepal");
ws = {35 15 85 55};
call gwindow(ws);
call gxaxis({40 20}, 40, 9, , , '5.1');
call gyaxis({40 20}, 28, 7, , , '5.1');
call gpoint(sepallen, sepalwid, spec_no, 'blue');
labs = "Sepallen vs Sepalwid";
call gstrlen(len, labs,2, 'swiss');
call gscript(60-len/2,16,labs,,,2,'swiss');

/*-- Creates a segment called spwid, petalwid by sepalwid --*/
call gopen("spwid");
wspwid = { 15 -5 55 30};
call gwindow(wspwid);
call gxaxis({20 0}, 28, 7,,, '5.1');
call gyaxis({20 0}, 25, 5,,, '5.1');
call gpoint(sepalwid, petalwid, spec_no, 'green');
labs = "Sepalwid vs Petalwid";
call gstrlen(len, labs,2, 'swiss');
call gscript(35-len/2,-4,labs,,,2,'swiss');

/*-- Creates a segment called splen, petallen by sepallen --*/
call gopen("splen");
wsplen = {35 -15 85 90};
call gwindow(wsplen);
call gxaxis({40 0}, 40, 9,,, '5.1');
call gyaxis({40 0}, 75, 6,,, '5.1');
call gpoint(sepallen, petallen, spec_no, 'red');
labs = "Sepallen vs Petallen";
call gstrlen(len, labs,2, 'swiss');

```

```

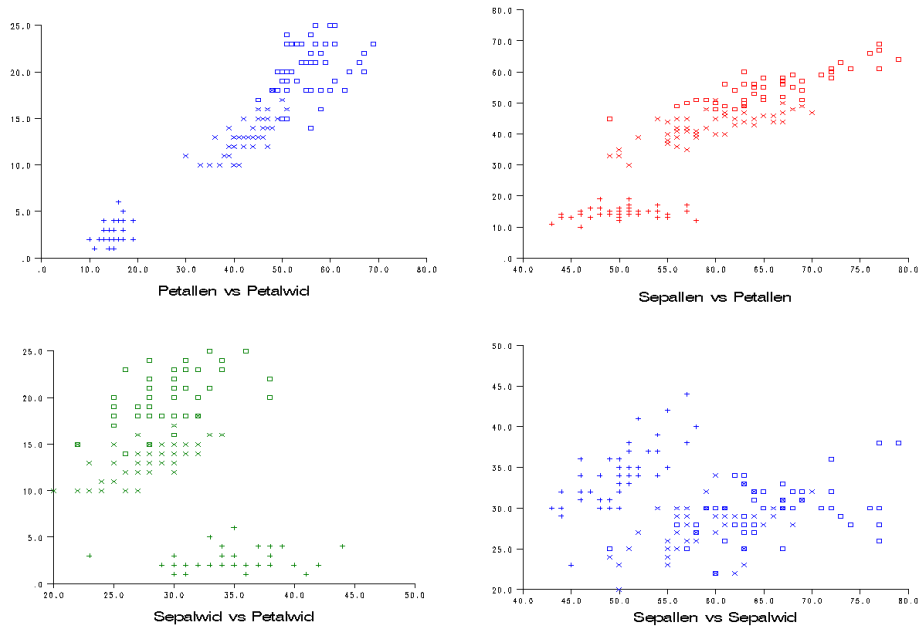
call gscript(60-len/2,-14,labs,,2,'swiss');

/*-- Create a new segment */
call gopen("all14");
call gport({50 0, 100 50}); /* change viewport, lower right ----*/
call ginclude("sepal");      /* include sepal in this graph ----*/
call gport({0 50, 50 100}); /* change the viewport, upper left */
call gininclude("petal");    /* include petal -----*/
call gport({0 0, 50 50});   /* change the viewport, lower left */
call gininclude("spwid");    /* include spwid -----*/
call gport({50 50, 100 100});/* change the viewport, upper right */
call gininclude("splen");    /* include splen -----*/

call gshow("all14");

```

Output 15.3.1 Petal Length versus Petal Width



Chapter 16

Window and Display Features

Contents

Overview	441
Creating a Display Window for Data Entry	442
Using the WINDOW Statement	444
Window Options	444
Field Specifications	445
Using the DISPLAY Statement	446
Group Specifications	446
Group Options	447
Details about Windows	447
Number and Position of Windows	447
Windows and the Display Surface	447
Deciding Where to Define Fields	448
Groups of Fields	448
Field Attributes	448
Display Execution	449
Field Formatting and Inputting	449
Display-Only Windows	450
Opening Windows	450
Closing Windows	450
Repeating Fields	450
Example	451

Overview

The dynamic nature of IML gives you the ability to create windows on your display for full-screen data entry or menuing. By using the [WINDOW statement](#), you can define a window, its fields, and its attributes. By using the [DISPLAY statement](#), you can display a window and await data entry.

These statements are similar in form and function to the corresponding statements in the SAS DATA step. The specification of fields in the [WINDOW](#) or [DISPLAY statement](#) is similar to the specifications used in the [INPUT](#) and [PUT statements](#). By using these statements you can write applications that behave similarly to other full-screen facilities in the SAS System, such as the BUILD procedure in SAS/AF software and the FSEDIT procedure in SAS/FSP software.

Creating a Display Window for Data Entry

Suppose that your application is a data entry system for a mailing list. You want to create a data set called MAILLIST by prompting the user with a window that displays all the entry fields. You want the data entry window to look as follows:

```
+---MAILLIST-----+
| Command==>      |
|                  |
|                  |
| NAME:           |
| ADDRESS:        |
| CITY: STATE: ZIP: |
| PHONE:          |
|                  |
+-----+
```

The process for creating a display window for this application consists of

- initializing the variables
- creating a SAS data set
- defining a module for collecting data that
 1. defines a window
 2. defines the data fields
 3. defines a loop for collecting data
 4. provides an exit from the loop
- executing the data-collecting routine

The whole system can be implemented with the following code to define modules INITIAL and MAILGET:

```
/*  module to initialize the variables      */
/*                                          */
start initial;
  name='          ';
  addr='              ';
  city='              ';
  state='  ';
  zip='  ';
  phone='          ';
finish initial;
```

This defines a module named INITIAL that initializes the variables you want to collect. The initialization sets the string length for the character fields. You need to do this prior to creating your data set.

Now define a module for collecting the data, as follows:

```

/* module to collect data                                */
/*                                                        */
start mailget;                                          */
/* define the window                                    */
    window maillist cmdndline=cmdnd msgline=msg
        group=addr
        #2 " NAME: " name
        #3 " ADDRESS:" addr
        #4 " CITY: " city +2 "STATE: " state +2 "ZIP: " zip
        #5 " PHONE: " phone;
/*                                                        */
/* collect addresses until the user enters exit          */
/*                                                        */
    do until (cmdnd="EXIT");
        run initial;
        msg="ENTER SUBMIT TO APPEND OBSERVATION, EXIT TO END";
/*                                                        */
/* loop until user types submit or exit                  */
/*                                                        */
        do until (cmdnd="SUBMIT"|cmdnd="EXIT");
            display maillist.addr;
        end;
        if cmdnd="SUBMIT" then append;
    end;
    window close=maillist;
finish mailget;
/* initialize variables                                */
run initial;
/* create the new data set                              */
create maillist var{name addr city state zip phone};
/* collect data                                          */
run mailget;
/* close the new data set                               */
close maillist;

```

In the module MAILGET, the WINDOW statement creates a window named MAILLIST with a group of fields (the group is named ADDR) presenting data fields for data entry. The program sends messages to the window through the MSGLINE= variable MSG. The program receives commands you enter through the CMNDLINE= variable CMND.

You can enter data into the fields after each prompt field. After you are finished with the entry, press a key defined as SUBMIT, or type SUBMIT in the command field. The data are appended to the data set MAILLIST. When data entry is complete, type EXIT in the command field. If you enter a command other than SUBMIT, EXIT, or a valid SAS windowing environment command in the command field, you get the following message on the message line:

```
ENTER SUBMIT TO APPEND OBSERVATION, EXIT TO END.
```

Using the WINDOW Statement

You use the WINDOW statement to define a window, its fields, and its attributes. The general form of the WINDOW statement is as follows:

```
WINDOW < CLOSE=> window-name < window-options > < GROUP=group-name-1 field-specs < ... GROUP=group-name-n field-specs > > ;
```

The following options can be used with the WINDOW statement:

CLOSE=

is used only when you want to close the window.

window-name

is a valid SAS name for the window. This name is displayed in the upper-left border of the window.

window-options

control the size, position, and other attributes of the window. You can change the attributes interactively with window commands such as WGROW, WDEF, WSHRINK, and COLOR. These options are described in the next section.

GROUP=*group-name*

starts a repeating sequence of groups of fields defined for the window. The *group-name* is a valid SAS variable name used to identify a group of fields in a DISPLAY statement that occurs later in the program.

field-specs

is a sequence of field specifications made up of positionals, field operands, formats, and options. These are described in the section “[Field Specifications](#)” on page 445.

Window Options

Window options control the attributes of the window. The following options are valid in the WINDOW statement:

CMNDLINE=*name*

names a character variable in which the command line entered by the user is stored.

COLOR=*operand*

specifies the background color for the window. The *operand* can be either a quoted character literal or the name of a character variable that contains the color. The valid values are BLACK, GREEN, MAGENTA, RED, CYAN, GRAY, and BLUE. The default is BLACK.

COLUMNS=*operand*

specifies the starting number of columns of the window. The *operand* can be either a literal number, a variable name, or an expression in parentheses. The default is 78.

ICOLUMN=*operand*

specifies the initial column position of the window on the display screen. The *operand* can be either a literal number or a variable name. The default is column 1.

IROW=*operand*

specifies the initial row position of the window on the display screen. The *operand* can be either a literal number or a variable name. The default is row 1.

MSGLINE=*operand*

specifies the message to be displayed on the standard message line when the window is made active. The *operand* is a quoted character literal or the name of a character variable that contains the message.

ROWS=*operand*

determines the starting number of rows of the window. The *operand* is either a literal number, the name of a variable that contains the number, or an expression in parentheses yielding the number. The default is 23 rows.

Field Specifications

Both the WINDOW and DISPLAY statements accept field specifications. Field specifications have the following general form:

< positionals > field-operand < format > < field-options > ;

Positionals

The *positionals* are directives specifying the position on the screen in which to begin the field. There are four kinds of positionals, any number of which are accepted for each field operand. Positionals are the following:

# <i>operand</i>	specifies the row position; that is, it moves the current position to column 1 of the specified line. The <i>operand</i> is either a number, a variable name, or an expression in parentheses. The expression must evaluate to a positive number.
/	instructs IML to go to column 1 of the next row.
@ <i>operand</i>	specifies the column position. The <i>operand</i> is either a number, a variable name, or an expression in parentheses. The @ directive should come after the pound sign (#) positional, if it is specified.
+ <i>operand</i>	instructs IML to skip columns. The <i>operand</i> is either a number, a variable name, or an expression in parentheses.

Field Operands

The *field-operand* specifies what goes in the field. It is either a character literal in quotes or the name of a character variable.

Formats

The *format* is the format used for display, for the value, and also as the informat applied to entered values. If no format is specified, the standard numeric or character format is used.

Field Options

The *field-options* specify the attributes of the field as follows:

PROTECT=YES

P=YES

specifies that the field is protected; that is, you cannot enter values in the field. If the field operand is a literal, it is already protected.

COLOR=*operand*

specifies the color of the field. The *operand* can be either a literal character value in quotes, a variable name, or an expression in parentheses. The colors available are WHITE, BLACK, GREEN, MAGENTA, RED, YELLOW, CYAN, GRAY, and BLUE. The default is BLUE. Note that the color specification is different from that of the corresponding DATA step value because it is an operand rather than a name without quotes.

Using the DISPLAY Statement

After you have opened a window with the WINDOW statement, you can use the DISPLAY statement to display the fields in the window.

The DISPLAY statement specifies a list of groups to be displayed. Each group is separated from the next by a comma.

The general form of the DISPLAY statement is as follows:

```
DISPLAY < group-spec-1 group-options, < ... , group-spec-n group-options > > ;
```

Group Specifications

The group specification names a group, either a compound name of the form *windowname.groupname* or a *windowname* followed by a group defined by fields and enclosed in parentheses. For example, you can specify *windowname.groupname* or *windowname(field-specs)*, where *field-specs* are as defined earlier for the WINDOW statement.

In the example, you used the following statement to display the window MAILLIST and the group ADDR:

```
display maillist.addr;
```

Group Options

The *group-options* can be any of the following:

BELL

rings the bell, sounds the alarm, or causes the speaker at your workstation to beep when the window is displayed.

NOINPUT

requests that the group be displayed with all the fields protected so that no data entry can be done.

REPEAT

specifies that the group be repeated for each element of the matrices specified as *field-operands*. See the section “[Repeating Fields](#)” on page 450.

Details about Windows

The following sections discuss some of the ideas behind windows.

Number and Position of Windows

You can have any number of windows. They can overlap each other or be disjoint. Each window behaves independently from the others. You can specify the starting size, position, and color of the window when you create it. Each window responds to SAS windowing environment commands so that it can be moved, sized, or changed in color dynamically by the user.

You can list all active windows in a session by using the SHOW WINDOWS command. This makes it easy to keep track of multiple windows.

Windows and the Display Surface

A window is really a viewport into a display. The display can be larger or smaller than the window. If the display is larger than the window, you can use scrolling commands to move the surface under the window (or equivalently, move the window over the display surface). The scrolling commands are as follows:

RIGHT < *n* > scrolls right.

LEFT < <i>n</i> >	scrolls left.
FORWARD < <i>n</i> >	scrolls forward (down).
BACKWARD < <i>n</i> >	scrolls backward (up).
TOP	scrolls to the top of the display surface.
BOTTOM	scrolls to the bottom of the display surface.

The argument *n* is an optional numeric argument that indicates the number of positions to scroll. The default is 5.

Only one window is active at a time. You can move, zoom, enlarge, shrink, or recolor inactive windows, but you cannot scroll or enter data.

Each display starts with the same standard lines: first a command line for entering commands, then a message line for displaying messages (such as error messages).

The remainder of the display is up to you to design. You can put fields in any positive row and column position of the display surface, even if it is off the displayed viewport.

Deciding Where to Define Fields

You have a choice of whether to define your fields in the WINDOW statement, the DISPLAY statement, or both. Defining field groups in the WINDOW statement saves work if you access the window from many different DISPLAY statements. Specifying field groups in the DISPLAY statement provides more flexibility.

Groups of Fields

All fields must be part of field groups. The group is just a mechanism to treat multiple fields together as a unit in the DISPLAY statement. There is only one rule about the field positions of different groups: active fields must not overlap. Overlapping is acceptable among fields as long as they are not simultaneously active. Active fields are the ones that are specified together in the current DISPLAY statement.

You name groups specified in the WINDOW statement. You specify groups in the DISPLAY statement just by putting them in parentheses; they are not named.

Field Attributes

There are two types of fields you can define:

- Protected fields are for constants on the screen.
- Unprotected fields accept data entry.

If the field consists of a character string in quotes, it is protected. If the field is a variable name, it is not protected unless you specify `PROTECT=YES` as a field option. If you want all fields protected, specify the `NOINPUT` group option in the `DISPLAY` statement.

Display Execution

When you execute a `DISPLAY` statement, the SAS System displays the window with all current values of the variables. You can then enter data into the unprotected fields. All the basic editing keys (cursor controls, delete, end, insert, and so forth) work, as well as SAS windowing environment commands to scroll or otherwise manage the window. Control does not return to the IML code until you enter a command on the command line that is not recognized as a SAS windowing environment command. Typically, a `SUBMIT` command is used since most users define a function key for this command. Before control is returned to you, IML moves all modified field values from the screen back into IML variables by using standard or specified informat routines. If you have specified the `CMNDLINE=` option in the `WINDOW` statement, the current command line is passed back to the specified variable.

The window remains visible with the last values entered until the next `DISPLAY` statement or until the window is closed by a `WINDOW` statement with the `CLOSE=` option.

Only one window is active at a time. Every window can be subject to SAS windowing environment commands, but only the window specified in the current `DISPLAY` statement transfers data to IML.

Each window is composed dynamically every time it is displayed. If you position fields by variables, you can make them move to different parts of the screen simply by programming the values of the variables.

The `DISPLAY` statement even accepts general expressions in parentheses as positional or field operands. The `WINDOW` statement only accepts literal constants or variable names as operands. If a field operand is an expression in parentheses, then it is always a protected field. You cannot use the following statement and expect it to return the log function of the data entered:

```
display w(log(X)) ;
```

Instead you would need the following code:

```
lx=log(x) ;  
display w(lx) ;
```

Field Formatting and Inputting

The length of a field on the screen is specified in the format after the field operand, if you give one. If a format is not given, IML uses standard character or numeric formats and informats. Numeric informats allow scientific notation and missing values (represented with periods). The default length for character variables is the size of the variable element. The default size for numeric fields is given with the `FW=` option (see the discussion of the `RESET` statement in [Chapter 23](#)).

If you specify a named format (such as DATE7.), IML attempts to use it for both the output format and the input informat. If IML cannot find an input informat of that name, it uses the standard informats.

Display-Only Windows

If a window consists only of protected fields, it is merely displayed; that is, it does not wait for user input. These display-only windows can be displayed rapidly.

Opening Windows

The WINDOW statement is executable. When a WINDOW statement is executed, IML checks to see if the specific window has already been opened. If it has not been opened, then the WINDOW statement opens it; otherwise, the WINDOW statement does nothing.

Closing Windows

To close a window, use the CLOSE= option in the WINDOW statement. In the example given earlier, you closed MAILLIST with the following statement:

```
window close=maillist;
```

Repeating Fields

If you specify an operand for a field that is a multi-element matrix, the routines deal with the first value of the matrix. However, there is a special group option, REPEAT, that enables you to display and retrieve values from all the elements of a matrix. If the REPEAT option is specified, IML determines the maximum number of elements of any field-operand matrix, and then it repeats the group that number of times. If any field operand has fewer elements, the last element is repeated the required number of times (the last one becomes the data entered). Be sure to write your specifications so that the fields do not overlap. If the fields overlap, an error message results. Although the fields must be matrices, the positional operands are never treated as matrices.

The repeat feature can come in very handy in situations where you want to create a menu for a list of items. For example, suppose you want to build a restaurant billing system and you have stored the menu items and prices in the matrices ITEM and PRICE. You want to obtain the quantity ordered in a matrix called AMOUNT. Enter the following code:

```
item={ "Hamburger", "Hot Dog", "Salad Bar", "Milk" };
```

```

price={1.10 .90 1.95 .45};
amount= repeat(0,nrow(item),1);
window menu
group=top
#1 @2 "Item" @44 "Price" @54 "Amount"
group=list
/ @2 item $10. @44 price 6.2 @54 amount 4.
;
display menu.top, menu.list repeat;

```

This creates the following window:

```

+-----Menu-----+
+  Command --->    +
+                  +
+  Item            Price   Amount   +
+                  +
+  Hamburger       1.10     0        +
+  Hot Dog         0.90     0        +
+  Salad Bar       1.95     0        +
+  Milk            0.45     0        +
+                  +
+-----+

```

Example

This example illustrates the following features:

- multiple windows
- the repeat feature
- command- and message-line usage
- a large display surface needing scrolling
- windows linked to data set transactions

This example uses two windows, FIND and ED. The FIND window instructs you to enter a name. Then a data set is searched for all the names starting with the entered value. If no observations are found, you receive the following message:

```
Not found, enter request
```

If any observations are found, they are displayed in the ED window. You can then edit all the fields. If several observations are found, you need to use the scrolling commands to view the entire display surface. If you enter the SUBMIT command, the data are updated in place in the data set. Otherwise, you receive the following message:

Not replaced, enter request

If you enter a blank field for the request, you are advised that EXIT is the keyword needed to exit the system. Here is the code:

```
start findedit;
  window ed rows=10 columns=40 icolumn=40 cmdndline=c;
  window find rows=5 columns=35 icolumn=1 msgline=msg;
  edit user.class;
  display ed ( "Enter a name in the FIND window, and this"
    / "window will display the observations "
    / "starting with that name. Then you can"
    / "edit them and enter the submit command"
    / "to replace them in the data set. Enter cancel"
    / "to not replace the values in the data set."
    /
    / "Enter exit as a name to exit the program." );
do while(1);
  msg=' ';
  again:
  name=" ";
  display find ("Search for name: " name);
  if name=" " then
    do;
      msg='Enter exit to end';
      goto again;
    end;
  if name="exit" then goto x;
  if name="PAUSE" then
    do;
      pause;
      msg='Enter again';
      goto again;
    end;
  find all where(name=:name) into p;
  if nrow(p)=0 then
    do;
      msg='Not found, enter request';
      goto again;
    end;
  read point p;
  display ed (/" name: " name
    " sex: " sex
    " age: " age
    /" height: " height
    " weight: " weight ) repeat;
  if c='submit' then
    do;
      msg="replaced, enter request";
      replace point p;
    end;
  else
    do;
```

```
        msg='Not replaced, enter request';
    end;
end;
x:
display find ("Closing Data Set and Exiting");
close user.class;
window close=ed;
window close=find;
finish findedit;
run findedit;
```


Chapter 17

Storage Features

Contents

Overview	455
Storage Catalogs	455
Catalog Management	456
Restoring Matrices and Modules	456
Removing Matrices and Modules	457
Specifying the Storage Catalog	457
Listing Storage Entries	458
Storing Matrices and Modules	458

Overview

SAS/IML software can store user-defined modules and the values of matrices in special library storage on disk for later retrieval. The library storage feature enables you to perform the following tasks:

- store and reload IML modules and matrices
- save work for a later session
- keep records of work
- conserve space by saving large, intermediate results for later use
- communicate data to other applications through the library
- store and retrieve data in general

Storage Catalogs

SAS/IML storage catalogs are specially structured SAS files that are located in a SAS data library. A SAS/IML catalog contains *entries* that are either matrices or modules. Like other SAS files, SAS/IML

catalogs have two-level names in the form *libref.catalog*. The first-level name, *libref*, is a name assigned to the SAS data library to which the catalog belongs. The second-level name, *catalog*, is the name of the catalog file.

The default libref is initially SASUSER, and the default catalog is IMLSTOR. Thus, the default storage catalog is called SASUSER.IMLSTOR. You can change the storage catalog with the RESET STORAGE command (see the discussion of the RESET statement in [Chapter 23](#)).

By using this command, you can change either the catalog or the libref.

When you store a matrix, IML automatically stores the matrix name, its type, its dimension, and its current values. Modules are stored in the form of their compiled code. Once modules are loaded, they do not need to be parsed again, making their use very efficient.

Catalog Management

IML provides you with all the commands necessary to reference a particular storage catalog, to list the modules and matrices in that catalog, to store and remove modules and matrices, and to load modules and matrices back to IML. The following commands enable you to perform all necessary catalog management functions:

LOAD	recalls entries from storage.
REMOVE	removes entries from storage.
RESET STORAGE	specifies the library name.
SHOW STORAGE	lists all entries currently in storage.
STORE	saves modules or matrices to storage.

Restoring Matrices and Modules

You can restore matrices and modules from storage back into the IML active workspace by using the LOAD command. The LOAD command has the general form

```
LOAD ;
LOAD matrices ;
LOAD MODULE= module ;
LOAD MODULE= (modules) ;
LOAD MODULE= (modules) matrices ;
```

Some examples of valid LOAD commands are as follows:


```
load a b c;                      /* load matrices A, B, and C */
load module=mymod1;              /* load module MYMOD1      */
load module=(mymod1 mymod2) a b; /* load modules and matrices */
```

The special operand `_ALL_` can be used to load all matrices or modules, or both. For example, if you want to load all modules, use the following statement:

```
load module=_all_;
```

If you want to load all matrices and modules in storage, use the `LOAD` command by itself, as follows:

```
load;                          /* loads all matrices and modules */
```

The `LOAD` command can be used with the `STORE` statement to save and restore an IML environment between sessions.

Removing Matrices and Modules

You can remove modules or matrices from the catalog by using the `REMOVE` command. The `REMOVE` command has the same form as the `LOAD` command. Some examples of valid `REMOVE` statements are as follows:

```
remove a b c;                      /* remove matrices A, B, and C */
remove module=mymod1;              /* remove module MYMOD1      */
remove module=(mymod1 mymod2) a; /* remove modules and matrices */
```

The special operand `_ALL_` can be used to remove all matrices or modules, or both. For example, if you want to remove all matrices, use the following statement:

```
remove _all_;
```

If you want to remove everything from storage, use the `REMOVE` command by itself, as follows:

```
remove;
```

Specifying the Storage Catalog

To specify the name of the storage catalog, use one of the following general forms of the `STORAGE=` option in the `RESET` statement:

```
RESET STORAGE= catalog ;
```

RESET STORAGE= *libref.catalog* ;

Each time you specify the STORAGE= option, the previously opened catalog is closed before the new one is opened.

You can have any number of catalogs, but you can have only one open at a time. A SAS data library can contain many IML storage catalogs, and an IML storage catalog can contain many entries (that is, many matrices and modules).

For example, you can change the name of the storage catalog without changing the libref by using the following statement:

```
reset storage=mystor;
```

To change the libref as well, use the following statement:

```
reset storage=mylib.mystor;
```

Listing Storage Entries

You can list all modules and matrices in the current storage catalog by using the SHOW STORAGE command, which has the general form

SHOW STORAGE ;

Storing Matrices and Modules

You can save modules or matrices in the storage catalog by using the STORE command. The STORE command has the same general form as the LOAD command. Several examples of valid STORE statements are as follows:

```
store a b c;                /* store matrices A, B, and C */
store module=mymod1;        /* store module MYMOD1      */
store module=(mymod1 mymod2) a; /* storing modules and matrices */
```

The special operand `_ALL_` can be used to store all matrices or modules. For example, if you want to store everything, use the following statement:

```
store _all_ module=_all_;
```

Alternatively, to store everything, you can also enter the STORE command by itself, as follows:

```
store;
```

This can help you to save your complete IML environment before exiting an IML session. Then you can use the `LOAD` statement in a subsequent session to restore the environment and resume your work.

Chapter 18

Using SAS/IML Software to Generate SAS/IML Statements

Contents

Overview	461
Generating and Executing Statements	461
Executing a String Immediately	462
Feeding an Interactive Program	463
Calling the Operating System	464
Calling the SAS Windowing Environment	464
Executing Any Command in an EXECUTE Call	464
Making Operands More Flexible	465
Interrupt Control	466
Specific Error Control	467
General Error Control	468
Macro Interface	470
IML Line Pushing Contrasted with Using the Macro Facility	470
Example 18.1: Full-Screen Editing	471
Summary	475

Overview

This chapter describes ways of using SAS/IML software to generate and execute statements from within the Interactive Matrix Language. You can execute statements generated at run time, execute global SAS commands under program control, or create statements dynamically to get more flexibility.

Generating and Executing Statements

You can push generated statements into the input command stream (queue) with the PUSH, QUEUE, and EXECUTE subroutines. This can be very useful in situations that require added flexibility, such as menu-driven applications or interrupt handling.

The PUSH command inserts program statements at the front of the input command stream, whereas the QUEUE command inserts program statements at the back. In either case, if they are not input to an interactive application, the statements remain in the queue until IML enters a pause state, at which point they are executed. The pause state is usually induced by a program error or an interrupt control sequence. Any subsequent RESUME statement resumes execution of the module from the point where the PAUSE command was issued. For this reason, the last statement put into the command stream for PUSH or QUEUE is usually a RESUME command.

The EXECUTE statement also pushes program statements like PUSH and QUEUE, but it executes them immediately and returns. It is not necessary to push a RESUME statement when you use the CALL EXECUTE command.

Executing a String Immediately

The PUSH, QUEUE, and EXECUTE commands are especially useful when used in conjunction with the pause and resume features because they enable you to generate a pause-interrupt command to execute the code you push and return from it via a pushed RESUME statement. In fact, this is precisely how the EXECUTE subroutine is implemented generally.

CAUTION: Note that the push and resume features work this way only in the context of being inside modules. You cannot resume an interrupted sequence of statements in immediate mode—that is, not inside a module.

For example, suppose that you collect program statements in a matrix called CODE. You push the code to the command input stream along with a RESUME statement and then execute a PAUSE statement. The PAUSE statement interrupts the execution, parses and executes the pushed code, and returns to the original execution via the RESUME statement. Here is the code:

```
proc iml;
start testpush;
  print '*** ENTERING MODULE TESTPUSH ***';
  print '*** I should be 1,2,3: ';
  /* constructed code */
  code = ' do i = 1 to 3; print i; end;   ';
  /* push code+resume */
  call push (code, 'resume;');
  /* pause interrupt */
  pause;
  print '*** EXITING MODULE TESTPUSH ***';
finish;
```

When the PAUSE statement interrupts the program, the IML procedure then parses and executes the following line:

```
do i=1 to 3; print i; end; resume;
```

The RESUME command then causes the IML procedure to resume the module that issued the PAUSE.

NOTE: The EXECUTE routine is equivalent to a PUSH command, but it also adds the push of a RESUME command, then issues a pause automatically.

A CALL EXECUTE command should be used only from inside a module because pause and resume features do not support returning to a sequence of statements in immediate mode.

Feeding an Interactive Program

Suppose that an interactive program gets responses from the statement INFILE CARDS. If you want to feed it under program control, you can push lines to the command stream that is read.

For example, suppose that a subroutine prompts a user to respond **YES** before performing some action. If you want to run the subroutine and feed the **YES** response without the user being bothered, you push the response as follows:

```

/* the function that prompts the user */
start delall;
file log;
put 'Do you really want to delete all records? (yes/no)';
infile cards;
input answer $;
if upcase(answer)='YES' then
  do;
    delete all;
    purge;
    print "*** FROM DELALL:
      should see End of File (no records to list)";
    list all;
  end;
finish;

```

The latter DO group is necessary so that the pushed **YES** is not read before the RUN statement. The following example illustrates the use of the preceding module DELALL:

```

/* Create a dummy data set for delall to delete records */
xnum = {1 2 3, 4 5 6, 7 8 0};
create dsnum1 from xnum;
append from xnum;
do;
  call push ('yes');
  run delall;
end;

```

Calling the Operating System

Suppose that you want to construct and execute an operating system command. Just push it to the token stream in the form of an X statement and have it executed under a pause interrupt.

The following module executes any system command given as an argument:

```
start system(command);
  call push(" x '",command,"'; resume;");
  pause;
finish;
run system('listc');
```

The call generates and executes a LISTC command under MVS as follows:

```
x 'listc'; resume;
```

Calling the SAS Windowing Environment

The same strategy used for calling the operating system works for SAS global statements as well, including calling the SAS windowing environment by generating DM statements.

The following subroutine executes a SAS windowing environment command:

```
start dm(command);
  call push(" dm '",command,"'; resume;");
  pause;
finish;

run dm('log; color source red');
```

The call generates and executes the following statements:

```
dm 'log; color source red'; resume;
```

These statements take you to the Log window, where all source code is written in red.

Executing Any Command in an EXECUTE Call

The EXECUTE command executes the statements contained in the arguments by using the same facilities as a sequence of CALL PUSH, PAUSE, and RESUME statements. The statements use the same symbol environment as that of the subroutine that calls them. For example, consider the following subroutine:


```

proc iml;
start exectest;
/*    IML STATEMENTS    */
  call execute ("xnum = {1 2 3, 4 5 6, 7 8 0};");
  call execute ("create dsnum1 from xnum;");
  call execute ("append from xnum;");
  call execute ("print 'DSNUM should have 3 obs and 3 var: '");
  call execute ("list all;");
/*    global (options) statement    */
  call execute ("options linesize=68;");
  call execute ("print 'Linesize should be 68'");
finish;
run exectest;

```

The following output generated from EXECTEST is exactly the same as if you had entered the statements one at a time:

```

      DSNUM should have 3 obs and 3 var:

      OBS      COL1      COL2      COL3
      ----      -
      1      1.0000      2.0000      3.0000
      2      4.0000      5.0000      6.0000
      3      7.0000      8.0000           0

      Linesize should be 68

```

CALL EXECUTE could almost be programmed in IML as shown here; the difference between this and the built-in command is that the following subroutine would not necessarily have access to the same symbols as the calling environment:

```

start execute(command1,...);
  call push(command1,...," resume;");
  pause;
finish;

```

Making Operands More Flexible

Suppose that you want to write a program that prompts a user for the name of a data set. Unfortunately the USE, EDIT, and CREATE commands expect the data set name as a hardcoded operand rather than an indirect one. However, you can construct and execute a function that prompts the user for the data set name for a USE statement. Here is the code:

```

/* prompt the user to give dsname for use statement */
start flexible;
  file log;
  put 'What data set shall I use?';

```

```

infile cards;
input dsname $;
call execute('use', dsname, ');');
finish;
run flexible;

```

If you enter USER.A, the program generates and executes the following line:

```
use user.a;
```

Interrupt Control

Whenever a program error or interrupt occurs, IML automatically issues a pause, which places the module in a paused state. At this time, any statements pushed to the input command queue get executed. Any subsequent RESUME statement (including pushed RESUME statements) resume executing the module from the point where the error or interrupt occurred.

If you have a long application such as reading a large data set and you want to be able to find out where the data processing is just by entering a break-interrupt (sometimes called an attention signal), you push the interrupt text. The pushed text can, in turn, push its own text on each interrupt, followed by a RESUME statement to continue execution.

For example, suppose you have a data set called TESTDATA that has 4096 observations. You want to print the current observation number if an attention signal is given. The following code does this:

```

start obsnum;
  use testdata;
  brkcode={"print 'now on observation number',i;"
          "if (i<4096) then do;"
          "call push(brkcode);"
          "resume;"
          "end;"};
  call push(brkcode);
  do i=1 to 4096;
    read point i;
  end;
finish;
run obsnum;

```

After the module has been run, enter the interrupt control sequence for your operating system. Type S to suspend execution. The IML procedure prints a message telling which observation is being processed. Because the pushed code is executed at the completion of the module, the message is also printed when OBSNUM ends.

Each time the attention signal is given, OBSNUM executes the code contained in the variable BRKCODE. This code prints the current iteration number and pushes commands for the next interrupt. Note that the

PUSH and RESUME commands are inside a DO group, making them conditional and ensuring that they are parsed before the effect of the PUSH command is realized.

Specific Error Control

A PAUSE command is automatically issued whenever an execution error occurs, putting the module in a holding state. If you have some way of checking for specific errors, you can write an interrupt routine to correct them during the pause state.

In the following example, if a singular matrix is passed to the INV function, the IML procedure pauses and executes the pushed code to set the result for the inverse to missing values. The code uses the variable SINGULAR to detect if the interrupt occurred during the INV operation. This is particularly necessary because the pushed code is executed on completion of the routine, as well as on interrupts.

```
proc iml;
a = {3 3, 3 3};                               /* singular matrix */
/* If a singular matrix is sent to the INV function,      */
/* IML normally sets the resulting matrix to be empty     */
/* and prints an error message.                           */
b = inv(a);
print "*** A should be non-singular", a;
start singtest;
  msg="      Matrix is singular - result set to missing ";
  onerror=
    "if singular then do; b=a#.; print msg; print b;
    resume; end;";
  call push(onerror);
  singular = 1;
  b = inv(a);
  singular = 0;
finish ;
call singtest;
```

The resulting output is as follows:

```
ERROR: (execution) Matrix should be non-singular.

Error occurred in module SINGTEST at line    67 column    9
operation : INV                    at line    67 column   16
operands  : A

A                2 rows    2 cols    (numeric)

              3          3
              3          3

stmt: ASSIGN                    at line    67 column    9
```

Paused in module SINGTEST.

MSG

Matrix is singular - result set to missing

B

. .
. .

Resuming execution in module SINGTEST.

General Error Control

Sometimes, you might want to process or step over errors. To do this, put all the code into modules and push a code to abort if the error count exceeds some maximum. Often, you might submit a batch job and get a trivial mistake that causes an error, but you do not want to cause the whole run to fail because of it. On the other hand, if you have many errors, you do not want to let the routine run.

In the following example, up to three errors are tolerated. A singular matrix **A** is passed to the INV function, which would, by itself, generate an error message and issue a pause in the module. This module pushes three RESUME statements, so that the first three errors are tolerated. Messages are printed and execution is resumed. The DO loop in the module OOPS is executed four times, and on the fourth iteration, an ABORT statement is issued and you exit IML.

```
proc iml;
a={3 3, 3 3};                               /* singular matrix */
/*                                           */
/* GENERAL ERROR CONTROL -- exit iml for 3 or more errors */
/*                                           */
start;                                       /* module will be named MAIN */
  errcode = {" if errors >= 0 then do;",
             "   errors = errors + 1;",
             "   if errors > 2 then abort;",
             "   else do; call push(errcode); resume; end;",
             " end;" } ;
  call push (errcode);
  errors = 0;
  start oops;                               /* start module OOPS */
    do i = 1 to 4;
      b = inv(a);
    end;
  finish;                                   /* finish OOPS */
  run oops;
finish;                                     /* finish MAIN */
errors=-1;                                  /* disable */
run;
```

The output generated from this example is as follows:

ERROR: (execution) Matrix should be non-singular.

```

Error occurred in module OOPS      at line    41 column  17
called from module MAIN          at line    44 column  10
operation : INV                   at line    41 column  24
operands  : A

```

```

A              2 rows    2 cols    (numeric)

```

```

      3      3
      3      3

```

```

stmt: ASSIGN                                at line    41 column  17

```

Paused in module OOPS.

Resuming execution in module OOPS.

ERROR: (execution) Matrix should be non-singular.

```

Error occurred in module OOPS      at line    41 column  17
called from module MAIN          at line    44 column  10
operation : INV                   at line    41 column  24
operands  : A

```

```

A              2 rows    2 cols    (numeric)

```

```

      3      3
      3      3

```

```

stmt: ASSIGN                                at line    41 column  17

```

Paused in module OOPS.

Resuming execution in module OOPS.

ERROR: (execution) Matrix should be non-singular.

```

Error occurred in module OOPS      at line    41 column  17
called from module MAIN          at line    44 column  10
operation : INV                   at line    41 column  24
operands  : A

```

```

A              2 rows    2 cols    (numeric)

```

```

      3      3
      3      3

```

```

stmt: ASSIGN                                at line    41 column  17

```

Paused in module OOPS.

Exiting IML.

Actually, in this particular case it would probably be simpler to put three RESUME statements after the RUN statement to resume execution after each of the first three errors.

Macro Interface

The pushed text is scanned by the macro processor; therefore, the text can contain macro instructions. For example, here is an all-purpose routine that shows what the expansion of any macro is, assuming that it does not have embedded double quotes:

```

/* function: y = macxpand(x);                */
/* macro-processes the text in x             */
/* and returns the expanded text in the result. */
/* Do not use double quotes in the argument.  */
/*                                           */
start macxpand(x);
  call execute('Y="' || x || '"');
  return(y);
finish;

```

Consider the following statements:

```

%macro verify(index);
  data _null_;
    infile junk&index;
    file print;
    input;
    put _infile_;
  run;
%mend;
y = macxpand('%verify(1) ');
print y;

```

The output produced is as follows:

```

Y

DATA _NULL_;      INFILE JUNK1;      FILE PRINT;      INPUT;
PUT _INFILE_;     RUN;

```

IML Line Pushing Contrasted with Using the Macro Facility

The SAS macro language is a language embedded in and running on top of another language; it generates text to feed the other language. Sometimes it is more convenient to generate the text by using the primary language directly rather than embedding the text generation in macros. The preceding examples show that this can even be done at execution time, whereas pure macro processing is done only at parse time. The advantage of the macro language is its embedded, yet independent, nature: it needs little quoting, and it works for all parts of the SAS language, not just IML. The disadvantage is that it is a separate language that has its own learning burden, and it uses extra reserved characters to mark its programming constructs and

variables. Consider the quoting of IML versus the embedding characters of the macro facility: IML makes you quote every text constant, whereas the macro facility makes you use the special characters percent sign (%) and ampersand (&) on every macro item. There are some languages, such as REXX, that give you the benefits of both (no macro characters and no required quotes), but the cost is that the language forces you to discipline your naming so that names are not expanded inadvertently.

Example 18.1: Full-Screen Editing

The ability to form and submit statements dynamically provides a very powerful mechanism for making systems flexible. For example, consider the building of a data entry system for a file. It is straightforward to write a system by using WINDOW and DISPLAY statements for the data entry and data processing statements for the I/O, but once you get the system built, it is good only for that one file. With the ability to push statements dynamically, however, it is possible to make a system that dynamically generates the components that are customized for each file. For example, you can change your systems from static systems to dynamic systems.

To illustrate this point, consider an IML system to edit an arbitrary file, a system like the FSEDIT procedure in SAS/FSP software but programmed in IML. You cannot just write it with open code because the I/O statements hardcode the filenames and the WINDOW and DISPLAY statements must hardcode the fields. However, if you generate just these components dynamically, the problem is solved for any file, not just one. Here is the code:

```
proc iml;
/*          FSEDIT                      */
/* This program defines and stores the modules FSEINIT,      */
/* FSEDIT, FSEDIT, and FSETERM in a storage catalog called   */
/* FSED. To use it, load the modules and issue the command   */
/* RUN FSEDIT; The system prompts or menus the files and    */
/* variables to edit, then runs a full screen editing       */
/* routine that behaves similar to PROC FSEDIT              */
/*                                                         */
/* These commands are currently supported:                  */
/*                                                         */
/* END              gets out of the system. The user is prompted */
/*                  as to whether or not to close the files and */
/*                  window.                                     */
/* SUBMIT           forces current values to be written out,    */
/*                  either to append a new record or replace   */
/*                  existing ones                               */
/* ADD              displays a screen variable with blank values */
/*                  for appending to the end of a file         */
/* DUP              takes the current values and appends them to */
/*                  the end of the file                        */
/* number           goes to that line number                  */
/* DELETE           deletes the current record after confirmation */
/*                  by a Y response                             */
/* FORWARD1         moves to the next record, unless at eof    */
/* BACKWARD1        moves to the previous record, unless at eof */

```

```

/* EXEC          executes any IML statement          */
/* FIND          finds records and displays them      */
/*                                                      */
/* Use: proc iml;                                     */
/*      reset storage='fsed';                         */
/*      load module=_all_;                             */
/*      run fsedit;                                    */
/*                                                      */
/*---routine to set up display values for new problem--- */
start fseinit;
  window fsed0 rows=15 columns=60 icolumn=18 color='GRAY'
  cmdline=cmd group=title +30 'Editing a data set' color='BLUE';
  /*---get file name---                                */
  _file="          ";
  msg =
    'Please Enter Data Set Name or Nothing For Selection List';
  display fsed0.title,
    fsed0 ( / @5 'Enter Data Set:'
           +1 _file
           +4 '(or nothing to get selection list)' );
  if _file=' ' then
    do;
      loop:
      _f=datasets(); _nf=nrow(_f); _sel=repeat("_",_nf,1);
      display fsed0.title,
        fsed0 ( / "Select? File Name"/ ) ,
        fsed0 ( / @5 _sel +1 _f protect=yes ) repeat ;
      _l = loc(_sel^='_');
      if nrow(_l)^=1 then
        do;
          msg='Enter one S somewhere';
          goto loop;
        end;
      _file = _f[_l];
    end;
  /*---open file, get number of records---            */
  call queue(" edit ",_file,";
             setin ",_file," NOBS _nobs; resume;"); pause *;
  /*---get variables---                                */
  _var = contents();
  _nv = nrow(_var);
  _sel = repeat("_",_nv,1);
  display fsed0.title,
    fsed0 ( / "File:" _file) noinput,
    fsed0 ( / @10 'Enter S to select each var, or select none
               to get all.'
           // @3 'select? Variable ' ),
    fsed0 ( / @5 _sel +5 _var protect=yes ) repeat;
  /*---reopen if subset of variables---                */
  if any(_sel^='_') then
    do;
      _var = _var[loc(_sel^='_')];
      _nv = nrow(_var);
      call push('close ',_file,'; edit ',_file,' var

```



```

        _var; resume; '); pause *;
    end;
/*---close old window--- */
window close=fsed0;
/*---make the window---*/
call queue('window fsed columns=55 icolumn=25 cmdndline=cmdnd
           msgline=msg ', 'group=var/@20 "Record " _obs
           protect=yes');
call queue( concat('/',_var,': " color="YELLOW" ',
                 _var, ' color="WHITE"'));
call queue(';');
/*---make a missing routine---*/
call queue('start vmiss; ');
do i=1 to _nv;
    val = value(_var[i]);
    if type(val)='N' then call queue(_var[i], '=.;');
    else call queue(_var[i], '=',
                    cshape(' ',1,1,nleng(val)), '"');
end;
call queue('finish; resume;');
pause *;
/*---initialize current observation---*/
_obs = 1;
msg = Concat('Now Editing File ',_file);
finish;
/* */
/*---The Editor Runtime Controller--- */
start fsedt;
_old = 0; go=1;
do while(go);
/*---get any needed data---*/
    if any(_obs^=_old) then do; read point _obs; _old = _obs;
end;
/*---display the record---*/
display fsed.var repeat;
cmdnd = upcase(left(cmdnd));
msg=' ';
if cmdnd='END' then go=0;
else if cmdnd='SUBMIT' then
    do;
        if _obs<=_nobs then
            do;
                replace point _obs; msg='replaced';
            end;
        else do;
            append;
            _nobs=_nobs+nrow(_obs);
            msg='appended';
        end;
    end;
else if cmdnd="ADD" then
    do;
        run vmiss;
        _obs = _nobs+1;
    end;
end;

```

```

        msg='New Record';
    end;
else if cmnd='DUP' then
    do;
        append;
        _nobs=_nobs+1;
        _obs=_nobs;
        msg='As Duplicated';
    end;
else if cmnd>'0' & cmnd<'999999' then
    do;
        _obs = num(cmnd);
        msg=concat('record number ',cmnd);
    end;
else if cmnd='FORWARD1' then _obs=min(_obs+1,_nobs);
else if cmnd='BACKWARD1' then _obs=max(_obs-1,1);
else if cmnd='DELETE' then
    do;
        records=cshape(char(_obs,5),1,1);
        msg=concat('Enter command Y to Confirm delete of'
                    ,records);
        display fsed.var repeat;
        if (upcase(cmnd)='Y') then
            do;
                delete point _obs;
                _obs=1;
                msg=concat('Deleted Records',records);
            end;
        else msg='Not Confirmed, Not Deleted';
    end;
else if substr(cmnd,1,4)='FIND' then
    do;
        call execute("find all where(",
                     substr(cmnd,5),
                     ") into _obs;" );
        _nfound=nrow(_obs);
        if _nfound=0 then
            do;
                _obs=1;
                msg='Not Found';
            end;
        else
            do;
                msg=concat("Found ",char(_nfound,5)," records");
            end;
    end;
else if substr(cmnd,1,4)='EXEC' then
    do;
        msg=substr(cmnd,5);
        call execute(msg);
    end;
else msg='Unrecognized Command; Use END to exit.';
end;
finish;

```

```

/*---routine to close files and windows, clean up---*/
start fseterm;
    window close=fsed;
    call execute('close ',_file,';');
    free _q;
finish;
/*---main routine for FSEDIT---*/
start fsedit;
    if (nrow(_q)=0) then
        do;
            run fseinit;
        end;
    else msg = concat('Returning to Edit File ',_file);
    run fsedt;
    _q='_';
    display fsed ( "Enter 'q' if you want to close files and windows"
                  _q " (anything else if you want to return later"
                  pause 'paused before termination';
    run fseterm;
finish;
reset storage='fsed';
store module=_all_;

```

Summary

In this chapter you learned how to use SAS/IML software to generate IML statements. You learned how to use the PUSH, QUEUE, EXECUTE, and RESUME commands to interact with the operating system or with the SAS windowing environment. You also saw how to add flexibility to programs by adding interrupt control features and by modifying error control. Finally, you learned how IML compares to the SAS macro language.

Chapter 19

Wavelet Analysis

Contents

Overview	477
Some Brief Mathematical Preliminaries	477
Getting Started	479
Creating the Wavelet Decomposition	482
Wavelet Coefficient Plots	484
Multiresolution Approximation Plots	487
Multiresolution Decomposition Plots	489
Wavelet Scalograms	490
Reconstructing the Signal from the Wavelet Decomposition	493
Details	494
Using Symbolic Names	494
Obtaining Help for the Wavelet Macros and Modules	497
References	497

Overview

Wavelets are a versatile tool for understanding and analyzing data, with important applications in nonparametric modeling, pattern recognition, feature identification, data compression, and image analysis. Wavelets provide a description of your data that localizes information at a range of scales and positions. Moreover, they can be computed very efficiently, and there is an intuitive and elegant mathematical theory to guide you in applying them.

Some Brief Mathematical Preliminaries

The discrete wavelet transform decomposes a function as a sum of basis functions called wavelets. These basis functions have the property that they can be obtained by dilating and translating two basic types of wavelets known as the *scaling function*, or *father wavelet* ϕ , and The *mother wavelet* ψ . These translations

and dilations are defined as follows:

$$\begin{aligned}\phi_{j,k}(x) &= 2^{j/2}\phi(2^j x - k) \\ \psi_{j,k}(x) &= 2^{j/2}\psi(2^j x - k)\end{aligned}$$

The index j defines the dilation or *level* while the index k defines the translate. Loosely speaking, sums of the $\phi_{j,k}(x)$ capture low frequencies and sums of the $\psi_{j,k}(x)$ represent high frequencies in the data. More precisely, for any suitable function $f(x)$ and for any j_0 ,

$$f(x) = \sum_k c_k^{j_0} \phi_{j_0,k}(x) + \sum_{j \geq j_0} \sum_k d_k^j \psi_{j,k}(x)$$

where the c_k^j and d_k^j are known as the scaling coefficients and the detail coefficients, respectively. For orthonormal wavelet families these coefficients can be computed by

$$\begin{aligned}c_k^j &= \int f(x) \phi_{j,k}(x) dx \\ d_k^j &= \int f(x) \psi_{j,k}(x) dx\end{aligned}$$

The key to obtaining fast numerical algorithms for computing the detail and scaling coefficients for a given function $f(x)$ is that there are simple recurrence relationships that enable you to compute the coefficients at level $j - 1$ from the values of the scaling coefficients at level j . These formulas are

$$\begin{aligned}c_k^{j-1} &= \sum_i h_{i-2k} c_i^j \\ d_k^{j-1} &= \sum_i g_{i-2k} c_i^j\end{aligned}$$

The coefficients h_k and g_k that appear in these formulas are called *filter coefficients*. The h_k are determined by the father wavelet and they form a low-pass filter; $g_k = (-1)^k h_{1-k}$ and form a high-pass filter. The preceding sums are formally over the entire (infinite) range of integers. However, for wavelets that are zero except on a finite interval, only finitely many of the filter coefficients are nonzero, and so in this case the sums in the recurrence relationships for the detail and scaling coefficients are finite.

Conversely, if you know the detail and scaling coefficients at level $j - 1$, then you can obtain the scaling coefficients at level j by using the relationship

$$c_k^j = \sum_i h_{k-2i} c_i^{j-1} + \sum_i g_{k-2i} d_i^{j-1}$$

Suppose that you have data values

$$y_k = f(x_k), \quad k = 0, 1, 2, \dots, N - 1$$

at $N = 2^J$ equally spaced points x_k . It turns out that the values $2^{-J/2} y_k$ are good approximations of the scaling coefficients c_k^J . Then, by using the recurrence formula, you can find c_k^{J-1} and d_k^{J-1} , $k =$

$0, 1, 2, \dots, N/2 - 1$. The discrete wavelet transform of the y_k at level $J - 1$ consists of the $N/2$ scaling and $N/2$ detail coefficients at level $J - 1$. A technical point that arises is that in applying the recurrence relationships to finite data, a few values of the c_k^J for $k < 0$ or $k \geq N$ might be needed. One way to cope with this difficulty is to extend the sequence c_k^J to the left and right by using some specified boundary treatment.

Continuing by replacing the scaling coefficients at any level j by the scaling and detail coefficients at level $j - 1$ yields a sequence of N coefficients

$$\{c_0^0, d_0^0, d_0^1, d_1^1, d_0^2, d_1^2, d_2^2, d_3^2, d_1^3, \dots, d_7^3, \dots, d_0^{J-1}, \dots, d_{N/2-1}^{J-1}\}$$

This sequence is the finite discrete wavelet transform of the input data $\{y_k\}$. At any level j_0 the finite dimensional approximation of the function $f(x)$ is

$$f(x) \approx \sum_k c_k^{j_0} \phi_{j_0,k}(x) + \sum_{j=j_0}^{J-1} \sum_k d_k^j \psi_{j,k}(x)$$

Getting Started

Fourier Transform Infrared (FT-IR) spectroscopy is an important tool in analytic chemistry. The following example demonstrates wavelet analysis applied to an FT-IR spectrum of quartz (Sullivan 2000). The following DATA step creates a data set that contains the spectrum, expressed as an absorbance value for each of 850 wave numbers.

```
data quartzInfraredSpectrum;
  WaveNumber=4000.6167786 - _N_ *4.00084378;
  input Absorbance @@;
datalines;
4783 4426 4419 4652 4764 4764 4621 4475 4430 4618
4735 4735 4655 4538 4431 4714 4738 4707 4627 4523
4512 4708 4802 4811 4769 4506 4642 4799 4811 4732
4583 4676 4856 4868 4796 4849 4829 4677 4962 4994
4924 4673 4737 5078 5094 4987 4632 4636 5010 5166
5166 4864 4547 4682 5161 5291 5143 4684 4662 5221
5640 5640 5244 4791 4832 5629 5766 5723 5121 4690
5513 6023 6023 5503 4675 5031 6071 6426 6426 5723
5198 5943 6961 7135 6729 5828 6511 7500 7960 7960
7299 6484 7257 8180 8542 8537 7154 7255 8262 8898
8898 8263 7319 7638 8645 8991 8991 8292 7309 8005
9024 9024 8565 7520 7858 8652 8966 8966 8323 7513
8130 8744 8879 8516 7722 8099 8602 8729 8726 8238
7885 8350 8600 8603 8487 7995 8194 8613 8613 8408
7953 8236 8696 8696 8552 8102 7852 8570 8818 8818
8339 7682 8535 9038 9038 8503 7669 7794 8864 9163
9115 8221 7275 8012 9317 9317 8512 7295 7623 9021
9409 9338 8116 6860 7873 9282 9490 9191 7012 7392
9001 9483 9457 8107 6642 7695 9269 9532 9246 7641
6547 8886 9457 9457 8089 6535 7537 9092 9406 9178
```

7591	6470	7838	9156	9222	7974	6506	7360	8746	9057
8877	7455	6504	7605	8698	8794	8439	7057	7202	8240
8505	8392	7287	6634	7418	8186	8229	7944	6920	6829
7499	7949	7831	7057	6866	7262	7626	7626	7403	6791
7062	7289	7397	7397	7063	6985	7221	7221	7199	6977
7088	7380	7380	7195	6957	6847	7426	7570	7508	6952
6833	7489	7721	7718	7254	6855	7132	7914	8040	7880
7198	6864	7575	8270	8229	7545	7036	7637	8470	8570
8364	7591	7413	8195	8878	8878	8115	7681	8313	9102
9185	8981	8283	8197	8932	9511	9511	9101	8510	8670
9686	9709	9504	8944	8926	9504	9964	9964	9627	9212
9366	9889	10100	9939	9540	9512	9860	10121	10121	9828
9567	9513	9782	9890	9851	9510	9385	9339	9451	9451
9181	9076	9015	8960	9014	8957	8760	8760	8602	8584
8584	8459	8469	8373	8279	8327	8282	8341	8341	8155
8260	8260	8250	8350	8245	8358	8403	8355	8490	8490
8439	8689	8689	8621	8680	8661	8897	9028	8900	8873
8873	9187	9377	9377	9078	9002	9147	9635	9687	9535
9127	9242	9824	9928	9775	9200	9047	9572	10102	10102
9631	9024	9209	10020	10271	9830	9062	9234	10154	10483
10453	9582	9011	9713	10643	10701	10372	9368	9857	10865
10936	10572	9574	9691	10820	11452	11452	10623	9903	10787
11931	12094	11302	10604	11458	12608	12808	12589	11629	11795
12863	13575	13575	12968	12498	13268	14469	14469	13971	13727
14441	15334	15515	15410	14986	15458	16208	16722	16722	16618
17061	17661	18089	18089	18184	18617	19015	19467	19633	19830
20334	20655	20947	21347	21756	22350	22584	22736	22986	23412
24126	24498	24501	24598	24986	25729	26356	26356	26271	26754
27624	28162	28162	28028	28305	29223	30073	30219	30185	30308
31831	32699	32819	32793	33320	34466	35600	36038	36086	36518
37517	38765	39462	39681	40209	41243	42274	42772	42876	43172
43929	44842	45351	45395	45551	46035	46774	47353	47353	47362
47908	48539	48936	48978	49057	49497	50101	50670	50914	51134
51603	52276	53007	53399	53769	54281	54815	54914	55365	55874
56180	56272	56669	57076	57422	57458	57525	57681	57679	57318
57318	57181	57417	57409	57144	57047	56377	56551	56483	56098
56034	55598	55364	55364	55146	54904	54990	55501	55533	55362
54387	55340	55240	54748	53710	55346	55795	55795	55060	55945
55945	55753	56759	56859	57509	56741	56273	56961	58566	58566
58104	59275	59275	59051	59090	59461	60362	60560	61103	61272
61380	61878	62067	62237	62214	61182	61532	62173	62253	60473
61346	63143	63378	61519	61753	63078	63841	63841	62115	61227
63237	63237	61338	63951	63951	63604	63633	64625	65135	64976
63630	63494	63834	63338	63218	62324	64131	64234	65122	64551
64127	64415	64621	64621	63142	65344	65585	65476	65074	64714
63803	65085	65085	65646	65646	64851	65390	65390	64997	65541
65587	65682	65952	65952	65390	65702	65846	65734	65734	65628
65509	65571	65636	65636	65620	65487	65544	65547	65738	65758
65711	65360	65362	65362	65231	65333	65453	65473	65435	65302
65412	65412	65351	65242	65242	65170	65221	65297	65297	65202
65177	65183	65184	65179	65209	65209	65144	65134	65113	65009
64919	64945	64988	64988	64856	64686	64529	64370	64282	64233
64169	63869	63685	63480	63373	63349	63307	63131	63017	62885
62736	62736	62706	62666	62622	62671	62781	62853	62950	63106


```

63135 63141 63220 63263 63489 63807 63966 64132 64294 64612
64841 64985 65159 65204 65259 65540 65707 65749 65732 65719
65820 65895 65925 65925 65888 65937 66059 66109 66109 66078
66007 65897 65897 65747 65490 64947 64598 64363 64140 63801
63571 63395 63333 63442 63442 63339 63196 62911 62118 61795
61454 61456 61607 62025 62190 62190 62023 61780 61502 61482
61458 61320 61015 60852 60708 60684 60522 60488 60506 60640
60797 60995 61141 61141 61036 60664 60522 60017 59681 59129
58605 58035 57192 56137 54995 53586 52037 50283 48565 45419
43341 41111 36131 35377 34431 31679 29237 26898 24655 22417
19876 17244 15176 12575 10532 8180 6040 4059 2210 575
;

```

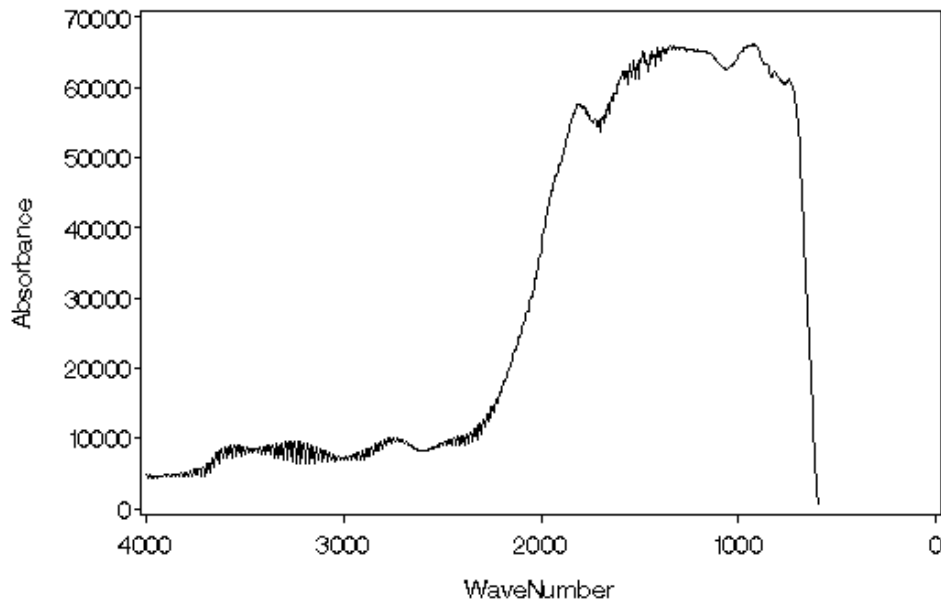
The following statements produce the line plot of these data displayed in [Figure 19.1](#).

```

symbol1 c=black i=join v=none;
proc gplot data=quartzInfraredSpectrum;
  plot Absorbance*WaveNumber/
    hminor = 0   vminor = 0
    vaxis = axis1
    hreverse frame;
    axis1 label = ( r=0 a=90 );
run;

```

Figure 19.1 FT-IR Spectrum of Quartz



These data contain information at two distinct scales, namely a low-frequency curve superimposed with a high-frequency oscillation. Notice that the oscillation is not uniform but occurs in several distinct bands. Wavelet analysis is an appropriate tool for providing insight into this type of data, as it enables you to identify the frequencies present in the absorbance data as the wave number changes. This property of wavelets is known as “time frequency localization”; in this case the role of time is played by WaveNumber.

Also note that the dependent variable **Absorbance** is measured at equally spaced values of the independent variable **WaveNumber**. This condition is necessary for the direct use of the discrete wavelet transform that is implemented in the SAS/IML wavelet functions.

Creating the Wavelet Decomposition

The following SAS code starts the wavelet analysis:

```
%wavginit;
proc iml;
    %wavinit;
```

Notice that the previous code segment includes two SAS macro calls. You can use the IML wavelet functions without using the WAVGINIT and WAVINIT macros. The macros are called to initialize and load IML modules that you can use to produce several standard wavelet diagnostic plots. These macros have been provided as autocall macros that you can invoke directly in your SAS code.

The WAVGINIT macro must be called prior to invoking PROC IML. This macro defines several macro variables that are used to adjust the size, aspect ratio, and font size for the plots produced by the wavelet plot modules. This macro can also take several optional arguments that control the positioning and size of the wavelet diagnostic plots. See the section “[Obtaining Help for the Wavelet Macros and Modules](#)” on page 497 for details about getting help about this macro call.

The WAVINIT macro must be called from within PROC IML. It loads the IML modules that you can use to produce wavelet diagnostic plots. This macro also defines symbolic macro variables that you can use to improve the readability of your code.

The following statements read the absorbance variable into an IML vector:

```
use quartzInfraredSpectrum;
read all var{Absorbance} into absorbance;
```

You are now in a position to begin the wavelet analysis. The first step is to set up the options vector that specifies which wavelet and what boundary handling you want to use. You do this as follows:

```
optn          = &waveSpec;    /* optn=j(1,4,.); */
optn[&family]  = &daubechies; /* optn[3] = 1;   */
optn[&member]  = 3;           /* optn[4] = 3;   */
optn[&boundary] = &polynomial; /* optn[1] = 2;   */
optn[&degree]  = &linear;     /* optn[2] = 1;   */
```

These statements use macro variables that are defined in the WAVINIT macro. The equivalent code without using these macro variables is given in the adjacent comments. As indicated by the suggestive macro variable names, this options vector specifies that the wavelet to be used is the third member of the Daubechies

wavelet family and that boundaries are to be handled by extending the signal as a linear polynomial at each endpoint.

The next step is to create the wavelet decomposition with the following call:

```
call wavft (decomp, absorbance, optn) ;
```

This call computes the wavelet transform specified by the vector `optn` of the input vector `absorbance`. The specified transform is encapsulated in the vector `decomp`. This vector is not intended to be used directly. Rather you use this vector as an argument to other IML wavelet subroutines and plot modules. For example, you use the `WAVPRINT` subroutine to print the information encapsulated in a wavelet decomposition. The following code produces the output in [Figure 19.2](#).

```
call wavprint (decomp, &summary) ;
call wavprint (decomp, &detailCoeffs, 1, 4) ;
```

Figure 19.2 Output of WAVPRINT CALLS

Decomposition Summary				
Decomposition Name		decomp		
Wavelet Family	Daubechies		Extremal	Phase
Family Member			3	
Boundary Treatment	Recursive Linear		Extension	
Number of Data Points			850	
Start Level			0	
Wavelet Detail Coefficients for decomp				
Translate	Level 1	Level 2	Level 3	Level 4
0	-1.70985E-9	1.31649E-10	-8.6402E-12	5.10454E-11
1	1340085.30	-128245.70	191.084707	4501.36
2		62636.70	6160.27	-1358.23
3		-238445.36	-54836.56	-797.724143
4			39866.95	676.034389
5			-28836.85	-5166.59
6			223421.00	-6088.99
7				-5794.67
8				30144.74
9				-3903.53
10				638.063264
11				-10803.45
12				33616.35
13				-50790.30

Usually such displayed output is of limited use. More frequently you want to represent the transformed data graphically or use the results in further computational routines. As an example, you can estimate the noise level of the data by using a robust measure of the standard deviation of the highest-level detail coefficients, as demonstrated in the following statements:

```

call wavget (tLevel,decomp,&topLevel);
call wavget (noiseCoeffs,decomp,&detailCoeffs,tLevel-1);

noiseScale=mad(noiseCoeffs,"nmad");
print "Noise scale = " noiseScale;

```

The result is shown in [Figure 19.3](#).

Figure 19.3 Scale of Noise in the Absorbance Data

noiseScale	
Noise scale =	169.18717

The first WAVGET call is used to obtain the top level number in the wavelet decomposition `decomp`. The highest level of detail coefficients is defined at one level below the top level in the decomposition. The second WAVGET call returns these coefficients in the vector `noiseCoeffs`. Finally, the MAD function computes a robust estimate of the standard deviation of these coefficients.

Wavelet Coefficient Plots

Diagnostic plots greatly facilitate the interpretation of a wavelet decomposition. One standard plot is the detail coefficients arranged by level. By using a module included by the WAVINIT macro call, you can produce the plot shown in [Figure 19.5](#) as follows:

```

call coefficientPlot(decomp, , , , "Quartz Spectrum");

```

The first argument specifies the wavelet decomposition and is required. All other arguments are optional and need not be specified. You can use the WAVHELP macro to obtain a description of the arguments of this and other wavelet plot modules. The WAVHELP macro is defined in the autocall WAVINIT macro. For example, invoking the WAVHELP macro as follows writes the calling information shown in [Figure 19.4](#) to the SAS log.

```

%wavhelp(coefficientPlot);

```

Figure 19.4 Log Output Produced by %wavhelp(coefficientPlot) Call

```

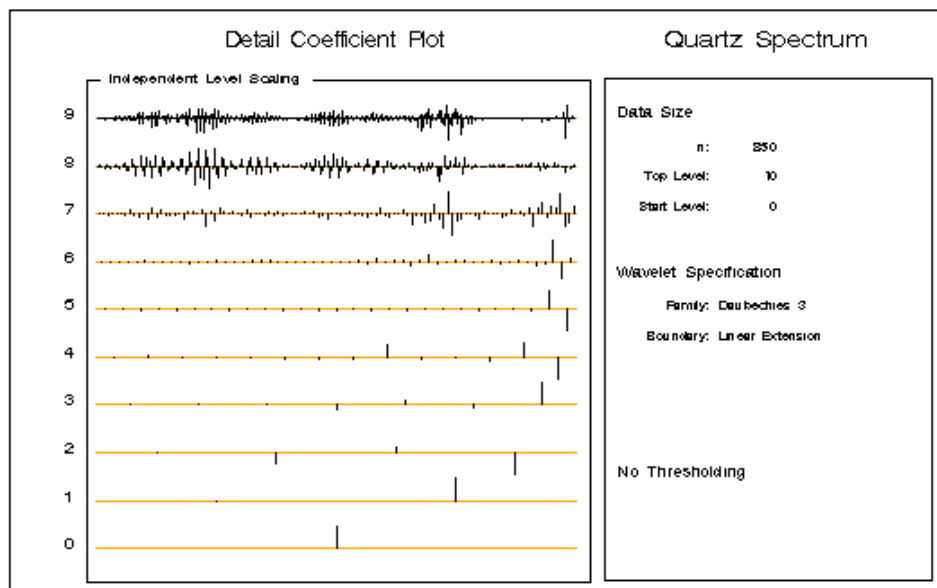
coefficientPlot Module

Function: Plots wavelet detail coefficients

Usage: call coefficientPlot(decomposition,
                           threshopt,
                           startLevel,
                           endLevel,
                           howScaled,
                           header);

Arguments:
  decomposition - (required) valid wavelet decomposition produced
                  by the IML subroutine WAVFT
  threshopt     - (optional) numeric vector of 4 elements
                  specifying thresholding to be used
                  Default: no thresholding
  startLevel    - (optional) numeric scalar specifying the lowest
                  level to be displayed in the plot
                  Default: start level of decomposition
  endLevel      - (optional) numeric scalar specifying the highest
                  level to be displayed in the plot
                  Default: end level of decomposition
  howScaled     - (optional) character: 'absolute' or 'uniform'
                  specifies coefficients are scaled uniformly
                  Default: independent level scaling
  header       - (optional) character string specifying a header
                  Default: no header

```

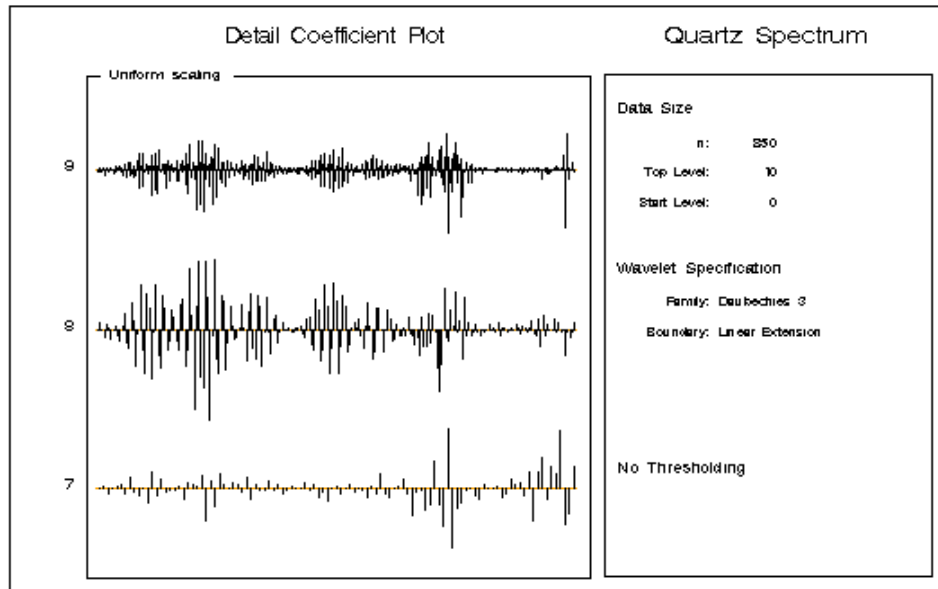
Figure 19.5 Detail Coefficients Scaled by Level

In this plot the detail coefficients at each level are scaled independently. The oscillations present in the absorbance data are captured in the detail coefficients at levels 7, 8, and 9. The following statement produces a coefficient plot of just these higher-level detail coefficients and shows them scaled uniformly.

```
call coefficientPlot(decomp, ,7, ,
                    'uniform','Quartz Spectrum');
```

The plot is shown in Figure 19.6.

Figure 19.6 Uniformly Scaled Detail Coefficients

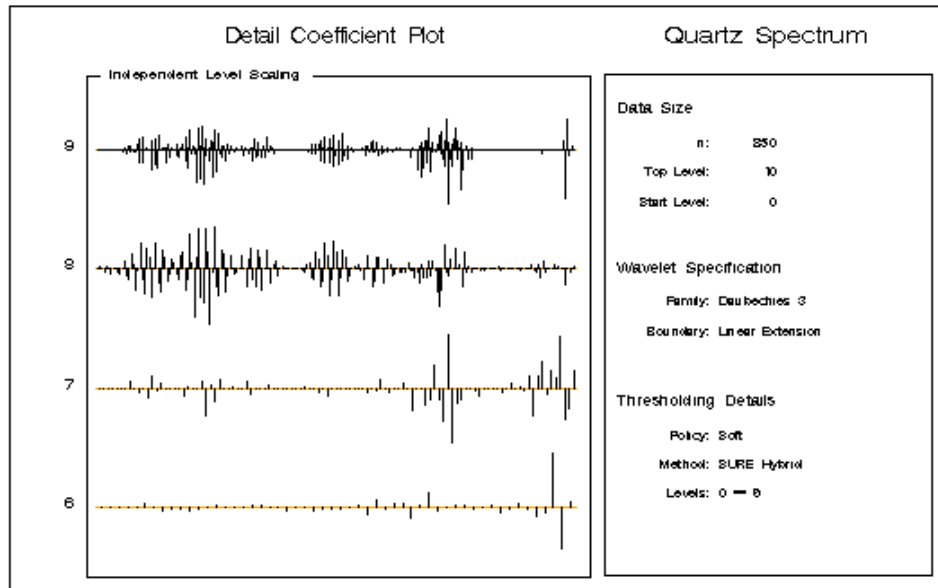


As noted earlier, noise in the data is captured in the detail coefficients, particularly in the small coefficients at higher levels in the decomposition. By zeroing or shrinking these coefficients, you can get smoother reconstructions of the input data. This is done by specifying a threshold value for each level of detail coefficients and then zeroing or shrinking all the detail coefficients below this threshold value. The IML wavelet functions and modules support several policies for how this thresholding is performed as well as for selecting the thresholding value at each level. See the section “[WAVIFT Call](#)” on page 1036 for details.

An options vector is used to specify the desired thresholding; several standard choices are predefined as macro variables in the WAVINIT module. The following statements produce the detail coefficient plot with the “SureShrink” thresholding algorithm of Donoho and Johnstone (1995).

```
call coefficientPlot(decomp,&SureShrink,6, , ,
                    "Quartz Spectrum");
```

The plot is shown in Figure 19.7.

Figure 19.7 Thresholded Detail Coefficients

You can see that “SureShrink” thresholding has zeroed some of the detail coefficients at the higher levels but the larger coefficients that capture the oscillation in the data are still present. Consequently, reconstructions of the input signal using the thresholded detail coefficients still capture the essential features of the data, but are smoother because much of the very fine scale detail has been eliminated.

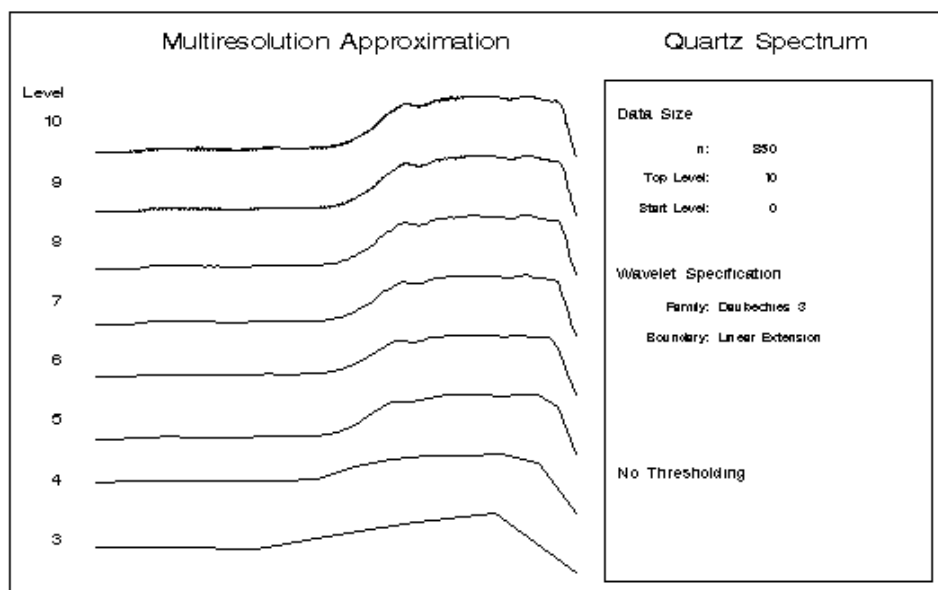
Multiresolution Approximation Plots

One way of presenting reconstructions is in a multiresolution approximation plot. In this plot reconstructions of the input data are shown by level. At any level the reconstruction at that level uses only the detail and scaling coefficients defined below that level.

The following statement produces such a plot, starting at level 3:

```
call mraApprox(decomp, ,3, ,"Quartz Spectrum");
```

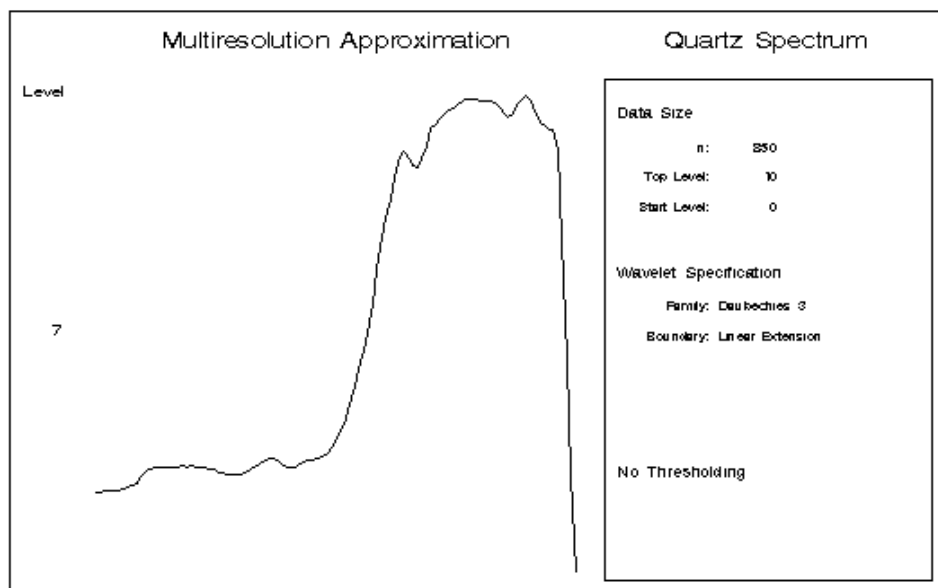
The results are shown in [Figure 19.8](#).

Figure 19.8 Multiresolution Approximation

You can see that even at level 3, the basic form of the input signal has been captured. As noted earlier, the oscillation present in the absorbance data is captured in the detail coefficients higher than level 7. Thus, the reconstructions at level 7 and lower are largely free of oscillation since they do not use any of the higher detail coefficients. You can confirm this observation by plotting just this level in the multiresolution analysis as follows:

```
call mraApprox(decomp, ,7,7,"Quartz Spectrum");
```

The results are shown in [Figure 19.9](#).

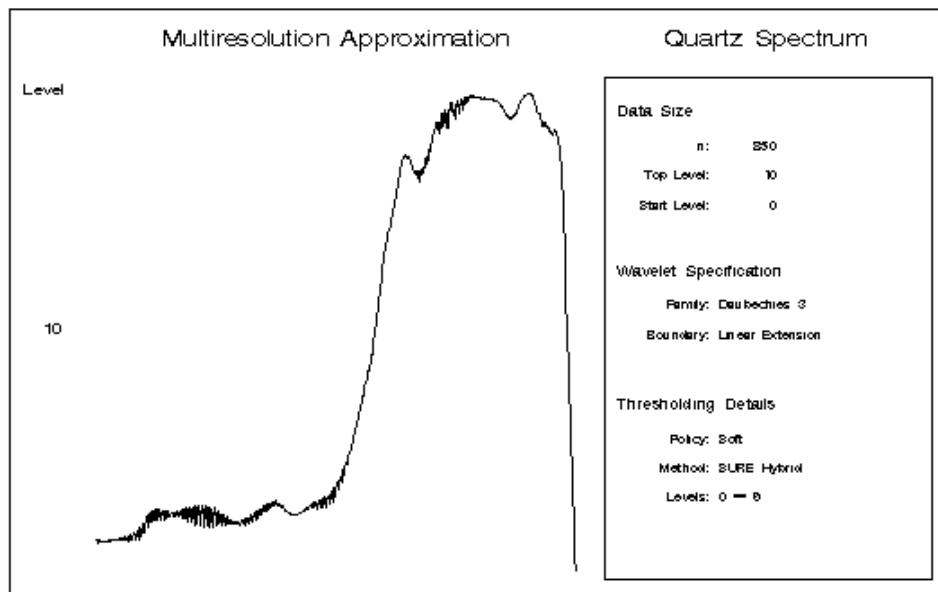
Figure 19.9 Level 7 of the Multiresolution Approximation

You can also plot the multiresolution approximations obtained with thresholded detail coefficients. For example, the following statement plots the top-level reconstruction obtained by using the “SureShrink” threshold:

```
call mraApprox(decomp, &SureShrink, 10, 10,
               "Quartz Spectrum");
```

The results are shown in Figure 19.10.

Figure 19.10 Top Level of Multiresolution Approximation with SureShrink Thresholding Applied

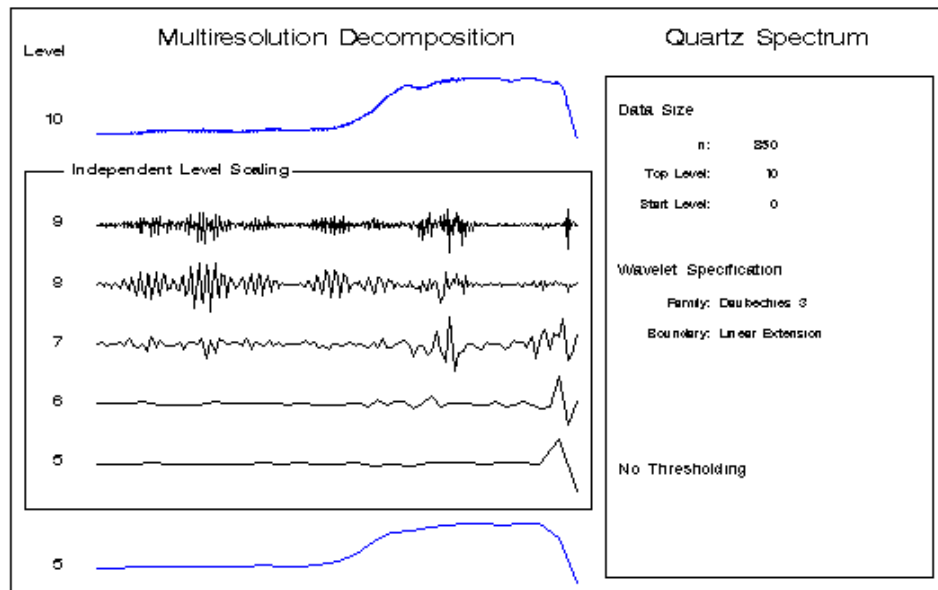


Note that the high-frequency oscillation is still present in the reconstruction even with “SureShrink” thresholding applied.

Multiresolution Decomposition Plots

A related plot is the multiresolution decomposition plot, which shows the detail coefficients at each level. For convenience, the starting-level reconstruction at the lowest level of the plot and the reconstruction at the highest level of the plot are also included. Adding suitably scaled versions of all the detail levels to the starting-level reconstruction recovers the final reconstruction. The following statement produces such a plot, yielding the results shown in Figure 19.11.

```
call mraDecomp(decomp, , 5, , , "Quartz Spectrum");
```

Figure 19.11 Multiresolution Decomposition

Wavelet Scalograms

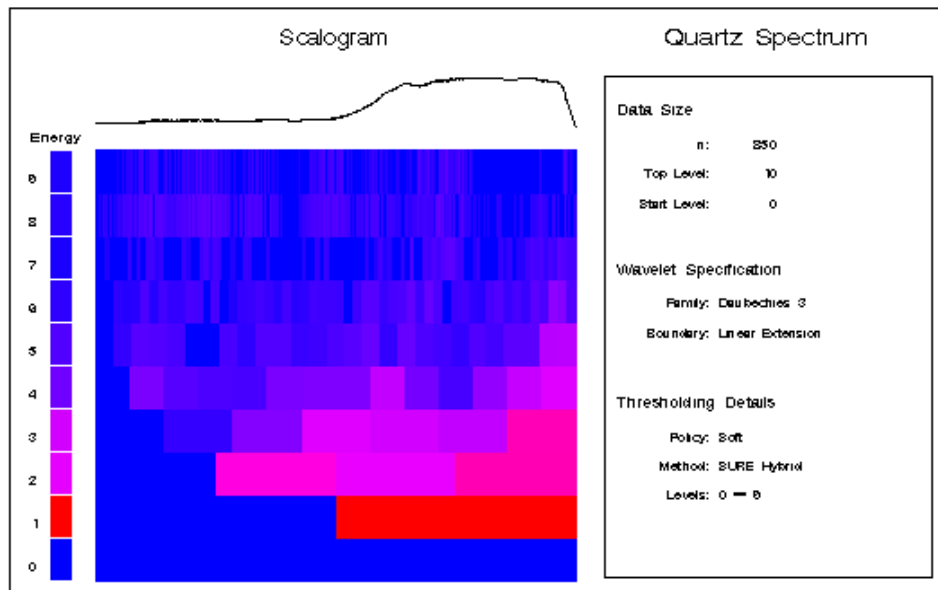
Wavelet scalograms communicate the time frequency localization property of the discrete wavelet transform. In this plot each detail coefficient is plotted as a filled rectangle whose color corresponds to the magnitude of the coefficient. The location and size of the rectangle are related to the time interval and the frequency range for this coefficient. Coefficients at low levels are plotted as wide and short rectangles to indicate that they localize a wide time interval but a narrow range of frequencies in the data. In contrast, rectangles for coefficients at high levels are plotted thin and tall to indicate that they localize small time ranges but large frequency ranges in the data. The heights of the rectangles grow as a power of 2 as the level increases. If you include all levels of coefficients in such a plot, the heights of the rectangles at the lowest levels are so small that they are not visible. You can use an option to plot the heights of the rectangles on a logarithmic scale. This results in rectangles of uniform height but requires that you interpret the frequency localization of the coefficients with care.

The following statement produces a scalogram plot of all levels with “SureShrink” thresholding applied:

```
call scalogram(decomp,&SureShrink, , ,0.25,
               'log',"Quartz Spectrum");
```

The sixth argument specifies that the rectangle heights are to be plotted on a logarithmic scale. The role of the fifth argument (0.25) is to amplify the magnitude of the small detail coefficients. This is necessary since the detail coefficients at the lower levels are orders of magnitude larger than those at the higher levels. The amplification is done by first scaling the magnitudes of all detail coefficients to lie in the interval $[0, 1]$ and then raising these scaled magnitudes to the power 0.25. Note that smaller powers yield larger amplification of the small detail coefficient magnitudes. The default amplification is $1/3$.

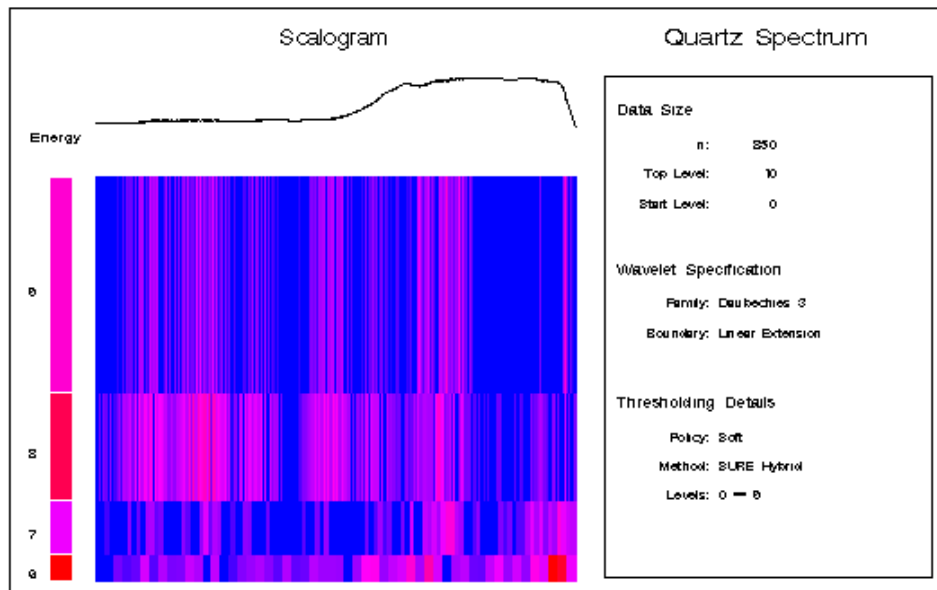
The results are shown in [Figure 19.12](#).

Figure 19.12 Scalogram Showing All Levels

The bar on the left-hand side of the scalogram plot indicates the overall energy of each level. This energy is defined as the sum of the squares of the detail coefficients for each level. These energies are amplified by using the same algorithm for amplifying the detail coefficient magnitudes. The energy bar in Figure 19.12 shows that higher energies occur at the lower levels whose coefficients capture the gross features of the data. In order to interpret the finer-scale details of the data it is helpful to focus on just the higher levels. The following statement produces a scalogram for levels 6 and higher without using a logarithmic scale for the rectangle heights, and using the default coefficient amplification.

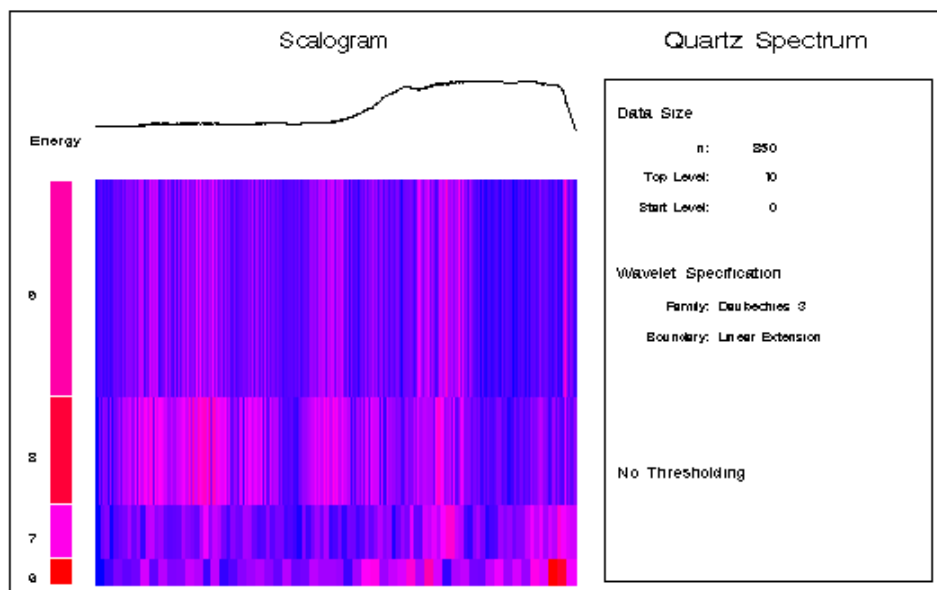
```
call scalogram(decomp,&SureShrink,6, , , ,
               "Quartz Spectrum");
```

The result is shown in Figure 19.13.

Figure 19.13 Scalogram of Levels 6 and Higher Using “SureShrink” Thresholding

The scalogram in Figure 19.13 reveals that most of the energy of the oscillation in the data is captured in the detail coefficients at level 8. Also note that many of the coefficients at the higher levels are set to zero by “SureShrink” thresholding. You can verify this by comparing Figure 19.13 with Figure 19.14, which shows the corresponding scalogram except that no thresholding is done. The following statement produces Figure 19.14:

```
call scalogram(decomp, ,6, , , "Quartz Spectrum");
```

Figure 19.14 Scalogram of Levels 6 and Higher Using No Thresholding

Reconstructing the Signal from the Wavelet Decomposition

You can use the WAVIFT subroutine to invert a wavelet transformation computed with the WAVFT subroutine. If no thresholding is specified, then up to numerical rounding error this inversion is exact. The following statements provide an illustration of this:

```
call wavift(reconstructedAbsorbance,decomp);
errorSS=ssq(absorbance-reconstructedAbsorbance);
print "The reconstruction error sum of squares = " errorSS;
```

The output is shown in [Figure 19.15](#).

Figure 19.15 Exact Reconstruction Property of WAVIFT

errorSS
The reconstruction error sum of squares = 1.288E-16

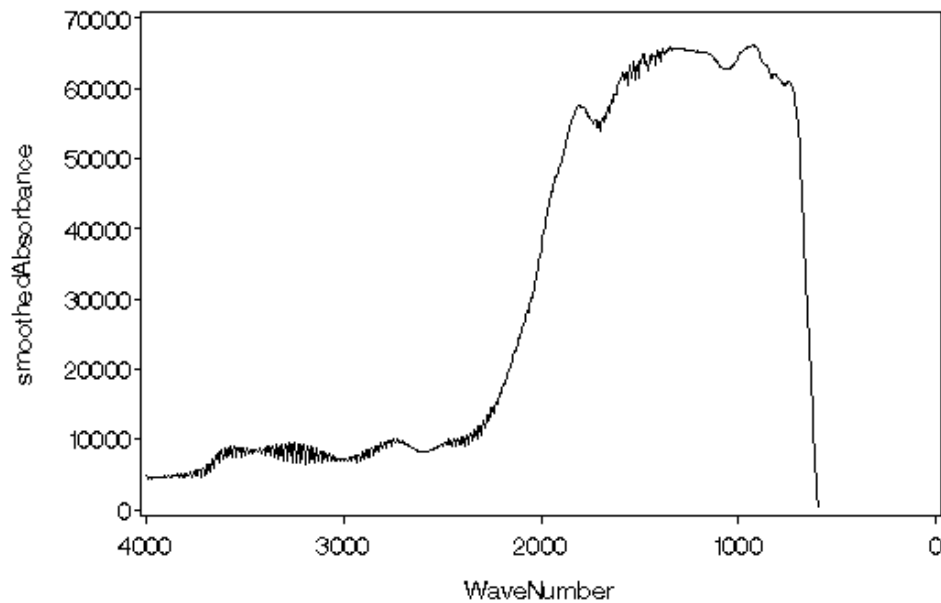
Usually you use the WAVIFT subroutine with thresholding specified. This yields a smoothed reconstruction of the input data. You can use the following statements to create a smoothed reconstruction of absorbance and add this variable to the QuartzInfraredSpectrum data set.

```
call wavift(smoothedAbsorbance,decomp,&SureShrink);
create temp from smoothedAbsorbance[colname='smoothedAbsorbance'];
  append from smoothedAbsorbance;
close temp;
quit;

data quartzInfraredSpectrum;
  set quartzInfraredSpectrum;
  set temp;
run;
```

The following statements produce the line plot of the smoothed absorbance data shown in [Figure 19.16](#):

```
symbol1 c=black i=join v=none;
proc gplot data=quartzInfraredSpectrum;
  plot smoothedAbsorbance*WaveNumber/
    hminor = 0   vminor = 0
    vaxis  = axis1
    hreverse frame;
    axis1 label = ( r=0 a=90 );
run;
```

Figure 19.16 Smoothed FT-IR Spectrum of Quartz

You can see by comparing [Figure 19.1](#) with [Figure 19.16](#) that the wavelet smooth of the absorbance data has preserved all the essential features of these data.

Details

Using Symbolic Names

Several of the wavelet subroutines take arguments that are options vectors that specify user input. For example, the third argument in a WAVFT subroutine call is an options vector that specifies which wavelet and which boundary treatment are used in computing the wavelet transform. Typical code that defines this options vector is as follows:

```
optn    = j(1, 4, .);
optn[1] = 0;
optn[3] = 1;
optn[4] = 3;
```

A problem with such code is that it is not easily readable. By using symbolic names readability is greatly enhanced. SAS macro variables provide a convenient mechanism for creating such symbolic names. For example, the previous code could be replaced by the following code:

```
optn      = &waveSpec;
```

```

optn[&family]    = &daubechies;
optn[&member]    = 3;
optn[&boundary]  = &zeroExtension;

```

where the symbolic macro variables (names with a preceding ampersand) resolve to the relevant quantities. Symbolic names also improve code readability when substituted for integer arguments that control what actions a multipurpose subroutine performs. Consider the following code:

```

call wavget (n, decomposition, 1);
call wavget (fWavelet, decompostion, 8);

```

This code can be replaced by the following statements:

```

call wavget (n, decomposition, &numPoints);
call wavget (fWavelet, decompostion, &fatherWavelet);

```

A set of symbolic names is defined in the autocall WAVINIT macro. The following tables list the symbolic names that are defined in this macro.

Table 19.1 Macro Variables for Wavelet Specification

Position		Admissible Values	
Name	Value	Name	Value
&boundary	1	&zeroExtension	0
		&periodic	1
		&polynomial	2
		&reflection	3
		&antisymmetricReflection	4
°ree	2	&constant	0
		&linear	1
		&quadratic	2
&family	3	&daubechies	1
		&symmlet	2
&member	4	1 - 10	

Table 19.2 Macro Variables for Threshold Specification

Position		Admissible Values	
Name	Value	Name	Value
&policy	1	&none	0
		&hard	1
		&soft	2
		&garrote	3
&method	2	&absolute	0
		&minimax	1
		&universal	2
		&sure	3
		&sureHybrid	4

		&nhoodCoffs	5
&value	3		positive real
&levels	4	&all	-1
			positive integer

Table 19.3 Symbolic Names for the Third Argument of WAVGET

Name	Value
&numPoints	1
&detailCoffs	2
&scalingCoffs	3
&thresholdingStatus	4
&specification	5
&topLevel	6
&startLevel	7
&fatherWavelet	8

Table 19.4 Macro Variables for the Second Argument of WAVPRINT

Name	Value
&summary	1
&detailCoffs	2
&scalingCoffs	3
&thresholdedDetailCoffs	4

Table 19.5 Macro Variables for Predefined Wavelet Specifications

Name	&boundary	°ree	&family	&member
&waveSpec	{	.	.	.
&haar	{	&periodic	.	&daubechies
&daubechies3	{	&periodic	.	&daubechies
&daubechies5	{	&periodic	.	&daubechies
&symmlet5	{	&periodic	.	&symmlet
&symmlet8	{	&periodic	.	&symmlet

Table 19.6 Macro Variables for Predefined Threshold Specifications

Name	&policy	&method	&value	&levels
&threshSpec	{	.	.	.
&RiskShrink	{	&hard	&minimax	.
&VisuShrink	{	&soft	&universal	.
&SureShrink	{	&soft	&sureHybrid	.

Obtaining Help for the Wavelet Macros and Modules

The WAVINIT macro that you call to define symbolic macro variables and wavelet plot modules also defines a macro WAVHELP that you can call to obtain help for the wavelet macros and plot modules. The syntax for calling the WAVHELP macro is as follows:

```
%WAVHELP < ( name ) > ;
```

In the macro call, *name* is either wavginit, wavinit, coefficientPlot, mraApprox, mraDecomp, or scalogram. This macro displays usage and argument information for the specified macro or module. If you call the WAVHELP macro with no arguments, it lists the names of the macros and modules for which help is available. Note that you can obtain help for the built-in IML wavelet subroutines by using the SAS Online Help.

References

- Daubechies, I. (1992), *Ten Lectures on Wavelets*, Volume 61, CBMS-NSF Regional Conference Series in Applied Mathematics, Philadelphia, PA: Society for Industrial and Applied Mathematics.
- Donoho, D. L. and Johnstone, I. M. (1994), “Ideal Spatial Adaptation via Wavelet Shrinkage,” *Biometrika*, 81, 425–455.
- Donoho, D. L. and Johnstone, I. M. (1995), “Adapting to Unknown Smoothness via Wavelet Shrinkage,” *Journal of the American Statistical Association*, 90, 1200–1224.
- Mallat, S. (1989), “Multiresolution Approximation and Wavelets,” *Transactions of the American Mathematical Society*, 315, 69–88.
- Ogden, R. T. (1997), *Essential Wavelets for Statistical Applications and Data Analysis*, Boston: Birkhäuser.

Chapter 20

Genetic Algorithms

Contents

Overview	499
Formulating a Genetic Algorithm Optimization	501
Choosing the Problem Encoding	501
Setting the Objective Function	502
Controlling the Selection Process	503
Using Crossover and Mutation Operators	504
Executing a Genetic Algorithm	509
Setting Up the IML Program	509
Incorporating Local Optimization	514
Handling Constraints	514
Example 20.1: Genetic Algorithm with Local Optimization	515
Example 20.2: Real-Valued Objective Optimization with Constant Bounds	517
Example 20.3: Integer Programming Knapsack Problem	521
Example 20.4: Optimization with Linear Constraints Using Repair Strategy	523
References	527

Overview

Genetic algorithms (referred to hereafter as GAs) are a family of search algorithms that seek optimal solutions to problems using the principles of natural selection and evolution. GAs can be applied to almost any optimization problem and are especially useful for problems where other calculus-based techniques do not work, such as when the objective function has many local optimums, it is not differentiable or continuous, or solution elements are constrained to be integers or sequences. In most cases GAs require more computation than specialized techniques that take advantage of specific problem structure or characteristics. However, for optimization problems with no such techniques available, GAs provide a robust general method of solution. The current GA implementation in IML is experimental, and will be further developed and tested in later SAS releases.

In general, GAs use the following procedure to search for an optimum solution:

initialization: An initial population of solutions is randomly generated, and an objective function value is evaluated for each member of the solution population.

regeneration: A new solution population is generated from the current solution population. First, individual members are chosen stochastically to parent the next generation such that those who are the “fittest” (have the best objective function values) are more likely to be picked. This process is called *selection*. Those chosen solutions are either copied directly to the next generation or passed to a crossover operator, with a user-specified crossover probability. The crossover operator combines two or more parents to produce new offspring solutions for the next generation. A fraction of the next generation solutions, selected according to a user-specified mutation probability, is passed to a mutation operator that introduces random variations in the solutions.

The crossover and mutation operators are commonly called *genetic operators*. The crossover operator passes characteristics from each parent to the offspring, especially those characteristics shared in common. It is selection and crossover that distinguish GAs from a purely random search, and direct the algorithm toward finding an optimum. Mutation is designed to ensure diversity in the search to prevent premature convergence to a local optimum.

As the final step in regeneration, the current population is replaced by the new solutions generated by selection, crossover, and mutation. The objective function values are evaluated for the new generation. A common variation on this approach that is supported in IML is to pass one or more of the best solutions from the current population on to the next population unchanged. This often leads to faster convergence, and assures that the best solution generated at any time during the optimization is never lost.

repeat: After *regeneration*, the process checks some stopping criteria, such as the number of iterations or some other convergence criteria. If the stopping criteria is not met, then the algorithm loops back to the *regeneration* step.

Although GAs have been demonstrated to work well for a variety of problems, there is no guarantee of convergence to a global optimum. Also, the convergence of GAs can be sensitive to the choice of genetic operators, mutation probability, and selection criteria, so that some initial experimentation and fine-tuning of these parameters is often required.

In the traditional formulation of GAs, the parameter set to be searched is mapped into finite-length bit strings, and the genetic operators applied to these strings, or chromosomes, are based on biological processes. While there is a theoretical basis for the effectiveness of GAs formulated in this way (Goldberg 1989), in practice most problems don’t fit naturally into this paradigm. Modern research has shown that optimizations can be set up using the natural solution domain (for example, a real vector or integer sequence) and applying crossover and mutation operators analogous to the traditional genetic operators, but more appropriate to the natural formulation of the problem (Michalewicz 1996). This latter approach is sometimes called *evolutionary computing*. IML implements the evolutionary computing approach because it makes it much easier to formulate practical problems with realistic constraints. Throughout this documentation, the term “genetic algorithm” is to be interpreted as evolutionary computing.

IML provides a flexible framework for implementing GAs, enabling you to write your own modules for the genetic operators and objective function, as well as providing some standard genetic operators that you can specify. This framework also enables you to introduce some variations to the usual GA, such as adapting the optimization parameters during the optimization, or incorporating some problem-specific local optimizations into the process to enhance convergence.

An IML program to do GA optimization is structured differently from a program doing nonlinear optimiza-

tion with the nlp routines. With the nlp routines, generally a single call is made in which the user specifies the objective and optimization parameters, and that call runs the optimization process to completion. In contrast, to perform a GA optimization you use separate calls to the GA routines to specify the problem encoding (GASETUP), genetic operators (GASETMUT and GASETCRO), objective function (GASETOBJ), and selection criteria (GASETSEL). You then call the GAINIT routine to initialize the problem population. After that, you advance the optimization process by calling GAREGEN (for the regeneration step) within an IML loop. Within the loop you can use GAGETMEM and GAGETVAL calls to retrieve population members and objective function values for examination. This strategy allows you to monitor the convergence of the GA, adjust optimization parameters with GA routine calls within the loop, and exit the loop when the GA is not producing further improvement in the objective function. The next section explains the optimization parameters in more detail and gives guidance on how they should be set.

Formulating a Genetic Algorithm Optimization

To formulate a GA in IML you must decide on five basic optimization parameters:

1. *Encoding:* The general structure and form of the solution.
2. *Objective:* The function to be optimized. IML also enables you to specify whether the function is to be minimized or maximized.
3. *Selection:* How members of the current solution population will be chosen to be parents to propagate the next generation.
4. *Crossover:* How the attributes of parent solutions will be combined to produce new offspring solutions.
5. *Mutation:* How random variation will be introduced into the new offspring solutions to maintain genetic diversity.

The following section discusses each of these items in more detail.

Choosing the Problem Encoding

Problem encoding refers to the structure or type of solution space that is to be optimized, such as real-valued fixed-length vectors or integer sequences. IML offers encoding options appropriate to several types of optimization problems.

General Numeric Matrix: With this encoding, solutions can take the form of a numeric matrix of any shape. Also, different solutions can have different dimensions. This is the most flexible option. If you use this encoding, IML makes no assumptions about the form of the solution, so you are required to specify user modules for crossover and mutation operators, and a user module for creating the initial solution population.

Fixed-Length Real-Valued Row Vector: If you use this encoding, you must also specify the number of components in the solution vector. Using this option, you can use some IML-supplied crossover and mutation operators later, or you can supply custom modules. You can also specify upper and lower bounds for each

component in the vector, and IML will generate an initial population for the GA randomly distributed between the bounds. If you don't explicitly set crossover and mutation operators, IML will provide default operators to be used in the optimization. This type of encoding is often used for general nonlinear optimization problems.

Fixed-Length Integer-Valued Row Vector: This option is similar to the fixed-length real-valued encoding already described, except that the IML-supplied genetic operators and initialization process will preserve and generate integer solutions. This type of encoding might be applicable, for example, in an assignment problem where the positions within the vector represent different tasks, and the integer values represent different machines or other resources that might be applied to each task.

Fixed-Length Integer Sequence: In this encoding, each solution is composed of a sequence of integers ranging from 1 to the length of the sequence, with different solutions distinguished by different ordering of the elements. For example, s_1 and s_2 are two integer sequences of length 6:

```
s1 = {1 2 3 4 5 6};
s2 = {2 6 5 3 4 1};
```

This type of encoding is often used for routing problems like the traveling salesman problem, where each element represents a city in a circular route, or scheduling problems.

Setting the Objective Function

Before executing a GA, you must specify the objective function to be optimized. There are currently two options available: a user function module and an IML-supplied traveling salesman problem (TSP) objective function.

User Function Module: The module must take exactly one parameter, which will be one solution, and return a numeric scalar objective function value. The module can also have a global clause, which may be used to pass in any other information required to determine the objective function value. If global parameters are used, you must be careful about changing them after the optimization has been initialized. If a change in a global parameter affects the objective function values, you must reevaluate the entire solution population (see GAREEVAL call) to ensure that the values are consistent with the changed global parameter.

The solution parameter passed into the routine is also written back out to the solution population when the module exits, so you should take care not to modify the parameter and therefore the solution population unintentionally. However, it is permissible and may prove very effective to add logic to the module to improve the solution through some heuristic technique or local optimization, and deliberately pass that improved solution back to the solution population by updating the parameter before returning. Using this hybrid approach may significantly improve the convergence of the GA, especially in later stages when solutions may be near an optimum.

TSP Objective Function: An objective function for the traveling salesman problem can be specified with integer sequence encoding. For the TSP, a solution sequence represents a circular route. For example, a solution s with the value

```
s = {2 4 3 1 5};
```

represents a route going from location 2 to location 4 to 3 to 1 to 5 and back to 2. You must also specify a cost matrix c , where $c[i,j]$ is the cost of going from location i to location j . The objective function is just the cost of traversing the route determined by s , and is equivalent to the IML code:

```
start TSPObjectiveFunction(s) global(c);
nc = ncol(s);
cost = c[s[nc],s[1]];
do i = 1 to nc-1;
  cost = cost + c[s[i],s[i+1]];
end;
return (cost);
finish;
```

The IML-supplied order crossover operator and invert mutation operator are especially appropriate for the TSP and other routing problems.

Controlling the Selection Process

There are two competing factors that need to be balanced in the selection process, the *selective pressure* and *genetic diversity*. Selective pressure, the tendency to select only the best members of the current generation to propagate to the next, is required to direct the GA to an optimum. Genetic diversity, the maintenance of a diverse solution population, is also required to ensure that the solution space is adequately searched, especially in the earlier stages of the optimization process. Too much selective pressure can lower the genetic diversity so that the global optimum is overlooked and the GA converges to a local optimum. Yet, with too little selective pressure the GA may not converge to an optimum in a reasonable time. A proper balance between the selective pressure and genetic diversity must be maintained for the GA to converge in a reasonable time to a global optimum.

IML offers two variants of a standard technique for the selection process commonly known as *tournament selection* (Miller and Goldberg 1995). In general, the tournament selection process randomly chooses a group of members from the current population, compares their objective values, and picks the one with the best objective value to be a parent for the next generation. Tournament selection was chosen for IML because it is one of the fastest selection methods, and offers you good control over the selection pressure. Other selection methods such as roulette and rank selection may be offered as options in the future.

In the first variant of tournament selection, you can control the selective pressure by specifying the tournament size, the number of members chosen to compete for parenthood in each tournament. This number should be two or greater, with two implying the weakest selection pressure. Tournament sizes from two to ten have been successfully applied to various GA optimizations, with sizes over four to five considered to represent strong selective pressure.

The second variant of tournament selection provides weaker selective pressure than the first variant just described. The tournament size is set at two, and the member with the best objective value is chosen with a probability that you specify. This best-player-wins probability can range from 0.5 to 1.0, with 1.0 implying that the best member is always chosen (equivalent to a conventional tournament of size two) and 0.5 implying an equal chance of either member being chosen (equivalent to pure random selection). Using this option, you could set the best-player-wins probability close to 0.5 in the initial stages of the

optimization, and gradually increase it to strengthen the selective pressure as the optimization progresses, in a similar manner to the simulated annealing optimization technique.

Another important selection option supported in IML is the *elite* parameter. If an elite value of n is specified, then the best n solutions will be carried over to the next generation unchanged, with the rest of the new population filled in by tournament selection, crossover, and mutation. Setting the elite parameter to one or greater will therefore guarantee that the best solution is never lost through selection and propagation, which often improves the convergence of the algorithm.

Using Crossover and Mutation Operators

IML enables you to employ user modules for crossover and mutation operators, or you may choose from the operators provided by IML. The IML operators are tied to the problem encoding options, and IML will check to make sure a specified operator is appropriate to the problem encoding. You can also turn off crossover, in which case the current population will pass on to the next generation subject only to mutation. Mutation can be turned off by setting the mutation probability to 0.

The IML-supplied genetic operators are described below, beginning with the crossover operators:

simple: This operator is defined for fixed-length integer and real vector encoding. To apply this operator, a position k within a vector of length n is chosen at random, such that $1 \leq k < n$. Then for parents $p1$ and $p2$ the offspring are

```
c1= p1[1,1:k] || p2[1,k+1:n];
```

```
c2= p2[1,1:k] || p1[1,k+1:n];
```

For real fixed-length vector encoding, you can specify an additional parameter, a , where a is a scalar and $0 < a \leq 1$. It modifies the offspring as follows:

```
x2 = a * p2 + (1-a) * p1;
c1 = p1[1,1:k] || x2[1,k+1:n];
```

```
x1 = a * p1 + (1-a) * p2
c2 = p2[1,1:k] || x1[1,k+1:n];
```

Note that for $a = 1$, which is the default value, $x2$ and $x1$ are the same as $p2$ and $p1$. Small values of a reduce the difference between the offspring and parents. For integer encoding a is always 1.

two-point: This operator is defined for fixed-length integer and real vector encoding with length $n \geq 3$. To apply this operator, two positions $k1$ and $k2$ within the vector are chosen at random, such that $1 \leq k1 < k2 < n$. Element values between those positions are swapped between parents. For parents $p1$ and $p2$ the offspring are

```
c1 = p1[1,1:k1] || p2[1,k1+1:k2] || p1[1,k2+1:n];
```

```
c2 = p2[1,1:k1] || p1[1,k1+1:k2] || p2[1,k2+1:n];
```


For real vector encoding you can specify an additional parameter, a , where $0 < a \leq 1$. It modifies the offspring as follows:

```
x2 = a * p2 + (1-a) * p1;
c1 = p1[1,1:k1] || x2[1,k1+1:k2] || p1[1,k2+1:n];

x1 = a * p1 + (1-a) * p2;
c2 = p2[1,1:k1] || x1[1,k1+1:k2] || p2[1,k2+1:n];
```

Note that for $a = 1$, which is the default value, $x2$ and $x1$ are the same as $p2$ and $p1$. Small values of a reduce the difference between the offspring and parents. For integer encoding a is always 1.

arithmetic: This operator is defined for real and integer fixed-length vector encoding. This operator computes offspring of parents $p1$ and $p2$ as

```
c1 = a * p1 + (1-a) * p2;

c2 = a * p2 + (1-a) * p1;
```

where a is a random number between 0 and 1. For integer encoding, each component is rounded off to the nearest integer. It has the advantage that it will always produce feasible offspring for a convex solution space. A disadvantage of this operator is that it will tend to produce offspring toward the interior of the search region, so that it may be less effective if the optimum lies on or near the search region boundary.

heuristic: This operator is defined for real fixed-length vector encoding. It computes the first offspring from the two parents $p1$ and $p2$ as

```
c1 = a * (p2 - p1) + p2;
```

where $p2$ is the parent with the better objective value, and a is a random number between 0 and 1. The second offspring is computed as in the arithmetic operator:

```
c2 = (1 - a) * p1 + a * p2;
```

This operator is unusual in that it uses the objective value. It has the advantage of directing the search in a promising direction, and automatically fine-tuning the search in an area where solutions are clustered. If the solution space has upper and lower bound constraints the offspring will be checked against the bounds, and any component outside its bound will be set equal to that bound. The heuristic operator will perform best when the objective function is smooth, and may not work well if the objective function or its first derivative is discontinuous.

pmatch: The partial match operator is defined for sequence encoding. It produces offspring by transferring a subsequence from one parent, and filling the remaining positions in a way consistent with the position and ordering in the other parent. Start with two parents and randomly chosen cutpoints as indicated:

```
p1 = {1 2|3 4 5 6|7 8 9};
p2 = {8 7|9 3 4 1|2 5 6};
```

The first step is to cross the selected segments (. indicates positions yet to be determined):

```
c1 = { . . 9 3 4 1 . . . };
c2 = { . . 3 4 5 6 . . . };
```

Next, define a mapping according to the two selected segments:

```
9-3, 3-4, 4-5, 1-6
```

Next, fill in the positions where there is no conflict from the corresponding parent:

```
c1 = { . 2 9 3 4 1 7 8 . };
c2 = { 8 7 3 4 5 6 2 . . };
```

Last, fill in the remaining positions from the subsequence mapping. In this case, for the first child $1 \rightarrow 6$ and $9 \rightarrow 3$, and for the second child $5 \rightarrow 4$, $4 \rightarrow 3$, $3 \rightarrow 9$ and $6 \rightarrow 1$.

```
c1 = { 6 2 9 3 4 1 7 8 5 };
c2 = { 8 7 3 4 5 6 2 9 1 };
```

This operator will tend to maintain similarity of both the absolute position and relative ordering of the sequence elements, and is useful for a wide range of sequencing problems.

order:

This operator is defined for sequence encoding. It produces offspring by transferring a subsequence of random length and position from one parent, and filling the remaining positions according to the order from the other parent. For parents $p1$ and $p2$, first choose a subsequence:

```
p1 = { 1 2 | 3 4 5 6 | 7 8 9 };
p2 = { 8 7 | 9 3 4 1 | 2 5 6 };

c1 = { . . 3 4 5 6 . . . };
c2 = { . . 9 3 4 1 . . . };
```

Starting at the second cutpoint, the elements of $p2$ in order are (cycling back to the beginning)

```
2 5 6 8 7 9 3 4 1
```

After removing 3, 4, 5 and 6, which have already been placed in $c1$, we have

```
2 8 7 9 1
```

Placing these back in order starting at the second cutpoint yields

```
c1 = { 9 1 3 4 5 6 2 8 7 };
```

Applying this logic to $c2$ yields

```
c2 = { 5 6 9 3 4 1 7 8 2 };
```

This operator maintains the similarity of the relative order, or adjacency, of the sequence elements of the parents. It is especially effective for circular path-oriented optimizations, such as the traveling salesman problem.

cycle:

This operator is defined for sequence encoding. It produces offspring such that the position of each element value in the offspring comes from one of the parents. For example, for parents $p1$ and $p2$,

```
p1 = {1 2 3 4 5 6 7 8 9};
p2 = {8 7 9 3 4 1 2 5 6};
```

For the first child, pick the first element from the first parent:

```
c1 = {1 . . . . . . .};
```

To maintain the condition that the position of each element value must come from one of the parents, the position of the '8' value must come from $p1$, because the '8' position in $p2$ is already taken by the '1' in $c1$:

```
c1 = {1 . . . . . 8 .};
```

Now the position of '5' must come from $p1$, and so on until the process returns to the first position:

```
c1 = {1 . 3 4 5 6 . 8 9};
```

At this point, choose the remaining element positions from $p2$:

```
c1 = {1 7 3 4 5 6 2 8 9};
```

For the second child, starting with the first element from the second parent, similar logic produces

```
c2 = {8 2 9 3 4 1 7 5 6};
```

This operator is most useful when the absolute position of the elements is of most importance to the objective value.

The mutation operators supported by IML are as follows:

uniform:

This operator is defined for fixed-length real or integer encoding with specified upper and lower bounds. To apply this operator, a position k is randomly chosen within the solution vector v , and $v[k]$ is modified to a random value between the upper and lower bounds for element k . This operator may prove especially useful in early stages of the optimization, since it will tend to distribute solutions widely across the search space, and avoid premature convergence to a local optimum. However, in later stages of an optimization with real vector encoding, when the search needs to be fine-tuned to home in on an optimum, the uniform operator may hinder the optimization.

delta: This operator is defined for integer and real fixed-length vector encoding. It first chooses an element of the solution at random, and then perturbs that element by a fixed amount, set by a *delta* input parameter. *delta* has the same dimension as the solution vectors. To apply the mutation, a randomly chosen element k of the solution vector v is modified such that

```
v[k] = v[k] + delta[k]; /* with probability 0.5 */  
      or  
v[k] = v[k] - delta[k];
```

If upper and lower bounds are specified for the problem, then $v[k]$ is adjusted as necessary to fit within the bounds. This operator gives you the ability to control the scope of the search with the *delta* vector. One possible strategy is to start with a larger *delta* value, and then reduce it as the search progresses and begins to converge to an optimum. This operator is also useful if the optimum is known to be on or near a boundary, in which case *delta* can be set large enough to always perturb the solution element to a boundary.

swap: This operator is defined for sequence problem encoding. It picks two random locations in the solution vector, and swaps their value. You can also specify that multiple swaps be made for each mutation.

invert: This operator is defined for sequence encoding. It picks two locations at random, and then reverses the order of elements between them. This operator is most often applied to the traveling salesman problem.

The IML-supplied crossover and mutation operators that are allowed for each problem encoding are summarized in the following table.

Table 20.1 Valid Genetic Operators for Each Encoding

Encoding	Crossover	Mutation
general	user module	user module
fixed-length real vector	user module	user module
	simple	uniform
	two-point	delta
	arithmetic heuristic	
fixed-length integer vector	user module	user module
	simple	uniform
	two-point	delta
	arithmetic	
fixed-length integer sequence	user module	user module
	pmatch	swap
	order	invert
	cycle	

A user module specified as a crossover operator must be a subroutine with four parameters. The module should compute and return two new offspring solutions in the first two parameters, based on the two parent solutions, which will be passed into the module in the last two parameters. The module should not modify the parent solutions passed into it. A global clause can be used to pass in any additional information that the module might use.

A user module specified as a mutation operator must be a subroutine with exactly one parameter. When the module is called, the parameter will contain the solution that is to be mutated. The module will be expected to update the parameter with the new mutated value for the solution. As with crossover, a global clause can be used to pass in any additional information that the module might use.

Executing a Genetic Algorithm

Setting Up the IML Program

After you formulate the GA optimization problem as described in the previous section, executing the genetic algorithm in IML is simple and straightforward. Remember that the current GA implementation in IML is experimental, and will be further developed and tested in later SAS releases. The following table summarizes the IML GA modules used to set each of the optimization parameters. IML will use reasonable default values for some of the parameters if they are not specified by the GA calls, and these default values are also listed. Parameters shown in *italics* are not required in all cases.

Table 20.2 Establishing Optimization Parameters

Type	Set By	Parameter	Value
encoding	GASETUP	encoding	0 → general 1 → fixed-length real 2 → fixed-length integer 3 → fixed-length sequence
		<i>size</i>	fixed-length size
		<i>seed</i>	initial random seed
objective	GASETOBJ	id	returned from GASETUP
		objtype	0 → minimize user module 1 → maximize user module 2 → traveling salesman problem
		parm	if objtype=0 or 1, user module if objtype=2, cost coefficients
selection	GASETSEL	id	returned from GASETUP
		elite	integer in [0, population size]
		type	0 → conventional tournament 1 → dual tournament with BPW prob
		parm	if type = 0, tournament size if type = 1, real number in [0.5,1]
	default if not set	elite	1
		type	conventional tournament
crossover	GASETCRO	parm	2
		id	returned from GASETUP
		crossprob	crossover probability
		type	0 → user module 1 → simple

Table 20.2 (continued)

Type	Set By	Parameter	Value
			2 →two-point 3 →arithmetic 4 →heuristic 5 →pmatch 6 →cycle 7 →order
		<i>parm</i>	module name for type = 0
	default if not set	crossprob	0 <val≤ 1 if encoding=1, 0<type<3
		type	1.0 heuristic if encoding=1 simple if encoding=2 pmatch if encoding=3, objtype 0 order if objtype=2 (TSP)
mutation	GASETMUT	id	returned from GASETUP
		mutprob	mutation probability
		type	0 →user module 1 →uniform 2 →delta 3 →swap 4 →invert
		<i>parm</i>	delta value if type=2 number of swaps if type=3
	default if not set	mutprob	0.05
		type	uniform if encoding=1 or 2, bounded delta if encoding=1 or 2, no bounds swap if encoding=3, not TSP invert if objtype=1 (TSP)

After setting the optimization parameters, you are ready to execute the GA. First, an initial solution population must be generated with a GAINIT call. GAINIT implements the *initialization* phase of the GA, generating an initial population of solutions and evaluating the objective value of each member solution. In the GAINIT call you specify the population size and any constant bounds on the solution domain. Next comes an IML loop that contains a GAREGEN call. GAREGEN implements the *regeneration* phase of the GA, which generates a new solution population based on selection, crossover, and mutation of the current solution population, then replaces the current population with the new population and computes the new objective function values.

After the GAREGEN call, you can monitor the convergence of the GA by retrieving the objective function values for the current population with the GAGETVAL call. You might check the average value of the objective population, or check only the best value. If the elite parameter is 1 or more, then it is easy to check the best member of the population, since it will always be the first member retrieved.

After your stopping criteria have been reached, you can retrieve the members of the solution population with the GAGETMEM call. To end the optimization, you should always use the GAEND call to free up memory resources allocated to the GA.

Below are some example programs to illustrate setting up and executing a genetic algorithm. The first example illustrates a simple program, a 10-city TSP using all IML defaults. The cost coefficients correspond to the cities being laid out on a two-by-five grid. The optimal route has a total distance of 10.

```
proc iml;

/* cost coefficients for TSP problem */
coeffs = { 0 1 2 3 4 5 4 3 2 1,
           1 0 1 2 3 4 5 4 3 2,
           2 1 0 1 2 3 4 5 4 3,
           3 2 1 0 1 2 3 4 5 4,
           4 3 2 1 0 1 2 3 4 5,
           5 4 3 2 1 0 1 2 3 4,
           4 5 4 3 2 1 0 1 2 3,
           3 4 5 4 3 2 1 0 1 2,
           2 3 4 5 4 3 2 1 0 1,
           1 2 3 4 5 4 3 2 1 0 };

/* problem setup */
id = gasetup(3, /* 3 -> integer sequence encoding */
            10, /* number of locations */
            1234 /* initial seed */
            );
/* set objective function */
call gasetobj(id,
            2, /* 2 -> Traveling Salesman Problem */
            coeffs /* cost coefficient matrix */
            );

/* initialization phase */
call gainit(id,
            100 /* initial population size */
            );

/* execute regeneration loop */

niter = 20; /* number of iterations */
bestValue = j(niter,1); /* to store results */

call gagetval(value, id, 1); /* gets first value */
bestValue[1] = value;

do i = 2 to niter;
    call garegen(id);
    call gagetval(value, id, 1);
    bestValue[i] = value;
end;

/* print solution history */
print (t(1:niter))[1 = "iteration"] bestValue;

/* print final solution */
call gagemem(bestMember, value, id, 1);
```

```

print  "best member " bestMember [f = 3.0 l = ""],,
      "final best value " value [l = ""];

call gaend(id);

```

For this test case, there is no call to GASETSEL. Therefore IML will use default selection parameters: an elite value of 1 and a conventional tournament of size 2. Also, since there is no GASETCRO or GASETMUT call, IML will use default genetic operators: the order operator for crossover and the invert operator for mutation, and a default mutation probability of 0.05. The output results are

```

      iteration BESTVALUE
           1         18
           2         18
           3         16
           4         14
           5         14
           6         14
           7         12
           8         12
           9         12
          10         12
          11         12
          12         12
          13         12
          14         12
          15         12
          16         12
          17         12
          18         12
          19         10
          20         10

best member   10    1    2    3    4    5    6    7    8    9

      final best value           10

```

The optimal value was reached after 19 iterations. Because the elite value was 1, the best solution was retained and passed on to each successive generation, and therefore never lost. Note that out of 3,628,800 possible solutions (representing 362,800 unique paths), the GA found the optimum after only 1,900 function evaluations, without using any problem-specific information to assist the optimization. You could also do some experimentation, and specify different genetic operators with a GASETCRO and GASETMUT call, and different selection parameters with a GASETSEL call:

```

/* alternate problem setup */
id = gasetup(3, /* 3 -> integer sequence encoding */
            10, /* number of locations */
            1234 /* initial seed */
            );

```



```

/* set objective function */
call gasetobj(id,
              2, /* 2 -> Traveling Salesman Problem */
              coeffs /* cost coefficient matrix */
              );
call gasetcro(id,
              1.0, /* crossover probability 1 */
              5 /* 5 -> pmatch operator */
              );
call gasetmut(id,
              0.05, /* mutation probability */
              3 /* 3 -> swap operator */
              );
call gasetssel(id,
              3, /* set elite to 3 */
              1, /* dual tournament */
              0.95 /* best-player-wins probability 0.95 */
              );
/* initialization phase */
call gainit(id,
            100 /* initial population size */
            );

/* execute regeneration loop */

niter = 15; /* number of iterations */
bestValue = j(niter,1); /* to store results */

call gagetval(value, id, 1); /* gets first value */
bestValue[1] = value;

do i = 2 to niter;
  call garegen(id);
  call gagetval(value, id, 1);
  bestValue[i] = value;
end;

/* print solution history */
print (t(1:niter))[1 = "iteration"] bestValue;

/* print final solution */
call gagetmem(bestMember, value, id, 1);
print "best member " bestMember [f = 3.0 l = ""],,
      "final best value " value [l = ""];

call gaend(id);

```

The output of this test case is

```
iteration BESTVALUE
```

```
1          24
```

	2	18																	
	3	18																	
	4	16																	
	5	16																	
	6	14																	
	7	14																	
	8	14																	
	9	14																	
	10	12																	
	11	12																	
	12	12																	
	13	10																	
	14	10																	
	15	10																	
best member	3	4	5	6	7	8	9	10	1	2									
final best value								10											

Note that convergence was faster than for the previous case, reaching an optimum after 13 iterations. This illustrates that the convergence of a GA may be very sensitive to the choice of genetic operators and selection parameters, and for practical problems some experimental fine-tuning of optimization parameters may be required to obtain acceptable convergence.

Incorporating Local Optimization

One commonly used technique is to combine the GA with a local optimization technique specific to the problem being solved. This can be done within the IML GA framework by incorporating a local optimization into the objective function evaluation: return a locally optimized objective value, and optionally replace the original solution passed into the module with the optimized solution.

Always replacing the original solution with the locally optimized one will cause faster convergence, but it is also more likely to converge prematurely to a local optimum. One way to reduce this possibility is to not replace the original solution in every case, but replace it with some probability p . For some problems, values of p from 5 to 15 percent have been shown to significantly improve convergence, while avoiding premature convergence to a local optimum (Michalewicz 1996).

Handling Constraints

Practical optimization problems often come with constraints, which may make the problem difficult to solve. Constraints are handled in GAs in a variety of ways.

If it is possible, the most straightforward approach is to set the problem encoding, genetic operators, and initialization such that the constraints are automatically met. For example, a nonlinear optimization problem over n real variables with constant upper and lower bounds is easily formulated in IML using real fixed-

length encoding, arithmetic crossover, and uniform mutation. The arithmetic crossover operator can be used without modification in any optimization over a convex solution space, when the optimum is expected to be an interior point of the domain.

Another approach to satisfying constraints is to repair solutions after genetic operators have been applied. This is what IML does when using the heuristic crossover operator or delta mutation operator with fixed bounds: it adjusts any individual component that violates an upper or lower bound. You can repair a solution inside a user crossover or mutation module, or repairs can be made by modifying the solution in a user objective function module, as was described in the previous section.

Another technique is to allow solutions to violate constraints, but to impose a penalty in the objective function for unsatisfied constraints. If the penalty is severe enough, the algorithm should converge to an optimum point within the constraints. This approach should be used carefully. If most of the points in the solution space violate the constraints, then this technique may converge prematurely to the first feasible solution found. Also, convergence may be poor to a solution that lies on or near a constraint boundary.

Example 20.1: Genetic Algorithm with Local Optimization

For the symmetric traveling salesman problem, there is a simple local optimization that can be incorporated into a user objective function module, which is to check each pair of adjacent locations in the solution and swap their positions if that would improve the objective function value. Here is the previous TSP example, modified to use an objective function module that implements this strategy. In this initial example, the optimized solution is not written back out to the solution population (except to get the final solution at the end).

```
proc iml;

/* cost coefficients for TSP problem */
coeffs = { 0 1 2 3 4 5 4 3 2 1,
           1 0 1 2 3 4 5 4 3 2,
           2 1 0 1 2 3 4 5 4 3,
           3 2 1 0 1 2 3 4 5 4,
           4 3 2 1 0 1 2 3 4 5,
           5 4 3 2 1 0 1 2 3 4,
           4 5 4 3 2 1 0 1 2 3,
           3 4 5 4 3 2 1 0 1 2,
           2 3 4 5 4 3 2 1 0 1,
           1 2 3 4 5 4 3 2 1 0 };

start TSPObjectiveFunction(r) global(coeffs, p);
  s = r;
  nc = ncol(s);
  /* local optimization, assumes symmetric cost *
   * coefficients                               */
  do i = 1 to nc;
    city1 = s[i];
    inext = 1 + mod(i,nc);
    city2 = s[inext];
    if i=1 then
```

```

        before = s[nc];
    else
        before = s[i-1];
    after = s[1 + mod(inext,nc)];
    if (coeffs[before,city1] + coeffs[city2, after]) >
        (coeffs[before,city2] + coeffs[city1, after])
    then do;
        s[i] = city2;
        s[inext] = city1;
    end;
end;
/* compute objective function */
cost = coeffs[s[nc],s[1]];
do i = 1 to nc-1;
    cost = cost + coeffs[s[i],s[i+1]];
end;
if uniform(1234)<=p then
    r = s;
return (cost);
finish;

/* problem setup */
id = gasetup(3, /* 3 -> integer sequence encoding */
            10, /* number of locations */
            123 /* initial random seed */
            );
/* set objective function */
call gasetobj(id,
            0, /* 0 -> minimize a user-defined module */
            "TSPObjectiveFunction"
            );
call gasetcro(id, 1.0, 6);
call gasetmut(id, 0.05, 4);
call gasetssel(id, 1, 1, 0.95);
p = 0; /* probability of writing locally optimized
      * solution back out to population */
/* initialization phase */
call gainit(id,
            100 /* initial population size */
            );
/* execute regeneration loop */

niter = 10; /* number of iterations */
bestValue = j(niter,1); /* to store results */

call gagetval(value, id, 1); /* gets first (and best) value */
bestValue[1] = value;

do i = 2 to niter;
    call garegen(id);
    call gagetval(value, id, 1);
    bestValue[i] = value;
end;

```

```

/* print solution history */
print (t(1:niter))[1 = "iteration"] bestValue;

/* make sure local optimization is
 * written back to all solutions */
p = 1.; /* set global probability to 1 */
call gareeval(id);

/* print final solution */
call gagetmem(bestMember, value, id, 1);
print "best member " bestMember [f = 3.0 l = ""],,
      "final best value " value [l = ""];
call gaend(id);

```

The results of running this program are

	iteration	BESTVALUE
	1	12
	2	12
	3	12
	4	12
	5	10
	6	10
	7	10
	8	10
	9	10
	10	10

best member	7	6	5	4	3	2	1	10	9	8
final best value	10									

Convergence is much improved by the local optimization, reaching the optimum in just 5 iterations compared to 13 with no local optimization. Writing some of the optimized solutions back to the solution population, by setting the global probability p to 0.05 or 0.15, will improve convergence even more.

Example 20.2: Real-Valued Objective Optimization with Constant Bounds

The next example illustrates some of the strengths and weaknesses of the arithmetic and heuristic crossover operators. The objective function to be minimized is

```

start sin_obj(x) global(xopt);
  r = abs(sin(sum(abs(x-xopt))));
  return(r);
finish;

```

This function obviously has a minimum at $x=x_{opt}$, and is not differentiable at all points. The following program sets $x_{opt}=0$ and specifies constant boundary constraints such that the optimum is in the interior of the search space, and specifies the heuristic crossover operator:

```

proc iml;

/* objective function, has minimum of 0 at x = xopt */
start sin_obj(x) global(xopt);
  r = abs(sin(sum(abs(x-xopt))));
  return(r);
finish;

xopt = { 0 0 0 };
optimum = xopt;
optval = sin_obj(optimum);

id = gasetup(1, /* 1-> fixed-length floating point vector encoding */
            3, /* 3-> length of solution vectors */
            1234 /* 0-> initial random seed */
            );
call gasetobj(id,0,"sin_obj"); /* 0->minimize a user module,
                                * "sin_obj" is name of module */
call gasetcro(id, 0.9, 4); /* crossover probability 0.9,
                            * 4-> heuristic crossover operator */

call gasetmut(id,0.05,2,0.01); /* mutation probability 0.05,
                                * 2-> delta mutation operator
                                * 0.01 is delta value */

call gasetssel(id, 5, 1, 0.95); /* carry best 5 solutions over
                                * to the next generation, dual
                                * tournament with 0.95 best-player
                                * wins probability */

bounds = {-1 -1 -1, 1 1 1};
call gainit(id,200,bounds); /* initialize population with
                              * 200 members, "bounds" gives
                              * upper and lower bounds for
                              * components of randomly
                              * randomly generated vectors */

summary = j(20,2);
mattrib summary [c = {"bestValue", "avgValue"}];
call gagetval(value, id);
summary[1,1] = value[1];
summary[1,2] = value[:];

do i = 2 to 20;

  call garegen(id);

  call gagetval(value, id); /* get all objective values of
                              * the population */
  summary[i,1] = value[1];

```

```

summary[i,2] = value[:];

end;

iteration = t(1:20);
print iteration summary;
call gaend(id);

```

The output results are

SUMMARY		
ITERATION	bestValue	avgValue
1	0.894517	0.8926763
2	0.894517	0.752227
3	0.1840732	0.6087493
4	0.14112	0.4848342
5	0.14112	0.3991614
6	0.14112	0.3539561
7	0.0481937	0.3680798
8	0.0481937	0.3243406
9	0.0481937	0.3027395
10	0.0481937	0.2679123
11	0.0481937	0.2550643
12	0.0481937	0.2582514
13	0.0481937	0.2652337
14	0.0481937	0.2799655
15	0.0383933	0.237546
16	0.0383933	0.3008743
17	0.0383933	0.2341022
18	0.0383933	0.1966969
19	0.0383933	0.2778152
20	0.0383933	0.2690036

To show the convergence of the overall population, the average value of the objective function for the whole population is printed out as well as the best value. The optimum value for this formulation is 0, and the optimum solution is (0 0 0). The output shows the convergence of the GA to be slow, especially as the solutions get near the optimum. This is the result of applying the heuristic crossover operator to an ill-behaved objective function. If you change the crossover to the arithmetic operator by changing the GASETCRO call to

```
call gasetcro(id, 0.9, 3); /* 3-> arithmetic crossover operator */
```

you get the following output:

SUMMARY		
ITERATION	bestValue	avgValue
1	0.894517	0.8926763
2	0.894517	0.8014329

```

3 0.1840732 0.6496871
4 0.1705931 0.4703868
5 0.0984926 0.2892114
6 0.076859 0.1832358
7 0.0287965 0.1123732
8 0.0273074 0.0720792
9 0.018713 0.0456323
10 0.0129708 0.0309648
11 0.0087931 0.0240822
12 0.0087931 0.0172102
13 0.0050753 0.0128258
14 0.0019603 0.0092872
15 0.0016225 0.0070575
16 0.0016225 0.0051149
17 0.0012465 0.0036445
18 0.0011895 0.002712
19 0.0007646 0.0023329
20 0.0007646 0.0020842

```

For this case, the arithmetic operator shows improved convergence. Suppose you change the problem characteristics again by changing the constraints so that the optimum lies on a boundary. The following statement moves the optimum to a boundary:

```
bounds = {0 0 0, 1 1 1};
```

The output using the arithmetic operator is

```

                SUMMARY
ITERATION bestValue avgValue

1 0.8813497 0.8749132
2 0.8813497 0.860011
3 0.3721446 0.8339357
4 0.3721446 0.79106
5 0.3721446 0.743336
6 0.3721446 0.7061592
7 0.3721446 0.6797346
8 0.3721446 0.6302206
9 0.3721446 0.5818008
10 0.3721446 0.5327339
11 0.3721446 0.5149562
12 0.3721446 0.48525
13 0.3721446 0.4708617
14 0.3721446 0.4582203
15 0.3721446 0.433538
16 0.3721446 0.4256162
17 0.3721446 0.4236062
18 0.3721446 0.4149336
19 0.3721446 0.4135214
20 0.3721446 0.4078068

```


In this case, the algorithm fails to converge to the true optimum, given the characteristic of the arithmetic operator to converge on interior points. However, if you switch back to the heuristic crossover operator the results are

SUMMARY		
ITERATION	bestValue	avgValue
1	0.8813497	0.8749132
2	0.8813497	0.7360591
3	0.3721446	0.5465098
4	0	0.3427185
5	0	0.2006271
6	0	0.0826017
7	0	0.0158228
8	0	0.0002602
9	0	0.00005
10	0	0.00065
11	0	0.0003
12	0	0.0002
13	0	0.0002
14	0	0.000285
15	0	0.0005
16	0	0.0002952
17	0	0.0002
18	0	0.0001761
19	0	0.00035
20	0	0.00035

These results show a rapid convergence to the optimum. This example illustrates how the results of a GA are very operator-dependent. For complicated problems with unknown solution, you might need to try a number of different combinations of parameters in order to have confidence that you have converged to a true global optimum.

Example 20.3: Integer Programming Knapsack Problem

The next example uses the integer encoding, along with user modules for crossover and mutation. It formulates the knapsack problem using fixed-length integer encoding. The integer vector solution s is a vector of ones and zeros, where $s[i]=1$ implies that item i is packed in the knapsack. The weight constraints of the problem are not handled explicitly, but are accounted for by including a penalty for overweight in the objective function. The crossover operator randomly chooses a value for each element of the solution vector from each parent. The mutation operator randomly changes the values of a user-set number of elements in the solution vector. For this problem the value of the global optimum is 18.

```
proc iml;
weight = {2 3 4 4 1 1 1 1 1 1 1 1 1 1 1};
limit = 9; /* weight limit */
reward = {6 6 6 5 1.3 1.2 1.1 1.0 1.1 1.3 1.0 1.0 0.9 0.8 0.6};
```

```

start knapsack( x ) global( weight, reward, limit);
    wsum = sum(weight # x);
    rew = sum(reward # x);
    /* subtract penalty for exceeding weight */
    if wsum>limit then
        rew = rew - 5 * (wsum - limit);
    return(rew);
finish;

start switch_mut(s) global(nswitches);
    n = ncol(s);
    do i = 1 to nswitches;
        k = int(uniform(1234) * n) + 1;
        if s[k]=0 then
            s[k] = 1;
        else
            s[k] = 0;
        end;
    end;
finish;

start uniform_cross(child1, child2, parent1, parent2);
    child1 = parent1;
    child2 = parent2;
    do i = 1 to ncol(parent1);
        r = uniform(1234);
        if r<=0.5 then do;
            child1[i] = parent2[i];
            child2[i] = parent1[i];
        end;
    end;
finish;

id = gasetup(2,15, 123);
call gasetobj(id, 1, "knapsack"); /* maximize objective module */
call gasetcro(id, 1.0, 0,"uniform_cross"); /* user crossover module */
call gasetmut(id,
    0.20,          /* mutation probabiltiy */
    0, "switch_mut" /* user mutation module */
);
nswitches = 3;
call gasetssel(id, 3,      /* carry 3 over to next generation */
    1,      /* dual tournament */
    0.95    /* best-player-wins probabiltiy */
);
call gainit(id,100,{0 0 0 0 0 0 0 0 0 0 0 0 0 0 0,
    1 1 1 1 1 1 1 1 1 1 1 1 1 1 1});

niter = 20;
summary = j(niter,2);
mattrib summary [c = {"bestValue", "avgValue"}];
call gagetval(value, id);
summary[1,1] = value[1];
summary[1,2] = value[:];

do i = 1 to niter;

```

```

    call garegen(id);
    call gagetval(value, id);
    summary[i,1] = value[1];
    summary[i,2] = value[:];
end;
call gagetmem(mem, value, id, 1);
print "best member " mem[f = 1.0 1 = "],
      "best value " value[1 = "];
iteration = t(1:niter);
print iteration summary;
call gaend(id);

```

The output of the program is

```

best member  1 1 1 0 0 0 0 0 0 0 0 0 0 0 0
best value           18

```

SUMMARY		
ITERATION	bestValue	avgValue
1	16	2.44
2	16	6.257
3	16	6.501
4	16.7	7.964
5	16.7	8.812
6	16.7	9.254
7	16.7	10.021
8	16.8	11.216
9	16.9	12.279
10	16.9	12.094
11	16.9	11.633
12	16.9	11.431
13	18	11.502
14	18	13.2
15	18	13.128
16	18	13.282
17	18	12.876
18	18	13.715
19	18	12.889
20	18	13.15

Note that for this problem, the mutation parameters are set higher than is often seen for GAs. For this example, this is necessary to prevent premature convergence.

Example 20.4: Optimization with Linear Constraints Using Repair Strategy

This problem seeks a minimum within a convex domain specified by a convex hull, a set of points such that all points in the search space are normalized linear combinations of those points. Each solution is represented by a set of weights w such that there is one w_i for each point in the convex hull, $0 \leq w_i \leq 1$,

and $\sum w_i = 1$. In this example the feasible region is the convex hull defined by the set of points (-3 -2), (3 -2), (-3 2), and (3 2). The objective function is a six-hump camel-back function (see Michalewicz (1996), Appendix B), with a known global minimum value of -1.0316 at two different points, (-0.0898,0.7126) and (0.0898,-0.7126). A user mutation module is specified, and the simple crossover operator is used. Both the mutation operator and the crossover operator will produce solutions that violate the constraints, so in the objective function each solution will be checked and renormalized to bring it back within the convex hull.

```

proc iml;

/* Test case using user modules for the mutation operator and
 * for initialization
 */

start sixhump(w) global(cvxhull);
/* Function has global minimum value of -1.0316
 * at x = {-0.0898  0.7126} and
 *      x = { 0.0898 -0.7126}
 */
sum = w[1,+];

/* guard against the remote possibility of all-0 weights */
if sum=0 then do;
    nc = ncol(w);
    w = j(1, nc, 1/nc );
    sum = 1;
end;

/* re-normalize weights */
w = w/sum;

/* convert to x-coordinate form */
x = (w * cvxhull) [+ ,];
x1 = x[1];
x2 = x[2];

/* compute objective value */
r = (4 - 2.1*x1##2 + x1##4/3)*x1##2 + x1*x2 +
    (-4 + 4*x2*x2)*x2##2;
return(r);
finish;

/* each row is one point on the boundary of
 * the convex hull */
cvxhull = {-3 -2,
           3 -2,
           -3 2,
           3 2};

/* initialization module */
start cvxinit( w ) global(cvxhull);
sum = 0;
a = j(1, nrow(cvxhull), 1234);
do while(sum = 0);

```

```

    r = uniform(a);
    sum = r[1,+];
end;
w = r / sum;
finish;

/* mutation module */
start cvxmut(w)global(cvxhull);
    row = int(uniform(1234) * nrow(cvxhull)) + 1;
    r = uniform(1234);
    w[1,row] = r;
finish;

id = gasetup(1, /* real fixed-length vector encoding */
            nrow(cvxhull), /* vector size = number of points
                           * specifying convex hull
                           */
            1234);
call gasetobj(id,
    0, /* minimize a user-specified objective function */
    "sixhump"
);
call gasetset(id,
    5, /* carry over the best 5 from each generation */
    1, /* dual tournament */
    0.95 /* best-player-wins probability */
);
call gasetcro(id,
    0.8, /* crossover probability */
    1 /* simple crossover operator */
);
call gasetmut(id,0.05,0,"cvxmut");

call gainit(id,
    100, /* population size */
    , /* not using constant bounds */
    "cvxinit" /* initialization module */
);

niter = 35; /* number of iterations */
summary = j(niter,2);
mattrib summary [c = {"bestValue", "avgValue"}];
call gaetval(value, id);
summary[1,1] = value[1];
summary[1,2] = value[:];

do i = 1 to niter;
    call garegen(id);
    call gaetval(value, id);
    summary[i,1] = value[1];
    summary[i,2] = value[:];
end;
call gaetmem(mem, value, id, 1);
bestX = (mem * cvxhull)[+,1];

```

```

print "best X " bestX[l = ""],
      "best value " value[l = ""];
iteration = t(1:niter);
print iteration summary;
call gaend(id);

```

The output results are

```

best X    0.089842 -0.712658
best value -1.031628

SUMMARY
ITERATION bestValue avgValue
1 -0.082301 0.9235856
2 -0.948434 0.1262678
3 -0.956136 0.2745601
4 -1.017636 0.1367912
5 -1.028457 -0.241069
6 -1.028457 -0.353218
7 -1.028457 -0.56789
8 -1.028457 -0.73044
9 -1.028457 -0.854496
10 -1.028509 -0.941693
11 -1.031334 -0.936541
12 -1.031334 -0.90363
13 -1.031373 -0.774917
14 -1.031614 -0.873418
15 -1.031614 -0.886818
16 -1.031618 -0.95678
17 -1.031619 -0.933061
18 -1.031626 -0.885132
19 -1.031628 -0.936944
20 -1.031628 -0.906637
21 -1.031628 -0.925809
22 -1.031628 -0.860156
23 -1.031628 -0.946146
24 -1.031628 -0.817196
25 -1.031628 -0.883284
26 -1.031628 -0.904361
27 -1.031628 -0.974893
28 -1.031628 -0.975647
29 -1.031628 -0.872004
30 -1.031628 -1.031628
31 -1.031628 -0.897558
32 -1.031628 -0.922121
33 -1.031628 -0.855045
34 -1.031628 -0.922061
35 -1.031628 -0.958257

```

Any problem with linear constraints could be formulated in this way, by determining the convex hull that corresponds to the constraints. The genetic operators and the repair strategy are straightforward to apply, and as this case shows, can give reasonable convergence to a global optimum.

References

- Goldberg, D. E. (1989), *Genetic Algorithms in Search, Optimization and Machine Learning*, Reading, MA: Addison-Wesley.
- Michalewicz, Z. (1996), *Genetic Algorithms + Data Structures = Evolution Programs*, New York: Springer-Verlag.
- Miller, B. L. and Goldberg, D. E. (1995), *Genetic Algorithms, Tournament Selection, and the Effects of Noise*, Technical Report 95006, Illinois Genetic Algorithm Laboratory, University of Urbana-Champaign.

Chapter 21

Sparse Matrix Algorithms

Contents

Overview	529
Iterative Methods	530
Input Data Description	530
Example: Conjugate Gradient Algorithm	531
Example: Minimum Residual Algorithm	533
Example: Biconjugate Gradient Algorithm	534
Symbolic LDL and Cholesky Factorizations	535
References	536

Overview

This chapter documents direct and iterative algorithms for large sparse systems of linear equations:

$$Ax = b, \quad A \in R^{n \times n}, \quad x, b \in R^n$$

where A is a nonsingular square matrix.

The ITSOLVER call supports the following classes of iterative solvers:

- conjugate gradient for symmetric positive-definite systems
- conjugate gradient squared for general nonsingular systems
- minimum residual for symmetric indefinite systems
- biconjugate gradient for general nonsingular systems

Iterative algorithms incur zero or controlled amounts of fill-in, have relatively small working memory requirements, and can converge as fast as $O(n)$ or $O(n^2)$ versus direct dense methods that are typically $O(n^3)$. Each iteration of an iterative algorithm is very inexpensive and typically involves a single matrix-vector multiplication and a pair of forward/backward substitutions.

Convergence of an iterative method depends upon the distribution of eigenvalues for the matrix A , and can be rather slow for badly conditioned matrices. For such cases SAS/IML offers hybrid algorithms, which combine an incomplete factorization (a modified direct method) used in the preconditioning phase with an iterative refinement procedure. The following preconditioners are supported:

- incomplete Cholesky factorization (“IC”)
- diagonal Jacobi preconditioner (“DIAG”)
- modified incomplete LU factorization (“MILU”)

For more information, see the description of the *precond* parameter in the section “Input Data Description” on page 530.

The SOLVELIN call supports the following direct sparse solvers for symmetric positive-definite systems:

- symbolic LDL
- Cholesky

Classical factorization-based algorithms share one common complication: the matrix A usually suffers *fill-in*, which means additional operations and computer memory are required to complete the algorithm. A symmetric permutation of matrix rows and columns can lead to a dramatic reduction of fill-in. To compute such a permutation, SAS/IML implements a minimum degree ordering algorithm, which is an automatic step in the SOLVELIN function.

Iterative Methods

The conjugate gradient algorithm can be interpreted as the following optimization problem: minimize $\phi(x)$ defined by

$$\phi(x) = 1/2x^T Ax - x^T b$$

where $b \in R^n$ and $A \in R^{n \times n}$ are symmetric and positive definite.

At each iteration $\phi(x)$ is minimized along an A -conjugate direction, constructing orthogonal residuals:

$$r_i \perp \mathcal{K}_i(A; r_0), \quad r_i = Ax_i - b$$

where \mathcal{K}_i is a Krylov subspace:

$$\mathcal{K}_i(A; r) = \text{span}\{r, Ar, A^2r, \dots, A^{i-1}r\}$$

Minimum residual algorithms work by minimizing the Euclidean norm $\|Ax - b\|_2$ over \mathcal{K}_i . At each iteration, x_i is the vector in \mathcal{K}_i that gives the smallest residual.

The biconjugate gradient algorithm belongs to a more general class of Petrov-Galerkin methods, where orthogonality is enforced in a different i -dimensional subspace (x_i remains in \mathcal{K}_i):

$$r_i \perp \{w, A^T w, (A^T)^2 w, \dots, (A^T)^{i-1} w\}$$

Input Data Description

The ITSOLVER call has the following syntax and arguments:

```
call ITSOLVER (x, error, iter, method, A, b,
               precondition, tol, maxiter, start, history);
```

The conjugate gradient and minimum residual algorithms (*method* = 'CG' or *method* = 'MINRES') require *A* to be symmetric; hence you must specify only the lower triangular part of *A*, while the remaining algorithms require *all* nonzero coefficients to be listed. The following table lists valid values for the *precond* parameter for each class of algorithm.

Table 21.1 Subroutine Definitions and Valid Preconditioners

Method Value	Algorithm	Preconditioners
"CG"	conjugate gradient	"NONE" "IC" "DIAG"
"MINRES"	minimum residual	"NONE" "IC" "DIAG"
"BICG"	biconjugate gradient	"NONE" "MILU"
"CGS"	conjugate gradient squared	"NONE"

<i>x</i>	solution vector
<i>error</i>	final solution error (optional)
<i>iter</i>	resultant number of iterations (optional)
<i>A</i>	three-column matrix of triplets, where the first column contains the value, the next column contains the row indices, and the third column contains the column indices of the nonzero matrix coefficients. The order in which triplets are listed is insignificant. For symmetric matrices specify only the lower triangular part, including the main diagonal (row indices must be greater than or equal to the corresponding column indices). Zero coefficients should not be included. No missing values or duplicate entries are allowed.
<i>b</i>	the right-hand-side vector
<i>precond</i>	preconditioner, default value "NONE"
<i>tol</i>	desired tolerance, default value 10^{-7}
<i>maxiter</i>	maximum number of iterations, default value 10^5
<i>start</i>	initial guess
<i>history</i>	the history of errors for each iteration

Example: Conjugate Gradient Algorithm

Consider the following small example: $Ax = b$, where

$$A = \begin{pmatrix} 3 & 1 & 0 & 0 \\ 1 & 4 & 1 & 3 \\ 0 & 1 & 10 & 0 \\ 0 & 3 & 0 & 3 \end{pmatrix}$$

and the vector of right-hand sides $b = (1 \ 1 \ 1 \ 1)^T$. Since the matrix is positive definite and symmetric, you can apply the conjugate gradient algorithm to solve the system. Remember that you must specify only the

lower-triangular part of the matrix (so row indices must be greater than or equal to the corresponding column indices.)

The code for this example is as follows:

```

/* value    row    col */
A = { 3      1      1,
      1      2      1,
      4      2      2,
      1      3      2,
      3      4      2,
      10     3      3,
      3      4      4 };

/* right-hand sides */
b = {1, 1, 1, 1};

/* desired solution tolerance (optional) */
tol = 1e-7;

/* maximum number of iterations (optional) */
maxit = 200;

/* allocate iteration progress (optional) */
hist = j(50, 1);

/* provide an initial guess (optional) */
start = {2, 3, 4, 5};

/* invoke conjugate gradient method */
call itsolver (
    x, st, it,          /* output parameters */
    'cg', A, b, 'ic',   /* input parameters */
    tol,               /* optional control parameters */
    maxit,
    start,
    hist
);

print x; /* print solution */
print st; /* print solution tolerance */
print it; /* print resultant number of iterations */

```

Notice that the example used an incomplete Cholesky preconditioner (which is recommended). Here is the program output:

```

      X
0.5882353
-0.764706
0.1764706
1.0980392

```

```

      ST

```

1.961E-16

IT

3

The conjugate gradient method converged successfully within three iterations. You can also print out the `hist` (iteration progress) array. Different starting points result in different iterative histories.

Example: Minimum Residual Algorithm

For symmetric indefinite matrices it is best to use the minimum residual algorithm. The following example is slightly modified from the previous example by negating the first matrix element:

```
/* minimum residual algorithm */

/* value    row    col */
A = { -3     1     1,
      1     2     1,
      4     2     2,
      1     3     2,
      3     4     2,
     10     3     3,
      3     4     4 };

/* right-hand sides b = (1 1 1 1) */
b = {1, 1, 1, 1};

/* desired solution tolerance (optional) */
tol = 1e-7;

/* maximum number of iterations (optional) */
maxit = 200;

/* allocate iteration progress (optional) */
hist = j(50, 1);

/* initial guess (optional) */
start = {2, 3, 4, 5};

/* invoke minimum residual method */
call itsolver (
    x, st, it,          /* output parameters */
    'minres', a, b, 'ic', /* input parameters */
    tol,               /* optional control parameters */
    maxit,
    start,
    hist
);
```

```

print x; /* print solution */
print st; /* print solution tolerance */
print it; /* print resultant number of iterations */

```

```

      x
    -0.27027
    0.1891892
    0.0810811
    0.1441441

```

```

      ST
    1.283E-15

```

```

      IT
      4

```

Example: Biconjugate Gradient Algorithm

The biconjugate gradient algorithm is meant for general sparse linear systems. Matrix symmetry is no longer assumed, and a complete list of nonzero coefficients must be provided. Consider the following matrix:

$$A = \begin{pmatrix} 10 & 0 & 0.2 \\ 0.1 & 3 & 0 \\ 0 & 0 & 4 \end{pmatrix}$$

with $b = (1 \ 1 \ 1)^T$.

The code for this example is as follows:

```

/* biconjugate gradient algorithm */

/* value row column */
A = { 10    1    1,
      3     2    2,
      4     3    3,
      0.1   2    1,
      0.2   1    3 };

/* vector of right-hand sides */
b = {1, 1, 1};

/* desired solution tolerance */
tol = 1e-9;

/* maximum number of iterations */
maxit = 10000;

```

```

/* allocate history/progress */
hist = j(50, 1);

/* initial guess (optional) */
start = {2, 3, 4};

/* call biconjugate gradient subroutine */
call itsolver (
    x, st, it,          /* output parameters */
    'bicg', a, b, 'milu', /* input parameters */
    tol,               /* optional control parameters */
    maxit,
    start,
    hist);

/* Print results */
print x;
print st;
print it;

```

Here is the output:

```

      X
      0.095
0.3301667
      0.25

      ST
1.993E-16

      IT
      3

```

It is important to observe the resultant tolerance in order to know how effective the solution is.

Symbolic LDL and Cholesky Factorizations

Symbolic LDL and Cholesky factorization algorithms are meant for symmetric positive definite systems; hence, again, only the lower-triangular part of the matrix must be provided. The PROC IML function `SOLVELIN` provides an interface to both algorithms; the minimum degree ordering heuristic is invoked automatically as follows:

```
SOLVELIN (x, status, A, b, method)
```

x solution vector

status status indicator 0 success, 1 matrix is not positive-definite, 2 out of memory

A	sparse matrix (lower-triangular part)
b	vector of right-hand sides
<i>method</i>	a character string, which specifies factorization type, possible values: "LDL" for LDL factorization, and "CHOL" for Cholesky.

The code for this example is as follows:

```

/* value   row   col */
A = { 3     1     1,
      1     2     1,
      4     2     2,
      1     3     2,
      3     4     2,
      10    3     3,
      3     4     4 };

/* right-hand side */
b = {1, 1, 1, 1};

/* invoke LDL factorization */
call solvelin (x, status, a, b, "LDL");

print x; /* print solution */

```

Here is the program output:

```

      x
0.5882353
-0.764706
0.1764706
1.0980392

```

References

- Golub, G. H. and Van Loan, C. F. (1996), *Matrix Computations*, 3 Edition, Baltimore: Johns Hopkins University Press.
- Greenbaum, A. (1997), *Iterative Methods for Solving Linear Systems*, Philadelphia: Society for Industrial and Applied Mathematics.
- Hestenes, M. R. and Stiefel, E. (1952), "Methods of Conjugate Gradients for Solving Linear Systems," *Journal of Research of the National Bureau of Standards*, 46, 409–436.
- Paige, C. C. and Saunders, M. A. (1975), "Solution of Sparse Indefinite Systems of Linear Equations," *SIAM Journal on Numerical Analysis*, 12, 617–629.

Chapter 22

Further Notes

Contents

Memory and Workspace	537
Accuracy	539
Error Diagnostics	539
Efficiency	540
Missing Values	540
Principles of Operation	541
Operation-Level Execution	542

Memory and Workspace

You do not need to be concerned about the details of memory usage in IML, because memory allocation is done automatically. However, if you are interested, the following sections explain how it works.

There are two logical areas of memory, *symbol space* and *workspace*. Symbol space contains symbol table information and compiled statements. Workspace contains matrix data values. Workspace itself is divided into one or more extents.

At the start of a session, the symbol space and the first extent of workspace are allocated automatically. More workspace is allocated as the need to store data values grows. The SYMSIZE= and WORKSIZE= options in the PROC IML statement give you control over the size of symbol space and the size of each extent of workspace. If you do not specify these options, PROC IML uses host-dependent defaults. For example, you can begin an IML session and set the SYMSIZE= and WORKSIZE= options with the statement

```
proc iml symsize=n1 worksize=n2;
```

where n1 and n2 are specified in kilobytes.

If the symbol space memory becomes exhausted, more memory is automatically acquired. The symbol space is stable memory and is not compressible like workspace. Symbol space is recycled whenever possible for reuse as the same type of object. For example, temporary symbols can be deleted after they are used in evaluating an expression. The symbol space formerly used by these temporaries is added to a list of free symbol-table nodes. When allocating temporary variables to evaluate another expression, IML looks for symbol-table nodes in this list first before consuming unused symbol space.

Workspace is compressible memory. Workspace fills up as more matrices are defined by operations. Holes in extents appear as you free matrices or as IML frees temporary intermediate results. When an extent fills up, compression reclaims the holes that have appeared in the extent. If compression does not reclaim enough memory for the current allocation, IML allocates a new extent. This procedure results in the existence of a list of extents, each of which contains a mixture of active memory and holes of unused memory. There is always a current extent, the one in which the last allocation was made.

For a new allocation, the search for free space begins in the current extent and proceeds around the extent list until finding enough memory or returning to the current extent. If the search returns to the current extent, IML begins a second transversal of the extent list, compressing each extent until either finding sufficient memory or returning to the current extent. If the second search returns to the current extent, IML opens a new extent and makes it the current one.

If the SAS System cannot provide enough memory to open a new extent with the full extent size, IML repeatedly reduces its request by 2K. In this case, the successfully opened extent is smaller than the standard size.

If a single allocation is larger than the standard extent size, IML requests an allocation large enough to hold the matrix.

The `WORKSIZE=` and `SYMSIZE=` options offer tools for tuning memory usage. For data-intensive applications that involve a few large matrices, use a high `WORKSIZE=` value and a low `SYMSIZE=` value. For symbol-intensive applications that involve many matrices, perhaps through the use of many IML modules, use a high `SYMSIZE=` value.

You can use the `SHOW SPACE` command to display the current status of IML memory usage. This command also lists the total number of compressions done on all extents.

Setting the `DETAILS` option in the `RESET` command prints messages in the output file when IML compresses an extent, opens a new extent, allocates a large object, or acquires more symbol space. These messages can be useful because these actions normally occur without the user's knowledge. The information can be used to tune `WORKSIZE=` and `SYMSIZE=` values for an application. However, the default `WORKSIZE=` and `SYMSIZE=` values should be appropriate in most applications.

Do not specify a very large value in the `WORKSIZE=` and `SYMSIZE=` options unless absolutely necessary. Many of the native functions and all of the `DATA` step functions used are dynamically loaded at execution time. If you use a large amount of the memory for symbol space and workspace, there might not be enough remaining to load these functions, resulting in the error message

Unable to load module *module-name*.

Should you run into this problem, issue a `SHOW SPACE` command to examine current usage. You might be able to adjust the `SYMSIZE=` or `WORKSIZE=` values.

The amount of memory your system can provide depends on the capacity of your computer and on the products installed. The following techniques for efficient memory use are recommended when memory is at a premium:

- Free matrices as they are no longer needed by using the `FREE` command.
- Store matrices you will need later in external library storage by using the `STORE` command, and then `FREE` their values. You can restore the matrices later by using the `LOAD` command. See [Chapter 17](#).

- Plan your work to use smaller matrices.

Accuracy

All numbers are stored and all arithmetic is done in double precision. The algorithms used are generally very accurate numerically. However, when many operations are performed or when the matrices are ill-conditioned, matrix operations should be used in a numerically responsible way because numerical errors add up.

Error Diagnostics

When an error occurs, several lines of messages are printed. The error description, the operation being performed, and the line and column of the source for that operation are printed. The names of the operation's arguments are also printed. Matrix names beginning with a pound sign (#) or an asterisk (*) can appear; these are temporary names assigned by the IML procedure.

If an error occurs while you are in immediate mode, the operation is not completed and nothing is assigned to the result. If an error occurs while executing statements inside a module, a PAUSE command is automatically issued. You can correct the error and resume execution of module statements with a RESUME statement.

The most common errors are described in the following list:

- referencing a matrix that has not been set to a value—that is, referencing a matrix that has no value associated with the matrix name
- making a subscripting error—that is, trying to refer to a row or column not present in the matrix
- performing an operation with nonconformable matrix arguments—for example, multiplying two matrices together that do not conform, or using a function that requires a special scalar or vector argument
- referencing a matrix that is not square for operations that require a square matrix (for example, INV, DET, or SOLVE)
- referencing a matrix that is not symmetric for operations that require a symmetric matrix (for example, GENEIG)
- referencing a matrix that is singular for operations that require a nonsingular matrix (for example, INV and SOLVE)
- referencing a matrix that is not positive definite or positive semidefinite for operations that require such matrices (for example, ROOT and SWEEP)

- not enough memory (see the section “[Memory and Workspace](#)” on page 537) to perform the computations and produce the resulting matrices.

These errors result from the actual dimensions or values of matrices and are caught only after a statement has begun to execute. Other errors, such as incorrect number of arguments or unbalanced parentheses, are syntax errors and resolution errors and are detected before the statement is executed.

Efficiency

The Interactive Matrix Language is an interpretive language executor that can be characterized as follows:

- efficient and inexpensive to compile
- inefficient and expensive for the number of operations executed
- efficient and inexpensive within each operation

Therefore, you should try to substitute matrix operations for iterative loops. There is a high overhead involved in executing each instruction; however, within the instruction IML runs very efficiently.

Consider the following four methods of summing the elements of a matrix:

```
s = 0;                                /* method 1 */
do i = 1 to m;
  do j = 1 to n;
    s = s + x[i,j];
  end;
end;
s = j[1,m] * x * j[n,1];             /* method 2 */
s = x[+,+];                          /* method 3 */
s = sum(x);                          /* method 4 */
```

Method 1 is the least efficient, method 2 is more efficient, method 3 is more efficient yet, and method 4 is the most efficient. The greatest advantage of using IML is reducing human programming labor.

Missing Values

An IML numeric element can have a special value called a *missing value* that indicates that the value is unknown or unspecified. (A matrix with missing values should not be confused with an empty or unvalued matrix—that is, a matrix with 0 rows and 0 columns.) A numeric matrix can have any mixture of missing and nonmissing values.

SAS/IML software supports missing values in a limited way. The operators in the following list recognize missing values and propagate them. For example, matrix multiplication of a matrix with missing values is not supported. Most matrix operators and functions do not support missing values. Furthermore, many linear algebraic operations are not mathematically defined for a matrix with missing values. For example, the inverse of a matrix with missing values is meaningless.

Missing values are coded in the bit pattern of very large negative numbers, as an IEEE “NAN” code, or as a special string, depending on the host system.

In literals, a numeric missing value is specified as a single period. In data processing operations, you can add or delete missing values. All operations that move values around move missing values properly. The following arithmetic operators propagate missing values.

addition (+)	subtraction (−)
multiplication (#)	division (/)
maximum (< >)	minimum (> <)
modulo (MOD)	exponentiation (##)

The comparison operators treat missing values as large negative numbers. The logical operators treat missing values as zeros. The operators SUM, SSQ, MAX, and MIN check for and exclude missing values.

The subscript reduction operators exclude missing values from calculations. If all of a row or column that is being reduced is missing, then the operator returns the result indicated in the following table.

Operator	Result If All Missing
addition (+)	0
multiplication (#)	1
maximum (< >)	large negative value
minimum (> <)	large positive value
sum squares (##)	0
index maximum (< : >)	1
index minimum (> : <)	1
mean (:)	missing value

Also note that, unlike the SAS DATA step, IML does not distinguish between special and generic missing values; it treats all missing values alike.

Principles of Operation

This section presents various technical details about the operation of SAS/IML software. Statements in IML go through three phases:

- The parsing phase includes text acquisition, word scanning, recognition, syntactical analysis, and enqueueing on the statement queue. This is performed immediately as IML reads the statements.

- The resolution phase includes symbol resolution, label and transfer resolution, and function and call resolution. Symbol resolution connects the symbolic names in the statement with their descriptors in the symbol table. New symbols can be added or old ones recognized. Label and transfer resolution connects statements and references affecting the flow of control. This connects LINK and GOTO statements with labels; it connects IF with THEN and ELSE clauses; it connects DO with END. Function-call resolution identifies functions and call routines and loads them if necessary. Each reference is checked with respect to the number of arguments allowed. The resolution phase begins after a module definition is finished or a DO group is ended. For all other statements outside any module or DO group, resolution begins immediately after parsing.
- The execution phase occurs when the statements are interpreted and executed. There are two levels of execution: statement and operation. Operation-level execution involves the evaluation of expressions within a statement.

Operation-Level Execution

Operations are executed from a chain of operation elements created at parse time and resolved later. For each operation, the interpreter performs the following steps:

1. Prints a record of the operation if the FLOW option is on.
2. Looks at the operands to make sure they have values. Only certain special operators are allowed to tolerate operands that have not been set to a value. The interpreter checks whether any argument has character values.
3. Inspects the operator and gives control to the appropriate execution routine. A separate set of routines is invoked for character values.
4. Checks the operands to make sure they are valid for the operation. Then the routine allocates the result matrix and any extra workspace needed for intermediate calculations. Then the work is performed. Extra workspace is freed. A return code notifies IML if the operation was successful. If unsuccessful, it identifies the problem. Control is passed back to the interpreter.
5. Checks the return code. If the return code is nonzero, diagnostic routines are called to explain the problem to the user.
6. Associates the results with the result arguments in the symbol table. By keeping results out of the symbol table until this time, the operation does not destroy the previous value of the symbol if an error has occurred.
7. Prints the result if RESET PRINT or RESET PRINTALL is specified. The PRINTALL option prints intermediate results as well as end results.
8. Moves to the next operation.

Chapter 23

Language Reference

Contents

Overview	551
Statements, Functions, and Subroutines by Category	551
Operators	563
Addition Operator: +	563
Comparison Operators: <, <=, >, >=, =, ^=	564
Concatenation Operator, Horizontal: 	566
Concatenation Operator, Vertical: //	567
Direct Product Operator: @	568
Division Operator: /	569
Element Maximum Operator: <>	570
Element Minimum Operator: ><	571
Index Creation Operator: :	572
Logical Operators: &, , ^	573
Multiplication Operator, Elementwise: #	574
Multiplication Operator, Matrix: *	576
Power Operator, Elementwise: ##	576
Power Operator, Matrix: **	577
Sign Reversal Operator: -	579
Subscripts: []	579
Subtraction Operator: -	581
Transpose Operator: `	582
Statements, Functions, and Subroutines	582
ABORT Statement	583
ABS Function	583
ALL Function	584
ALLCOMB Function	584
ALLPERM Function	586
ANY Function	587
APPCORT Call	587
APPEND Statement	589
APPLY Function	592
ARMACOV Call	594
ARMALIK Call	595
ARMASIM Function	597

BIN Function	598
BLOCK Function	600
BRANKS Function	601
BSPLINE Function	602
BTRAN Function	604
BYTE Function	605
CALL Statement	606
CHANGE Call	607
CHAR Function	607
CHOOSE Function	608
CLOSE Statement	609
CLOSEFILE Statement	610
COMPORT Call	611
CONCAT Function	614
CONTENTS Function	615
CONVEXIT Function	616
CORR Function	616
COUNTMISS Function	618
COUNTN Function	619
COUNTUNIQUE Function	620
COV Function	621
COVLAGE Function	622
CREATE Statement	623
CSHAPE Function	626
CUSUM Function	628
CUPROD Function	628
CVEXHULL Function	629
DATASETS Function	630
DELETE Call	630
DELETE Statement	631
DESIGN Function	633
DESIGNF Function	634
DET Function	635
DIAG Function	635
DIF Function	636
DISPLAY Statement	637
DO Function	638
DO Statement	638
DO Statement, Iterative	639
DO DATA Statement	640
DO Statement with an UNTIL Clause	641
DO Statement with a WHILE Clause	642
DURATION Function	643
ECHELON Function	644

EDIT Statement	644
EIGEN Call	647
EIGVAL Function	651
EIGVEC Function	651
ELEMENT Function	652
END Statement	653
ENDSUBMIT Statement	653
EXECUTE Call	653
EXP Function	654
EXPORTDATASETTOR Call	655
EXPORTMATRIXTOR Call	656
FARMACOV Call	657
FARMAFIT Call	658
FARMALIK Call	660
FARMASIM Call	661
FDIF Call	663
FFT Function	664
FILE Statement	666
FIND Statement	667
FINISH Statement	669
FORCE Statement	669
FORWARD Function	669
FREE Statement	670
FULL Function	671
GAEND Call	672
GAGETMEM Call	672
GAGETVAL Call	673
GAINIT Call	674
GAREEVAL Call	675
GAREGEN Call	675
GASETCRO Call	676
GASETMUT Call	680
GASETOBJ Call	681
GASETSEL Call	682
GASETUP Function	683
GBLKVP Call	686
GBLKVPD Call	686
GCLOSE Call	687
GDELETE Call	687
GDRAW Call	687
GDRAWL Call	688
GENEIG Call	689
GEOMEAN Function	690
GGRID Call	691

GINCLUDE Call	692
GINV Function	692
GOOPEN Call	694
GOTO Statement	695
GPIE Call	696
GPIEXY Call	697
GPOINT Call	698
GPOLY Call	699
GPORT Call	700
GPORTPOP Call	700
GPORTSTK Call	701
GSCALE Call	701
GSCRIPT Call	702
GSET Call	703
GSHOW Call	704
GSORTH Call	704
GSTART Call	706
GSTOP Call	707
GSTRLEN Call	707
GTEXT and GVTEXT Calls	708
GWINDOW Call	709
GXAXIS and GYAXIS Calls	709
HADAMARD Function	711
HALF Function	712
HANKEL Function	712
HARMEAN Function	714
HDIR Function	714
HERMITE Function	715
HOMOGEN Function	716
I Function	717
IF-THEN/ELSE Statement	717
IFFT Function	719
IMPORTDATASETFROMR Call	720
IMPORTMATRIXFROMR Call	722
INDEX Statement	723
INFILE Statement	724
INPUT Statement	725
INSERT Function	726
INT Function	727
INV Function	728
INVUPDT Function	729
IPF Call	731
ITSOLVER Call	743
J Function	747

JROOT Function	747
KALCVF Call	749
KALCVS Call	752
KALDFF Call	755
KALDFS Call	758
LAG Function	760
LAV Call	760
LCP Call	765
LENGTH Function	768
LINK Statement	769
LIST Statement	769
LMS Call	772
LOAD Statement	783
LOC Function	784
LOG Function	785
LP Call	785
LTS Call	787
LUPDT Call	795
MAD Function	796
MARG Call	798
MATTRIB Statement	801
MAX Function	802
MAXQFORM Call	803
MCD Call	805
MEAN Function	810
MIN Function	812
MOD Function	813
MODULEI Call	813
MODULEIC Function	814
MODULEIN Function	814
MVE Call	815
NAME Function	821
NCOL Function	822
NLENG Function	822
Nonlinear Optimization and Related Subroutines	823
NLPCG Call	826
NLPDD Call	826
NLPFDD Call	829
NLPFEA Call	832
NLPHQN Call	833
NLPLM Call	836
NLPNMS Call	837
NLPNRA Call	841
NLPNRR Call	844

NLPQN Call	847
NLPQUA Call	851
NLPTR Call	855
NORMAL Function	856
NROW Function	856
NUM Function	857
ODE Call	857
ODSGRAPH Call	864
OPSCAL Function	867
ORPOL Function	869
ORTVEC Call	875
PAUSE Statement	879
PGRAPH Call	880
POLYROOT Function	881
PRINT Statement	881
PROD Function	883
PRODUCT Function	884
PURGE Statement	885
PUSH Call	886
PUT Statement	887
PV Function	888
QNTL Call	890
QR Call	891
QUAD Call	896
QUEUE Call	902
QUIT Statement	903
RANCOMB Function	904
RANDGEN Call	905
RANPERM Function	912
RANDSEED Call	913
RANGE Function	914
RANK Function	914
RANKTIE Function	917
RATES Function	919
RATIO Function	920
RDODT and RUPDT Calls	921
READ Statement	925
REMOVE Function	928
REMOVE Statement	929
RENAME Call	929
REPEAT Function	930
REPLACE Statement	930
RESET Statement	933
RESUME Statement	935

RETURN Statement	936
ROOT Function	936
ROWCAT Function	937
ROWCATC Function	938
RUN Statement	939
RUPDT Call	940
RZLIND Call	940
SAVE Statement	948
SEQ, SEQSCALE, and SEQSHIFT Calls	948
SEQSCALE Call	960
SEQSHIFT Call	960
SETDIF Function	961
SETIN Statement	961
SETOUT Statement	962
SHAPE Function	962
SHAPECOL Function	964
SHOW Statement	965
SOLVE Function	965
SOLVELIN Call	966
SORT Call	967
SORT Statement	968
SORTNDX Call	969
SOUND Call	970
SPARSE Function	971
SPLINE and SPLINEC Calls	972
SPLINEV Function	979
SPOT Function	979
SQRSYM Function	980
SQRT Function	980
SQRVECH Function	981
SSQ Function	981
START Statement	982
STD Function	983
STOP Statement	983
STORAGE Function	984
STORE Statement	984
SUBMIT Statement	985
SUBSTR Function	987
SUM Function	987
SUMMARY Statement	988
SVD Call	991
SWEEP Function	992
SYMSQR Function	995
T Function	995

TABULATE Call	996
TOEPLITZ Function	997
TPSPLINE Call	998
TPSPLNEV Call	1000
TRACE Function	1003
TRISOLV Function	1004
TSBAYSEA Call	1005
TSDECOMP Call	1007
TSMLOCAR Call	1010
TSMLOMAR Call	1011
TSMULMAR Call	1012
TSPEARS Call	1013
TSPRED Call	1014
TSROOT Call	1015
TSTVCAR Call	1015
TSUNIMAR Call	1016
TYPE Function	1017
UNIFORM Function	1018
UNION Function	1019
UNIQUE Function	1019
UNIQUEBY Function	1019
USE Statement	1021
VALSET Call	1023
VALUE Function	1024
VAR Function	1024
VARMACOV Call	1025
VARMALIK Call	1026
VARMASIM Call	1028
VECDIAG Function	1029
VECH Function	1029
VNORMAL Call	1030
VTSROOT Call	1031
WAVFT Call	1032
WAVGET Call	1035
WAVIFT Call	1036
WAVPRINT Call	1038
WAVTHRSH Call	1039
WINDOW Statement	1040
XMULT Function	1042
XSECT Function	1043
YIELD Function	1043
Base SAS Functions Accessible from SAS/IML Software	1044
Bitwise Logical Operation Functions	1045
Character and Formatting Functions	1045

Character String Matching Functions and Subroutines	1049
Date and Time Functions	1049
Descriptive Statistics Functions and Subroutines	1050
Double-Byte Character String Functions	1051
External Files Functions	1051
File I/O Functions	1052
Financial Functions	1053
Macro Functions and Subroutines	1054
Mathematical Functions and Subroutines	1054
Probability Functions	1055
Quantile Functions	1055
Random Number Functions and Subroutines	1056
State and Zip Code Functions	1056
Trigonometric and Hyperbolic Functions	1056
Truncation Functions	1057
Web Tools	1057
References	1058

Overview

This chapter describes all operators, statements, functions, and subroutines that can be used in SAS/IML software. This chapter is divided into the following sections:

- The first section list all statements, functions, and subroutines available in SAS/IML software, grouped by functionality.
- The second section contains [operator](#) descriptions, ordered alphabetically by the name of the operator.
- The third section contains descriptions of [statements](#), [functions](#), and [subroutines](#) ordered alphabetically by name.

Statements, Functions, and Subroutines by Category

Mathematical Functions

ALLCOMB	generates all combinations of n elements taken k at a time
ALLPERM	generates all permutations of n elements
ABS function	computes the absolute value

EXP function	applies the exponential function
INT function	truncates a value
LOG function	computes the natural logarithm
MOD function	computes the modulo (remainder)
SQRT function	computes the square root
RANCOMB	returns random combinations of n elements taken k at a time
RANPERM	returns random permutations of n elements

You can also call any function in Base SAS software, such as those documented in the following sections:

- “Mathematical Functions and Subroutines” on page 1054
- “Probability Functions” on page 1055
- “Quantile Functions” on page 1055
- “Trigonometric and Hyperbolic Functions” on page 1056
- “Truncation Functions” on page 1057

Reduction Functions

MAX function	finds the maximum value of a matrix
MIN function	finds the smallest element of a matrix
PROD function	multiplies all elements
SSQ function	computes the sum of squares of all elements
SUM function	sums all elements

Matrix Inquiry Functions

ALL function	checks for all nonzero elements
ANY function	checks for any nonzero elements
COUNTMISS function	returns the number of missing values
COUNTN function	returns the number of nonmissing values
COUNTUNIQUE function	returns the number of unique values
CHOOSE function	conditionally chooses and changes elements
LOC function	finds indices for the nonzero elements of a matrix
NCOL function	finds the number of columns of a matrix
NLENG function	finds the size of an element
NROW function	finds the number of rows of a matrix
TYPE function	determines the type of a matrix

Matrix Sorting and BY-Group Processing Functions

<code>SORT</code> call	sorts a matrix by specified columns
<code>SORTNDX</code> call	creates a sorted index for a matrix
<code>UNIQUEBY</code> function	finds locations of unique BY groups in a sorted or indexed matrix

Matrix Reshaping Functions

<code>BLOCK</code> function	forms block-diagonal matrices
<code>BTRAN</code> function	computes a block transpose
<code>DIAG</code> function	creates a diagonal matrix
<code>DO</code> function	produces an arithmetic series
<code>FULL</code> function	converts a matrix stored in a sparse format into a full (dense) matrix
<code>I</code> function	creates an identity matrix
<code>INSERT</code> function	inserts one matrix inside another
<code>J</code> function	creates a matrix of identical values
<code>REMOVE</code> function	discards elements from a matrix
<code>REPEAT</code> function	creates a new matrix of repeated values
<code>SHAPE</code> function	reshapes and repeats values
<code>SHAPECOL</code> function	reshapes and repeats values by columns
<code>SPARSE</code> function	converts a matrix that contains many zeros into a matrix stored in a sparse format
<code>SQRSYM</code> function	converts a symmetric matrix to a square matrix
<code>SQRVECH</code> function	converts a symmetric matrix which is stored columnwise to a square matrix
<code>SYMSQR</code> function	converts a square matrix to a symmetric matrix
<code>T</code> function	transposes a matrix
<code>VECH</code> function	creates a vector from the columns of the lower triangular elements of a matrix
<code>VECDIAG</code> function	creates a vector from a diagonal

Character Manipulation Functions

<code>BYTE</code> function	translates numbers to ordinal characters
<code>CHANGE</code> call	replaces text
<code>CHAR</code> function	produces a character representation of a matrix
<code>CONCAT</code> function	concatenates elementwise strings
<code>CSHAPE</code> function	reshapes and repeats character values
<code>LENGTH</code> function	finds the lengths of character matrix elements
<code>NAME</code> function	lists the names of arguments

NUM function	produces a numeric representation of a character matrix
ROWCAT function	concatenates rows without using blank compression
ROWCATC function	concatenates rows by using blank compression
SUBSTR function	takes substrings of matrix elements

You can also call functions in Base SAS software such as those documented in “[Character and Formatting Functions](#)” on page 1045 and “[Character String Matching Functions and Subroutines](#)” on page 1049.

Functions for Random Number Generation

NORMAL function	generates a pseudorandom normal deviate
RANDGEN call	generates random numbers from specified distributions
RANDSEED call	initializes seed for subsequent RANDGEN calls
UNIFORM function	generates pseudorandom uniform deviates

You can also call functions in Base SAS software such as those documented in “[Random Number Functions and Subroutines](#)” on page 1056.

Statistical Functions

BIN function	divides numeric values into a set of disjoint intervals
BRANKS function	computes bivariate ranks
CORR function	computes correlation statistics
COUNTMISS function	counts the number of missing values
COUNTN function	counts the number of nonmissing values
COUNTUNIQUE function	returns the number of unique values
COV function	computes a sample variance-covariance matrix
CUSUM function	computes cumulative sums
CUPROD function	computes cumulative products
DESIGN function	creates a design matrix
DESIGNF function	creates a full-rank design matrix
GEOMEAN function	computes geometric means
HADAMARD function	creates a Hadamard matrix
HARMEAN function	computes harmonic means
IPF call	performs an iterative proportional fit of a contingency table
LAV call	performs linear least absolute value regression by solving the L_1 norm minimization problem
LMS call	performs robust least median of squares (LMS) regression

LTS call	performs robust least trimmed squares (LTS) regression
MAD function	finds the univariate (scaled) median absolute deviation
MARG call	evaluates marginal totals in a multiway contingency table
MAXQFORM call	computes the subsets of a matrix system that maximize the quadratic form
MCD call	finds the minimum covariance determinant estimator
MEAN function	computes sample means
MVE call	finds the minimum volume ellipsoid estimator
OPSCAL function	rescales qualitative data to be a least squared fit to qualitative data
QNTL call	computes sample quantiles (percentiles)
RANGE function	returns the range of values for a set of matrices.
RANK function	ranks elements of a matrix, breaking ties arbitrarily
RANKTIE function	ranks elements of a matrix
SEQ call	performs discrete sequential tests
SEQSCALE call	performs estimates of scales associated with discrete sequential tests
SEQSHIFT call	performs estimates of means associated with discrete sequential tests
STD function	computes a sample standard deviation
TABULATE call	counts the number of unique values in a vector
SWEEP function	sweeps a matrix
VAR function	computes a sample variance

You can also call functions in Base SAS software such as those documented in “[Descriptive Statistics Functions and Subroutines](#)” on page 1050.

Time Series Functions

ARMACOV call	computes an autocovariance sequence for an autoregressive moving average (ARMA) model
ARMALIK call	computes the log likelihood and residuals for an ARMA model
ARMASIM function	simulates an ARMA series
CONVEXIT function	computes convexity of a noncontingent cash flow
COVLAGE function	computes autocovariance estimates for a vector time series
DIF function	computes the difference between a value and a lagged value
DURATION function	computes modified duration of a noncontingent cash flow
FARMACOV call	computes the autocovariance function for an autoregressive fractionally integrated moving average (ARFIMA) model of the form $\text{ARFIMA}(p, d, q)$
FARMAFIT call	estimates the parameters of an $\text{ARFIMA}(p, d, q)$ model

FARMALIK call	computes the log-likelihood function of an ARFIMA(p, d, q) model
FARMASIM call	generates an ARFIMA(p, d, q) process
FDIF call	computes a fractionally differenced process
FORWARD function	computes forward rates
KALCVF call	computes the one-step prediction $z_{t+1 t}$ and the filtered estimate $z_{t t}$, in addition to their covariance matrices. The call uses forward recursions, and you can also use it to obtain k -step estimates.
KALCVS call	uses backward recursions to compute the smoothed estimate $z_{t T}$ and its covariance matrix, $P_{t T}$, where T is the number of observations in the complete data set
KALDFF call	computes the one-step forecast of state vectors in a state space model (SSM) by using the diffuse Kalman filter. The call estimates the conditional expectation of z_t , and it also estimates the initial random vector, δ , and its covariance matrix.
KALDFS call	computes the smoothed state vector and its mean squares error matrix from the one-step forecast and mean squares error matrix computed by the KALDFF subroutine.
LAG function	computes lagged values
PV function	computes the present value
RATES function	converts interest rates from one base to another
SPOT function	computes spot rates
TSBAYSEA call	performs Bayesian seasonal adjustment modeling
TSDECOMP call	analyzes nonstationary time series by using smoothness priors modeling
TSMLOCAR call	analyzes nonstationary or locally stationary time series by using a method that minimizes Akaike's information criterion (AIC)
TSMLOMAR call	analyzes nonstationary or locally stationary multivariate time series by using a method that minimizes Akaike's information criterion (AIC)
TSMULMAR call	estimates vector autoregressive (VAR) processes by minimizing the AIC
TSPEARS call	analyzes periodic autoregressive (AR) models by minimizing the AIC
TSPRED call	provides predicted values of univariate and multivariate ARMA processes when the ARMA coefficients are given
TSROOT call	computes AR and moving average (MA) coefficients from the characteristic roots of the model, or computes the characteristic roots of the model from the AR and MA coefficients
TSTVCAR call	analyzes time series that are nonstationary in the covariance function
TSUNIMAR call	determines the order of an AR process by minimizing the AIC, and estimates the AR coefficients
VARMACOV call	computes the theoretical cross-covariance matrices for a stationary vector autoregressive moving average (VARMA(p, q)) model
VARMALIK call	computes the log-likelihood function for a VARMA(p, q) model

VARMASIM call	generates VARMA(p, q) time series
VNORMAL call	generates multivariate normal random series
VTSROOT call	computes the characteristic roots for a VARMA(p, q) model
YIELD function	computes yield-to-maturity of a cash-flow stream

You can also call functions in Base SAS software such as those documented in “[Financial Functions](#)” on page 1053.

Numerical Analysis Functions

BSPLINE function	computes a B-spline basis
FFT function	performs the finite Fourier transform
IFFT function	computes the inverse finite Fourier transform
JROOT function	computes the first nonzero roots of a Bessel function of the first kind and the derivative of the Bessel function at each root
ODE call	performs numerical integration of first-order vector differential equations with initial boundary conditions
ORPOL function	generates orthogonal polynomials on a discrete set of data
ORTVEC call	provides columnwise orthogonalization by the Gram-Schmidt process and step-wise QR decomposition by the Gram-Schmidt process
POLYROOT function	finds zeros of a real polynomial
PRODUCT function	multiplies matrices of polynomials
QUAD call	performs numerical integration of scalar functions in one dimension over infinite, connected semi-infinite, and connected finite intervals
RATIO function	divides matrix polynomials
SPLINE call	fits a cubic spline to data
SPLINEC call	fits a cubic spline to data and returns the spline coefficients
SPLINEV function	evaluates a cubic spline at new data points
TPSPLINE call	computes thin-plate smoothing splines
TPSPLNEV call	evaluates the thin-plate smoothing spline at new data points

Linear Algebra functions

APPCORT call	computes a complete orthogonal decomposition
COMPORT call	computes a complete orthogonal decomposition by Householder transformations
CVEXHULL function	finds a convex hull of a set of planar points
DET function	computes the determinant of a square matrix
ECHELON function	reduces a matrix to row-echelon normal form

EIGEN call	computes eigenvalues and eigenvectors
EIGVAL function	computes eigenvalues
EIGVEC function	computes eigenvectors
GENEIG call	computes eigenvalues and eigenvectors of a generalized eigenproblem
GINV function	computes a generalized inverse
GSORTH call	computes the Gram-Schmidt orthonormalization
HALF function	computes the Cholesky decomposition
HANKEL function	generates a Hankel matrix
HDIR function	performs a horizontal direct product
HERMITE function	reduces a matrix to Hermite normal form
HOMOGEN function	solves homogeneous linear systems
INV function	computes the inverse
INVUPDT function	updates a matrix inverse
ITSOLVER call	solves a sparse general linear system by iteration
LUPDT call	provides updating and downdating for rank-deficient linear least squares solutions, complete orthogonal factorization, and Moore-Penrose inverses
QR call	computes the QR decomposition of a matrix by Householder transformations
RDODT call	downdates and updates QR and Cholesky decompositions
ROOT function	performs the Cholesky decomposition of a matrix
RUPDT call	updates QR and Cholesky decompositions
RZLIND call	updates QR and Cholesky decompositions
SOLVE function	solves a system of linear equations
SOLVELIN call	solves a sparse symmetric system of linear equations by direct decomposition
SVD call	computes the singular value decomposition
TOEPLITZ function	generates a Toeplitz or block-Toeplitz matrix
TRACE function	sums diagonal elements
TRISOLV function	solves linear systems with triangular matrices
XMULT function	performs extended-precision matrix multiplication

Optimization Subroutines

LCP call	solves the linear complementarity problem
LP call	solves the linear programming problem
NLPCG call	performs nonlinear optimization by conjugate gradient method
NLPDD call	performs nonlinear optimization by double-dogleg method
NLPFDD call	approximates derivatives by finite-differences method

NLPFEA call	computes feasible points subject to constraints
NLPHQN call	computes hybrid quasi-Newton least squares
NLPLM call	computes Levenberg-Marquardt least squares
NLPNMS call	performs nonlinear optimization by Nelder-Mead simplex method
NLPNRA call	performs nonlinear optimization by Newton-Raphson method
NLPNRR call	performs nonlinear optimization by Newton-Raphson ridge method
NLPQN call	performs nonlinear optimization by quasi-Newton method
NLPQUA call	performs nonlinear optimization by quadratic method
NLPTR call	performs nonlinear optimization by trust-region method
Nonlinear optimization and related subroutines	lists the nonlinear optimization and related subroutines in SAS/IML software

Set functions

ELEMENT function	finds elements that are contained in a set
SETDIF function	compares elements of two matrices
UNION function	performs unions of sets
UNIQUE function	sorts and removes duplicates
XSECT function	intersects sets

Control Statements

ABORT statement	ends PROC IML
APPLY function	applies a module to arguments
CALL statement	calls a subroutine or function
DO statement	groups statements as a unit
DO, iterative statement	iteratively executes a DO group
DO UNTIL statement	iteratively executes statements until a condition is satisfied
DO WHILE statement	iteratively executes statements while a condition is satisfied
END statement	ends a DO loop or DO statement
EXECUTE call	executes statements at run time
FINISH statement	denotes the end of a module
FREE statement	frees matrix storage space
GOTO statement	jumps to a new statement
IF-THEN/ELSE statement	conditionally executes statement
LINK statement	jumps to another statement

MATTRIB statement	associates printing attributes with matrices
PAUSE statement	interrupts module execution
PRINT statement	prints matrix values
PURGE statement	removes observations marked for deletion and renumbers records
PUSH call	pushes statements to the beginning of the command input stream
QUEUE call	queues statements at the end of the command input stream
QUIT statement	exits from PROC IML
REMOVE statement	removes matrices from storage
RESET statement	sets processing options
RESUME statement	resumes execution
RETURN statement	returns to caller
RUN statement	executes statements in a module
SHOW statement	prints system information
SOUND call	produces a tone
START statement	defines a module
STOP statement	stops execution of statements
STORAGE function	lists names of matrices and modules in storage
STORE statement	stores matrices and modules in library storage
VALSET call	performs indirect assignment
VALUE function	assigns values by indirect reference

Data Set and File Functions

APPEND statement	adds observations to SAS data set
CLOSE statement	closes a SAS data set
CLOSEFILE statement	closes a file
CONTENTS function	returns the variables in a SAS data set
CREATE statement	creates a new SAS data set
DATASETS function	obtains the names of SAS data sets
DELETE call	deletes a SAS data set
DELETE statement	marks observations in a data set for deletion
DO DATA statement	repeats a loop until an end of file occurs
EDIT statement	opens a SAS data set for editing
FILE statement	opens or points to an external file
FIND statement	finds observations
FORCE statement	is an alias for the SAVE statement

INDEX statement	indexes a variable in a SAS data set
INFILE statement	opens a file for input
INPUT statement	inputs data
LIST statement	displays observations of a data set
LOAD statement	loads modules and matrices from library storage
PUT statement	writes data to an external file
READ statement	reads observations from a data set
RENAME call	renames a SAS data set
REPLACE statement	replaces values in observations and updates observations
SAVE statement	saves data
SETIN statement	makes a data set current for input
SETOUT statement	makes a data set current for output
SORT statement	sorts a SAS data set
SUMMARY statement	computes summary statistics for SAS data sets
USE statement	opens a SAS data set for reading

Graphics and Window functions

DISPLAY statement	displays fields in a display window
GBLKVP call	defines a blanking viewport
GBLKVPD call	deletes the blanking viewport
GCLOSE call	closes the graphics segment
GDELETE call	deletes a graphics segment
GDRAW call	draws a polyline
GDRAWL call	draws individual lines
GGRID call	draws a grid
GINCLUDE call	includes a graphics segment
GOPEN call	opens a graphics segment
GPIE call	draws pie slices
GPIEXY call	converts from polar to world coordinates
GPOINT call	plots points
GPOLY call	draws and fills a polygon
GPORT call	defines a viewport
GPORTPOP call	pops the viewport
GPORTSTK call	stacks the viewport
GSCALE call	computes round numbers for labeling axes

GSCRIPT call	writes multiple text strings with special fonts
GSET call	sets attributes for a graphics segment
GSHOW call	shows a graph
GSTART call	initializes the graphics system
GSTOP call	deactivates the graphics system
GSTRLEN call	finds the string length
GTEXT call	places text horizontally on a graph
GVTEXT call	places text vertically on a graph
GWINDOW call	defines the data window
GXAXIS call	draws a horizontal axis
GYAXIS call	draws a vertical axis
PGRAF call	produces scatter plots
ODSGRAPH call	renders a graph by using ODS Statistical Graphics
WINDOW statement	opens a display window

Wavelet Analysis functions

WAVFT call	computes a wavelet transform of one dimensional data
WAVGET call	returns requested information about a wavelet transform
WAVIFT call	inverts a wavelet transform after applying thresholding to the detail coefficients
WAVPRINT call	displays information about a wavelet transform
WAVTHRSH call	applies specified thresholding to the detail coefficients of a wavelet transform

Genetic Algorithm functions

GAEND call	terminates a genetic algorithm and frees memory resources
GAGETMEM call	gets requested members and objective values from the current solution population
GAGETVAL call	gets objective function values for a requested member of current solution population
GAINIT call	initializes the initial solution population
GAREEVAL call	reevaluates the objective function for all solutions in the current population
GASETCRO call	specifies a current crossover operator
GASETMUT call	specifies a current mutation operator
GASETOBJ call	specifies a current objective function
GASETSEL call	specifies a current selection parameters
GASETUP function	sets up a specific genetic algorithm optimization problem

Calling External Modules

MODULEI call	calls an external routine that has no return code
MODULEIC call	calls an external routine that returns a character
MODULEIN call	calls an external routine that returns a numeric value

Calling SAS statements or R Functions

SUBMIT statement	calls SAS procedures, DATA steps, or macros. You can also use the R option to call functions in the R language.
ENDSUBMIT statement	defines a block of submitted statements. All statements between the SUBMIT and ENDSUBMIT statements are sent to the SAS System or R for processing.
EXPORTDATASETTOR call	transfers data from a SAS data set into an R data frame
EXPORTMATRIXTOR call	transfers data from a SAS/IML matrix into an R matrix
IMPORTDATASETFROMR call	transfers data from a matrix or data frame into a SAS data set
IMPORTMATRIXFROMR call	transfers data from a matrix or data frame into a SAS/IML matrix

Operators

This section describes all operators that are available in SAS/IML software. Each section shows how the operator is used, followed by a description of the operator.

Addition Operator: +

matrix1 + *matrix2* ;

matrix + *scalar* ;

matrix + *vector* ;

The addition operator (+) computes a new matrix that contains elements that are the sums of the corresponding elements of *matrix1* and *matrix2*. If *matrix1* and *matrix2* are both $n \times p$ matrices, then the addition operator adds the element in the i th row and j th column of the first matrix to the element in the i th row and j th column of the second matrix, for $i = 1 \dots n, j = 1 \dots p$.

For example, the following statements add two matrices and store the result in the matrix **c**, shown in Figure 23.1:

```
a = {1 2,
```

```

    3 4};
b = {1 1,
     1 1};
c = a+b;
print c;

```

Figure 23.1 Sum of Two Matrices

c	
2	3
4	5

You can also use the addition operator to conveniently add a value to each element of a matrix, to each column of a matrix, or to each row of a matrix.

- When you use the *matrix* + *scalar* form, the scalar value is added to each element of the matrix.
- When you use the *matrix* + *vector* form, the vector is added to each row or column of the $n \times p$ matrix.
 - If you add an $n \times 1$ column vector, each row of the vector is added to each row of the matrix.
 - If you add a $1 \times p$ row vector, each column of the vector is added to each column of the matrix.

For example, you can obtain the same result as the previous example with any of the following statements:

```

c = a+1;
c = a+{1 1};
c = a+{1,1};

```

When an element of a matrix contains a missing value, the corresponding element of the sum is also a missing value.

You can also use the addition operator on character operands. In this case, the operator implements element-wise concatenation exactly as the [CONCAT function](#).

Comparison Operators: <, <=, >, >=, =, ^=

```
matrix1 < matrix2 ;
```

```
matrix1 <= matrix2 ;
```

```
matrix1 > matrix2 ;
```

```
matrix1 >= matrix2 ;
```

```
matrix1 = matrix2 ;
```

```
matrix1 ^= matrix2 ;
```

Comparison operators compare two matrices element by element and compute a new matrix that contains only zeros and ones. If an element comparison is true, the corresponding element of the new matrix is 1. If the comparison is not true, the corresponding element is 0. Unlike in the SAS DATA step, the SAS/IML language does not accept the English equivalents GT and LT for the greater than and less than operators.

For example, the following statements assign the matrix **c**, shown in [Figure 23.2](#):

```
a = {1 7 3,
      6 2 4};
b = {0 8 2,
      4 1 3};
c = a>b;
print c;
```

Figure 23.2 Results of a Matrix Comparison

c		
1	0	1
1	1	1

You can also use the comparison operators to conveniently compare all elements of a matrix with a scalar.

- If either argument is a scalar, then an elementwise comparison is performed between each element of the matrix and the scalar.
- You can also compare an $n \times p$ matrix with a row or column vector.
 - If the comparison is with an $n \times 1$ column vector, each row of the vector is compared to each row of the matrix.
 - If the comparison is with a $1 \times p$ row vector, each column of the vector is compared to each column of the matrix.

For example, the following statements assign the matrix **d**, shown in [Figure 23.3](#):

```
d = (a>=4);      /* the parentheses are not necessary */
print d;
```

Figure 23.3 Results of a Comparison with a Scalar

d		
0	1	0
1	0	1

When you are making conditional comparisons, all values of the result must be nonzero for the condition to be evaluated as true, as shown in the following statements:

```
if a>=b then do;
  /* more statements */
end;
```

The previous DO block is executed only if *every* element of **a** is greater than or equal to the corresponding element in **b**. For the **a** and **b** matrices defined in this section, the DO block is not executed. See the descriptions of the [ALL](#) and [ANY](#) functions.

If a numeric missing value occurs in a matrix, the inequality comparison operators treat it as a value that is less than any valid nonmissing value.

You can compare elements of a character matrix. Character values are compared in ASCII order. In ASCII order, numerals precede uppercase letters, which precede lowercase letters. If the element lengths of two character matrices are different, the shorter elements are padded on the right with blanks for the comparison.

Concatenation Operator, Horizontal: ||

```
matrix1 || matrix2 ;
```

The horizontal concatenation operator (||) produces a new matrix by horizontally joining *matrix1* and *matrix2*. The matrices must have the same number of rows, which is also the number of rows in the new matrix. The number of columns in the new matrix is the number of columns in *matrix1* plus the number of columns in *matrix2*.

For example, the following statements produce the matrix **c**, shown in [Figure 23.4](#):

```
a = {1 1 1,
      7 7 7};
b = {0 0 0,
      8 8 8};
c = a||b;
print c;
```

Figure 23.4 Result of Horizontal Concatenation

c					
1	1	1	0	0	0
7	7	7	8	8	8

For character operands, the element size in the result matrix is the larger of the two operands. For example, the following statements produce a matrix **f** which has elements of size 2, which are shown in [Figure 23.5](#):

```
d = {A B C,
      D E F};
e = {"GH" "IJ",
      "KL" "MN"};
f = d||e;
print f;
```

Figure 23.5 Result of Horizontal Concatenation of Character Matrices

f					
A	B	C	GH	IJ	
D	E	F	KL	MN	

You can use the horizontal concatenation operator when one of the arguments has no value. For example, if **x** has not been defined and **y** is a matrix, **x||y** results in a new matrix equal to **y**.

Concatenation Operator, Vertical: //

```
matrix1 // matrix2 ;
```

The vertical concatenation operator (**//**) produces a new matrix by vertically joining *matrix1* and *matrix2*. The matrices must have the same number of columns, which is also the number of columns in the new matrix. The number of rows in the new matrix is the number of rows in *matrix1* plus the number of rows in *matrix2*.

For example, the following statements produce the matrix **c**, shown in [Figure 23.6](#):

```
a = {1 1 1,
      7 7 7};
b = {0 0 0,
      8 8 8};
c = a//b;
print c;
```

Figure 23.6 Result of Vertical Concatenation

c		
1	1	1
7	7	7
0	0	0
8	8	8

For character matrices, the element size of the result matrix is the larger of the element sizes of the two operands, as shown in [Figure 23.7](#):

```
d = {"AB" "CD",
      "EF" "GH"};
e = {"I" "J",
      "K" "L",
      "M" "N"};
f = d//e;
print f;
```

Figure 23.7 Result of Vertical Concatenation

f			
AB		CD	
EF		GH	
I		J	
K		L	
M		N	

You can use the vertical concatenation operator when one of the arguments has not been assigned a value. For example, if **x** has not been defined and **y** is a matrix, **x//y** results in a new matrix equal to **y**.

Direct Product Operator: @

matrix1 @ matrix2 ;

The direct product operator (@) computes a new matrix that is the direct product (also called the *Kronecker product*) of *matrix1* and *matrix2*. For matrices **A** and **B**, the direct product is denoted by $\mathbf{A} \otimes \mathbf{B}$. The number of rows in the new matrix equals the product of the number of rows in *matrix1* and the number of rows in *matrix2*; the number of columns in the new matrix equals the product of the number of columns in *matrix1* and the number of columns in *matrix2*.

Specifically, if **A** is an $n \times p$ matrix and **B** is a $m \times q$ matrix, then the Kronecker product $\mathbf{A} \otimes \mathbf{B}$ is the following $nm \times pq$ block matrix:

$$\mathbf{A} \otimes \mathbf{B} = \begin{bmatrix} A_{11}B & \cdots & A_{1p}B \\ \vdots & \ddots & \vdots \\ A_{n1}B & \cdots & A_{np}B \end{bmatrix}$$

For example, the following statements compute the matrices **c** and **d**, which are shown in [Figure 23.8](#):

```
a = {1 2,
      3 4};
b = {0 2};
c = a@b;
d = b@a;
print c, d;
```

Figure 23.8 Results of Direct Product Computation

c			
0	2	0	4
0	6	0	8

Figure 23.8 *continued*

d			
0	0	2	4
0	0	6	8

Notice that the direct product of two matrices is not commutative.

The direct product is used in several areas of statistics. For example, in complete balanced designs the sums of squares and the covariance matrices can be expressed in terms of direct products (Hocking 1985).

Division Operator: /

matrix1 / *matrix2* ;

matrix / *scalar* ;

matrix / *vector* ;

The division operator (/) divides each element of *matrix1* by the corresponding element of *matrix2*, producing a matrix of quotients.

You can also use the division operator to conveniently divide all elements of a matrix, each column of a matrix, or each row of a matrix.

- When you use the *matrix* / *scalar* form, each element of the matrix is divided by the scalar value.
- When you use the *matrix* / *vector* form, each row or column of the $n \times p$ matrix is divided by a corresponding element of the vector.
 - If you divide by an $n \times 1$ column vector, each row of the matrix is divided by the corresponding row of the vector.
 - If you divide by a $1 \times p$ row vector, each column of the matrix is divided by the corresponding column of the vector.

When an element of a matrix contains a missing value, the corresponding element of the quotient is also a missing value.

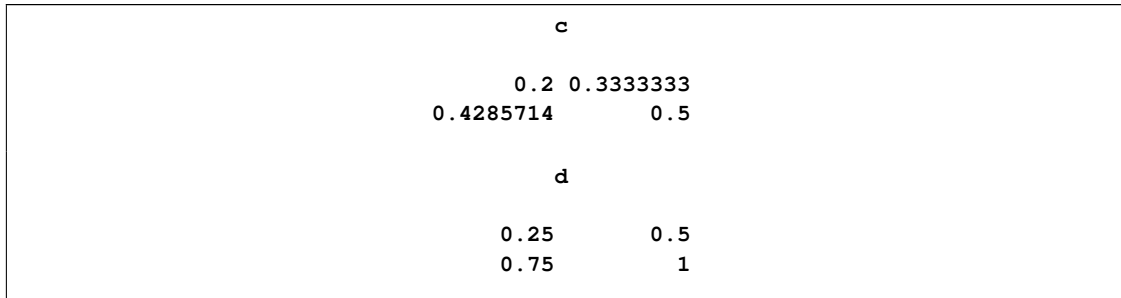
If a divisor is zero, the operation displays a warning and assigns a missing value for the corresponding element in the result.

The following statements compute the matrices **c** and **d**, shown in [Figure 23.9](#):

```
a = {1 2,
      3 4};
b = {5 6,
      7 8};
```

```
c = a/b;
d = a/4;
print c, d;
```

Figure 23.9 Results of Division



Element Maximum Operator: `<>`

```
matrix1 <> matrix2 ;
```

```
matrix <> scalar ;
```

```
matrix <> vector ;
```

The element maximum operator (`<>`) compares each element of *matrix1* to the corresponding element of *matrix2*. The two matrices must be conformable. The operator computes a new matrix that contains the larger of the two values that are being compared.

- If either argument is a scalar, then an elementwise comparison is performed between each element of the matrix and the scalar.
- You can also compare a matrix with a row or column vector, in which case the comparison is performed between the vector and each row or column of the $n \times p$ matrix.
 - If you compare with an $n \times 1$ column vector, each row of the matrix is compared with the corresponding row of the vector.
 - If you compare with a $1 \times p$ row vector, each column of the matrix is compared with the corresponding column of the vector.

If a numeric missing value occurs in a matrix, the operator treats it as a value that is less than any valid nonmissing value.

The element maximum operator can take as operands two character matrices or a character matrix and a character string. Character values are compared in ASCII order. In ASCII order, numerals precede uppercase letters, which precede lowercase letters. If the element lengths of character operands are different, the shorter elements are padded on the right with blanks. The element length of the result is the longer of the two operand element lengths.

For example, the following statements compute the matrix *c*, shown in [Figure 23.10](#):

```

a = { 2  4  6,
      10 11 12};
b = { 1  9  2,
      20 10 40};
c = a<>b;
print c;

```

Figure 23.10 Maximum Elements

c		
2	9	6
20	11	40

Element Minimum Operator: $><$

```
matrix1 >< matrix2 ;
```

```
matrix1 >< scalar ;
```

```
matrix1 >< vector ;
```

The element minimum operator ($><$) compares each element of *matrix1* with the corresponding element of *matrix2*. The two matrices must be conformable. The operator computes a new matrix that contains the smaller of the two values that are being compared.

- If either argument is a scalar, then an elementwise comparison is performed between each element of the matrix and the scalar.
- You can also compare a matrix with a row or column vector, in which case the comparison is performed between the vector and each row or column of the $n \times p$ matrix.
 - If you compare with an $n \times 1$ column vector, each row of the matrix is compared with the corresponding row of the vector.
 - If you compare with a $1 \times p$ row vector, each column of the matrix is compared with the corresponding column of the vector.

If a numeric missing value occurs in a matrix, the operator treats it as a value that is less than any valid nonmissing value.

The element minimum operator can take as operands two character matrices or a character matrix and a character string. Character values are compared in ASCII order. In ASCII order, numerals precede uppercase letters, which precede lowercase letters. If the element lengths of character operands are different, the shorter elements are padded on the right with blanks. The element length of the result is the longer of the two operand element lengths.

For example, the following statements compute the matrix **c**, shown in [Figure 23.10](#):

```

a = { 2  4  6,
      10 11 12};
b = { 1  9  2,
      20 10 40};
c = a>b;
print c;

```

Figure 23.11 Minimum Elements

c			
1	4	2	
10	10	12	

Index Creation Operator: :

value1 : *value2* ;

The index creation operator (:) creates a row vector with a first element that is *value1*. The second element is *value1*+1, and so on, until the last element which is less than or equal to *value2*.

For example, the following statement creates the vector **s** which contains consecutive integers, shown in Figure 23.12:

```

s = 7:10;
print s;

```

Figure 23.12 Increasing Sequence

s				
7	8	9	10	

If *value1* is greater than *value2*, a reverse-order index is created. For example, the following statement creates the vector **r** which contains a decreasing sequence of integers, shown in Figure 23.13:

```

r = 10:6;
print r;

```

Figure 23.13 Decreasing Sequence

r				
10	9	8	7	6

Neither *value1* nor *value2* is required to be an integer. Use the **DO** function if you want an increment other than 1 or -1.

The index creation operator also works on character arguments with a numeric suffix. For example, the following statements create a sequence of values that begin with the prefix “var”, shown in [Figure 23.14](#):

```
varList = "var1":"var5";
print varList;
```

Figure 23.14 Sequence of Character Values

varList				
var1	var2	var3	var4	var5

Sequences of character values are often used to assign names to variables. You can use the string concatenation operator to dynamically determine the length of a sequence, as shown in the following statements:

```
x = {1 2 3 4,
      5 6 7 8,
      7 6 5 4};
numVar = ncol(x);           /* 4 columns */
varNames = "X1":"X"+strip(char(numVar)); /* "X1":"X4" */
print x[colname=varNames];
```

Figure 23.15 Sequence of Variable Names

				x
	x1	x2	x3	x4
	1	2	3	4
	5	6	7	8
	7	6	5	4

Logical Operators: &, |, ^

matrix1 & *matrix2* ;

matrix & *scalar* ;

matrix & *vector* ;

matrix1 | *matrix2* ;

matrix | *scalar* ;

matrix | *vector* ;

^*matrix* ;

The logical operators compare two matrices element by element and create a new matrix. For logical comparisons, a missing value is handled as if it is a zero value. That is, in the text that follows in this section, “nonzero” really means “nonzero and nonmissing.”

An element of the new matrix computed by the OR operator (`|`) is 1 if either of the corresponding elements of *matrix1* and *matrix2* is nonzero. If both are zero (or missing), the new element is zero.

An element of the new matrix computed by the AND logical operator (`&`) is 1 if the corresponding elements of *matrix1* and *matrix2* are both nonzero; otherwise, it is zero.

If either operand is a scalar, the OR and AND operators perform a logical comparison between each element and the scalar value. If either operand is a row or column vector, then the operation is performed by using that vector on each of the rows or columns of the matrix.

The NOT prefix operator (`^`) examines each element of a matrix and computes a new matrix that contains elements that are ones and zeros. If an element of *matrix* is zero or missing, the corresponding element in the new matrix is 1. If an element of *matrix* is nonzero, the corresponding element in the new matrix is 0.

The following statements illustrate the use of these logical operators. The results are shown in [Figure 23.16](#):

```
x = {0 1 0 1 . .};
y = {1 1 0 0 1 0};
u = x|y;
v = x&y;
w = ^x;
print u, v, w;
```

Figure 23.16 Results of Logical Comparisons

u					
1	1	0	1	1	0
v					
0	1	0	0	0	0
w					
1	0	1	0	1	1

Multiplication Operator, Elementwise:

```
matrix1 # matrix2 ;
```

```
matrix # scalar ;
```

```
matrix # vector ;
```

The elementwise multiplication operator (`#`) computes a new matrix with elements that are the products of the corresponding elements of *matrix1* and *matrix2*.

For example, the following statements compute the matrix **ab**, shown in [Figure 23.17](#):

```
a = {1 2,
      3 4};
b = {4 8,
      0 5};
ab = a#b;
print ab;
```

Figure 23.17 Results of Elementwise Multiplication

ab	
4	16
0	20

In addition to multiplying matrices that have the same dimensions, you can use the elementwise multiplication operator to multiply a matrix and a scalar.

- When either argument is a scalar, each element in *matrix* is multiplied by the scalar value.
- When you use the *matrix* # *vector* form, each row or column of the $n \times p$ matrix is multiplied by a corresponding element of the vector.
 - If you multiply by an $n \times 1$ column vector, each row of the matrix is multiplied by the corresponding row of the vector.
 - If you multiply by a $1 \times p$ row vector, each column of the matrix is multiplied by the corresponding column of the vector.

For example, a 2×3 matrix can be multiplied on either side by a 2×3 , 1×3 , 2×1 , or 1×1 matrix. The following statements multiply the 2×2 matrix **a** by a column vector and a row vector. The results are shown in Figure 23.18.

```
c = {10, 100};      /* column vector */
r = {10 100};       /* row vector    */
ac = a#c;
ar = a#r;
print ac, ar;
```

Figure 23.18 Elementwise Multiplication with Vectors

ac	
10	20
300	400
ar	
10	200
30	400

Elementwise multiplication is also known as the Schur or Hadamard product. Elementwise multiplication (which uses the `#` operator) should not be confused with matrix multiplication (which uses the `*` operator).

When an element of a matrix contains a missing value, the corresponding element of the product is also a missing value.

Multiplication Operator, Matrix: `*`

```
matrix1 * matrix2 ;
```

The matrix multiplication operator (`*`) computes a new matrix by performing matrix multiplication. The first matrix must have the same number of columns as the second matrix has rows. The new matrix has the same number of rows as the first matrix and the same number of columns as the second matrix. That is, if A is an $n \times p$ matrix and B is a $p \times m$ matrix, then the product $A * B$ is an $n \times m$ matrix. The ij th element of the product is the sum $\sum_{k=1}^p A_{ik} B_{kj}$.

The matrix multiplication operator does not support missing values.

The following statements multiply matrices. The results are shown in [Figure 23.19](#).

```
a = {1 2,
      3 4};
b = {1 2};
c = b*a;
d = a*b`;
print c, d;
```

Figure 23.19 Result of Matrix Multiplication

	c	
	7	10
	d	
		5
		11

Power Operator, Elementwise: `##`

```
matrix1 ## matrix2 ;
```

```
matrix ## scalar ;
```

```
matrix ## vector ;
```

The elementwise power operator (`##`) creates a new matrix with elements that are the elements of *matrix1*

raised to the power of the corresponding element of *matrix2*. If any value in *matrix1* is negative, the corresponding element in *matrix2* must be an integer.

The elementwise power operator enables either operand to be a scalar or a row or column vector.

- If either operand is scalar, the operation applies the power operator to each element and the scalar value.
- When you use the *matrix / vector* form, each row or column of the $n \times p$ matrix is raised to a power given by a corresponding element of the vector.

When an element of either matrix contains a missing value, the corresponding element of the result is also a missing value.

For example, the following statements raise each element of a matrix to a power, as shown in [Figure 23.20](#):

```
a = {1 2 3};
b = a##3;
c = a##0.5;
print b, c;
```

Figure 23.20 Result of Raising Each Element to a Power

b		
1	8	27
c		
1	1.4142136	1.7320508

Power Operator, Matrix: **

matrix ** *scalar* ;

The matrix power operator (**) creates a new matrix that is *matrix* multiplied by itself *scalar* times. The *matrix* argument must be square; *scalar* must be an integer greater than or equal to -1 . If the scalar is not an integer, it is truncated to an integer.

For example, the following statements compute a matrix that is the result of multiplying a matrix by itself. The result is shown in [Figure 23.21](#).

```
a = {1 2,
     1 1};
c = a**2;
print c;
```

Figure 23.21 Result of Raising a Matrix to a Power

c	
3	4
2	3

Note that the expression `a**(-1)` is shorthand for matrix inversion, as shown by the following statements:

```
inv = a**(-1);           /* shorthand for matrix inversion */
ident = inv * a;
print inv, ident;
```

Figure 23.22 Matrix Inversion by Using the Power Operator

inv	
-1	2
1	-1
ident	
1	0
0	1

The matrix power operator does not support missing values.

Raising a matrix to a large power can cause numerical precision problems. If the matrix is symmetric, it is preferable to operate on its eigenvalues (see the [EIGEN call](#)) rather than to use the matrix power operator directly on the matrix, as shown in the following example:

```
b = {2 1,
     1 1};
call eigen(lambda, E, b); /* recall that b = E*diag(lambda)*E` */
power = 20;
d = lambda##power;
a20 = E*diag(d)*E`;      /* a**20 since E`*E = Identity */
print a20;
```

Figure 23.23 Matrix Powers by Using Eigenvalues

a20	
165580141	102334155
102334155	63245986

Sign Reversal Operator: $-$

$-matrix$;

The sign reversal operator ($-$) computes a new matrix that contains elements that are formed by reversing the sign of each element in *matrix*. The sign reversal operator is also called the *unary minus* operator.

When an element of the matrix contains a missing value, the corresponding element of the result also contains a missing value.

The following statements reverse the signs of each element of a matrix, as shown in [Figure 23.24](#):

```
a = {-1  7  6,
      2  0 -8};
b = -a;
print b;
```

Figure 23.24 The Result of a Sign Reversal Operator

b		
1	-7	-6
-2	0	8

Subscripts: []

matrix[*rows*, *columns*] ;

matrix[*elements*] ;

Subscripts are used with matrices to select submatrices, where *rows* and *columns* are expressions that evaluate to scalars or vectors. If these expressions are numeric, they must contain valid subscript values of rows and columns in the argument matrix.

For example, the following statements select elements from the second row of the matrix **x**:

```
x = {1 2 3,
      4 5 6,
      7 8 9};
a = 3;
y = x[2, a];
b = 1:3;
z = x[2, b];
w = x[{4 6}];
print y, z, w;
```

Figure 23.25 Submatrices Formed by Specifying Indices

			y		
				6	
			z		
	4		5		6
			w		
				4	
				6	

The output is shown in [Figure 23.25](#). The matrix **y** contains the element of **x** from the second row and the third column. The matrix **z** contains the entire second row of **x**. The matrix **w** contains the fourth and sixth elements of **x**. Because SAS/IML software store matrices in row-major order, **w** contains the first and third elements from the second row of **x**.

If a row or column expression is a character matrix, then it refers to columns or rows in the argument matrix that are assigned corresponding labels by a [MATTRIB statement](#) or [READ statement](#). For example, the following statements select elements from the second row of **x**, and from the first and third columns:

```
x = {1 2 3,
      4 5 6,
      7 8 9};
c = "col1":"col3";
r = "row1":"row3";
mattrib x colname=c rowname=r;
a = {"col1" "col3"};
m = x["row2", a];
print m;
```

Figure 23.26 Submatrices Formed by Specifying Column Names

		m	
	4	6	

A subscripted matrix can appear on the left side of the equal sign. The dimensions of the target submatrix must conform to the dimensions of the source matrix, as shown in the following statements:

```
x[1, {1 3}] = .;
x[{1 2}, 2] = {0, 1};
x[7] = -1;
print x;
```

Figure 23.27 Result of Assigning Submatrices of an Existing Matrix

	x		
	col1	col2	col3
row1	.	0	.
row2	4	1	6
row3	-1	8	9

See the section “Using Matrix Expressions” on page 50 for further information about matrix subscripts.

Subtraction Operator: –

matrix1 – *matrix2* ;

matrix – *scalar* ;

matrix – *vector* ;

The subtraction operator (–) computes a new matrix that contains elements that are formed by subtracting the corresponding elements of *matrix2* from those of *matrix1*.

In addition to subtracting conformable matrices, you can also use the subtraction operator to subtract a scalar from a matrix or subtract a vector from a matrix.

- When either argument is a scalar, the subtraction is performed between the scalar and each element of the matrix argument. For example, when you use the *matrix* – *scalar* form, the scalar value is subtracted from each element of the matrix.
- When you use the *matrix* – *vector* form, the vector is subtracted from each row or column of the $n \times p$ matrix.
 - If you subtract an $n \times 1$ column vector, each row of the vector is subtracted from each row of the matrix.
 - If you subtract a $1 \times p$ row vector, each column of the vector is subtracted from each column of the matrix.

When an element of the matrix contains a missing value, the corresponding element of the result also contains a missing value.

For example, the following statements subtract two matrices and store the result in the matrix **c**, shown in Figure 23.28:

```
a = {1 2,
      3 4};
b = {1 1,
      1 1};
c = a-b;
```

```
print c;
```

Figure 23.28 Difference of Two Matrices

c		
0	1	
2	3	

Transpose Operator: `

```
matrix `;
```

The transpose operator, denoted by the backquote character (`), exchanges the rows and columns of *matrix*, producing the transpose of *matrix*. If v is the value in the i th row and j th column of *matrix*, then the transpose of *matrix* contains v in the j th row and i th column. If *matrix* contains n rows and p columns, the transpose has p rows and n columns.

For example, the following statements transpose the matrix **a**, shown in [Figure 23.29](#):

```
a = {1 2,
      3 4,
      5 6};
b = a`;
print b;
```

Figure 23.29 Transpose of a Matrix

b		
1	3	5
2	4	6

You can also transpose a matrix with the [T function](#).

Statements, Functions, and Subroutines

This section presents descriptions of all statements, functions, and subroutines that are available in SAS/IML software.

ABORT Statement

ABORT ;

The ABORT statement instructs PROC IML to stop executing statements. It also stops PROC IML from parsing any further statements, causing PROC IML to close its files and exit. See also the description of the **STOP** statement.

The ABORT statement is the run-time equivalent of the QUIT statement. That is, you can use the ABORT statement as part of logical statements such as IF-THEN/ELSE statements, as shown in the following statements:

```
proc iml;
do i = 1 to 10;
  if i>2 then
    abort;
  print i;
end;
/* SAS/IML statements after this line are never executed. */
```

Figure 23.30 Result of Aborting a Computation

i
1
i
2

ABS Function

ABS(matrix);

The ABS function returns the absolute value of every element of the argument matrix, as shown in the following statements:

```
x = -2:2;
a = abs(x);
print a;
```

Figure 23.31 Absolute Values

a				
2	1	0	1	2

ALL Function

ALL(*matrix*);

The ALL function returns a value of 1 if all elements in *matrix* are nonzero. If any element of *matrix* is zero or missing, the ALL function returns a value of 0.

You can use the ALL function to express the results of a comparison operator as a single 1 or 0. For example, the following statement compares elements in two matrices:

```
a = { 1 2, 3 4};
b = {-1 0, 0 1};
if all(a>b) then
  msg = "a[i,j] > b[i,j] for all i,j";
else
  msg = "for some element, a[i,j] is not greater than b[i,j]";
print msg;
```

Figure 23.32 Result of Comparing All Elements

<p style="text-align: center;">msg</p> <p style="text-align: center;">a[i,j] > b[i,j] for all i,j</p>
--

In the preceding statements, the comparison operation **a>b** creates a matrix of zeros and ones. The ALL function returns a value of 1 because every element of **a** is greater than the corresponding element of **b**.

The ALL function is implicitly applied to the evaluation of all conditional expressions, so in fact the previous IF-THEN statement is equivalent to the following:

```
if a>b then      /* implicit ALL */
  msg = "a[i,j] > b[i,j] for all i,j";
```

ALLCOMB Function

ALLCOMB(*n*, *k*);

ALLCOMB(*n*, *comb*, <, *idx*>);

The ALLCOMB function generates all combinations of *k* elements taken from a set of *n* numerical indices. The combinations are produced in the same order and using the same algorithm (Nijenhuis and Wilf 1978) as the ALLCOMBI function in Base SAS software. In particular, the function returns indices in the range 1–*n*, and each combination is in sorted order.

By default, the ALLCOMB function returns a matrix with $\binom{n}{k}$ rows and *k* columns. Each row of the returned matrix represents a single combination. The following statements generate all combinations of two elements from the set {1, 2, 3, 4}:


```

n = 4; /* used throughout this example */
k = 2; /* used throughout this example */
c = allcomb(n, k);
print c;

```

Figure 23.33 All Pairwise Combinations of Four Items

c	
1	2
2	3
1	3
3	4
2	4
1	4

The second argument can be a scalar or a vector. If it is a vector, it must contain a valid combination of the set $\{1, 2, \dots, n\}$. (To be valid, the *comb* elements must be in increasing order.) The number of elements in the vector determines the value of k . For example, the following statements generate all combinations of length two from a set with four elements, beginning with the third combination that is shown in [Figure 23.33](#):

```
d = allcomb(4, {1 3});
```

To obtain all combinations in order, initialize the *comb* argument to $1:k$ or to the zero vector with k elements.

The optional third argument, *idx*, controls the number of rows in the output of the function. If you specify *idx*, then the sequence is initialized with the *comb* argument and the first row of the output is the combination that occurs *after* the *comb* argument. For example, the following statements generate five pairwise combinations, beginning *after* the third combination shown in [Figure 23.33](#):

```
e = allcomb(n, {1 3}, 1:5);
```

The *idx* argument must consist of consecutive integers; you cannot use it to randomly access combinations that are out of sequence. The *idx* argument is often used to generate one or more combinations in a loop so that you do not need to allocate a huge matrix that contains all of the combinations at once. The following statements illustrate this usage. Notice that you should initialize the *comb* argument to the zero vector if you want the first result to be the combination $1:k$.

```

ncomb = comb(n, k);
comb = j(1, k, 0);
do i=1 to ncomb;
    comb = allcomb(n, comb, i);
    /* do something with the i_th combination */
end;

```

If you want the combinations in lexicographic order, generate the combinations and then use the [SORT subroutine](#), as follows:

```

c = allcomb(n, k);
call sort(c, 1:k);

```

ALLPERM Function

ALLPERM(*n*);

ALLPERM(*set*, <, *idx*>);

The ALLPERM function generates all permutations of a set with n elements. The permutations are produced in the same order and using the same algorithm (Trotter 1962) as the ALLPERM function in Base SAS software.

By default, the ALLPERM function returns a matrix with $n!$ rows and n columns. Each row of the returned matrix represents a single permutation. The following statements generate all permutations of the set {1, 2, 3}:

```
n = 3;
p = allperm(n);
print p;
```

Figure 23.34 All Permutations of Three Items

p		
1	2	3
1	3	2
3	1	2
3	2	1
2	3	1
2	1	3

The first argument can be a scalar or a vector. If it is a vector, the number of elements in the vector determines the value of n . The ALLPERM function can compute permutations of arbitrary numeric or character matrices. For example, the following statements compute permutations of an unsorted character vector:

```
a = allperm({'C B A'});
print a;
```

Figure 23.35 All Permutations of a Character Vector

a		
C	B	A
C	A	B
A	C	B
A	B	C
B	A	C
B	C	A

The optional second argument, *idx*, can be used to control the number of rows in the output of the function. The argument must consist of consecutive integers; you cannot use it to randomly access permutations that

are out of sequence. The second argument is often used to generate one or more permutations in a loop so that you do not need to allocate a huge matrix that contains all of the permutations at once. The following statements illustrate this usage:

```
perm = 1:n;
do i=1 to fact(n);
  perm = allperm(perm, i);
  /* do something with the i_th permutation */
end;
```

If you want the permutations in lexicographic order, generate the permutations and then use the [SORT subroutine](#), as follows:

```
p = allperm(n);
call sort(p, 1:n);
```

ANY Function

ANY(*matrix*);

The ANY function returns a value of 1 if any of the elements in *matrix* are nonzero. If all the elements of *matrix* are zero or missing, the ANY function returns a value of 0.

You can use the ANY function to compare elements in two matrices, as shown in the following statements:

```
a = {1 2, 3 4};
b = {3 2, 1 0};
if any(a=b) then
  msg = "for some element, a[i,j] equals b[i,j]";
else
  msg = "a ^= b";
print msg;
```

Figure 23.36 Result of Comparing Elements

<p style="text-align: center;">msg</p> <p style="text-align: center;">for some element, a[i,j] equals b[i,j]</p>
--

In the preceding statements, the IF-THEN expression is true if at least one element in **a** is the same as the corresponding element in **b**. You can use the [ALL](#) function to compare all of the elements in two matrices.

APPCORT Call

CALL APPCORT(*prqb, lindep, a, b, <, sing>*);

If \mathbf{A} is rank-deficient, then the least squares problem $\min_{\mathbf{x}} \|\mathbf{Ax} - \mathbf{b}\|_2^2$ has infinitely many solutions (Golub and Van Loan 1989, p. 241). However, there is a unique solution which has the smallest Euclidean norm. The APPCORT subroutine computes the minimum Euclidean-norm solution of the (rank-deficient) least squares problem by applying a complete orthogonal decomposition by Householder transformations to the vector \mathbf{b} .

The input arguments to the APPCORT subroutine are as follows:

a is an $m \times n$ matrix \mathbf{A} , with $m \geq n$, which is to be decomposed into the product of the $m \times m$ orthogonal matrix \mathbf{Q} , the $n \times n$ upper triangular matrix \mathbf{R} , and the $n \times n$ orthogonal matrix \mathbf{P} ,

$$\mathbf{A} = \mathbf{Q} \begin{bmatrix} \mathbf{R} \\ \mathbf{0} \end{bmatrix} \mathbf{\Pi}' \mathbf{P}' \mathbf{\Pi}$$

b is a $m \times p$ matrix, \mathbf{B} .

sing is an optional scalar that specifies a singularity criterion.

The APPCORT subroutine returns the following values:

prqb is an $n \times p$ matrix product

$$\mathbf{P}\mathbf{\Pi} \begin{bmatrix} (\mathbf{L}')^{-1} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} \end{bmatrix} \mathbf{Q}'\mathbf{B}$$

which is the minimum Euclidean-norm solution of the rank-deficient least squares problem $\|\mathbf{Ax} - \mathbf{b}\|_2^2$.

lindep is the number of linearly dependent columns in the matrix \mathbf{A} that are detected by applying the r Householder transformations. That is, *lindep* is $n - r$, where r is the numerical rank of \mathbf{A} .

See the section “COMPORT Call” on page 611 for information about complete orthogonal decomposition.

The following example uses the APPCORT call to solve a rank-deficient least squares problem:

```
/* compute solution for rank-deficient least squares problem:
   min |Ax-b|^2
   The range of A is a line; b is a point not on the line. */
A = {1  2,
     2  4,
     -1 -2};
b = {1, 3, -2};
call appcort(x, lindep, A, b);
print x;
```

Figure 23.37 Solution to a Rank-Deficient Least Squares Problem

\mathbf{x}
0.3
0.6

The argument *b* can also be a matrix. If *b* is an identity matrix, then you can use the APPCORT subroutine to form a generalized inverse, as shown in the following example:

```

/* A has only four linearly independent columns */
A = {1 0 1 0 0,
      1 0 0 1 0,
      1 0 0 0 1,
      0 1 1 0 0,
      0 1 0 1 0,
      0 1 0 0 1 };

/* compute Moore-Penrose generalized inverse */
b = i(nrow(A));          /* identity matrix */
call appcort(Ainv, lindep, A, b);
print Ainv;

/* verify generalized inverse conditions (Golub & Van Loan, p. 243) */
eps = 1e-12;
if any(A*Ainv*A-A > eps) |
   any(Ainv*A*Ainv-Ainv > eps) |
   any((A*Ainv)`-A*Ainv > eps) |
   any((Ainv*A)`-Ainv*A > eps) then
   msg = "Pseudoinverse conditions not satisfied";
else
   msg = "Pseudoinverse conditions satisfied";
print msg;

```

Figure 23.38 Generalized Inverse

Ainv					
0.2666667	0.2666667	0.2666667	-0.0666667	-0.0666667	-0.0666667
-0.0666667	-0.0666667	-0.0666667	0.2666667	0.2666667	0.2666667
0.4	-0.1	-0.1	0.4	-0.1	-0.1
-0.1	0.4	-0.1	-0.1	0.4	-0.1
-0.1	-0.1	0.4	-0.1	-0.1	0.4
msg					
Pseudoinverse conditions satisfied					

APPEND Statement

APPEND <VAR *operand*> ;

APPEND <FROM *matrix*> <[**ROWNAME**=*row-name*]> ;

The APPEND statement adds observations to the end of a SAS data set.

The arguments to the APPEND statement are as follows:

operand is specified as one of the following:

- a literal matrix that contains variable names
- a character matrix that contains variable names
- an expression in parentheses that yields variable names
- one of the following keywords:

ALL	for all variables
CHAR	for all character variables
NUM	for all numeric variables

matrix is the name of a matrix that contains data to append.

row-name is a character matrix or quoted literal that contains descriptive row names.

You can use the APPEND statement to add data to the end of the current output data set. The appended observations are from either the variables specified in the VAR clause or variables created from the columns of *matrix*. The FROM clause and the VAR clause cannot be specified together.

The APPEND statement is usually used without any arguments. A common practice is to specify the data in the CREATE statement, as shown in the following example:

```
proc iml;
  x = {1,2,3,4};          /* 4 x 1 vector */
  y = {4 3,2 1};          /* 2 x 2 matrix */
  z = {2,3,4};            /* 3 x 1 vector */
  c = {A,B,C,D};          /* 4 x 1 character vector */

  create Temp1 var {x y}; /* Temp1 contains two variables */
  append;                 /* appends data from x and y */
  close Temp1;
  quit;

  proc print data=Temp1 noobs;
  run;
```

The values in the Temp1 data set are shown in [Figure 23.39](#). Notice that the 2×2 matrix **y** is written to the data set in row-major order.

Figure 23.39 Data Set That Contains One Variable for Each Specified Matrix

	x	y
1	1	4
2	2	3
3	3	2
4	4	1

If you omit the VAR (and FROM) clause in the CREATE statement, then the new data set contains a variable for each SAS/IML matrix that is in scope. You can use the VAR clause in the APPEND statement to write specific variables. Variables that are not explicitly specified receive missing values, as shown in the

following statements:

```
proc iml;
  x = {1,2,3,4};          /* 4 x 1 vector */
  y = {4 3,2 1};          /* 2 x 2 matrix */
  z = {2,3,4};            /* 3 x 1 vector */
  c = {A,B,C,D};          /* 4 x 1 character vector */

  create Temp2;            /* Temp2 contains a variable for each matrix */
  append var {c x z};      /* y gets missing values */
  close Temp2;
  quit;

proc print data=Temp2 noobs;
run;
```

The values in the Temp2 data set are shown in [Figure 23.40](#). The data set contains four observations because that is the number of elements in the matrix with the greatest number of elements. Elements are appended in row-major order. Notice that the variable *z* contains a missing value at the end because the variable was created from a SAS/IML matrix that contained fewer than four elements.

Figure 23.40 Data Set That Contains One Variable for Each Matrix

	c	x	y	z
	A	1	.	2
	B	2	.	3
	C	3	.	4
	D	4	.	.

As shown in the previous example, the default variables for the APPEND statement are all matrices that match variables in the current data set with respect to name and type.

The ROWNAME= option in the FROM clause specifies the name of a character matrix to contain row titles. Use this option in conjunction with the IDENTICAL option in the FROM clause of the CREATE statement, as shown in the following statements:

```
proc iml;
  VarName = {"x" "y"};
  w = {3 96,
        4 90,
        2 100,
        4 92};          /* data matrix */
  cov = cov(w);          /* sample covariance matrix of data */

  create Temp3 from cov[rowname=VarName colname=VarName];
  append from cov[rowname=VarName];
  close Temp3;
  quit;

proc print data=Temp3 noobs;
run;
```

The values in the Temp3 data set are shown in [Figure 23.41](#). The matrix *cov* contains the data that is saved

to the Temp3 data set. The character vector **VarName** contains the names of the variables for the Temp3 data set. (If you use the FROM clause in the CREATE statement, but do not specify the COLNAME= option, then the variables are named COL1, COL2, and so on.) The ROWNAME= option enables you to specify a single character variable when you are creating a data set from a numerical matrix. This is useful for specifying variable names in a correlation or covariance matrix, but can also be used more generally to specify a row label for each observation.

Figure 23.41 Data Set That Contains Row Labels

Var Name	x	y
x	0.91667	-4.1667
y	-4.16667	19.6667

If you do not specify the ROWNAME= option in the CREATE statement, then you do not need to specify the ROWNAME= option in the APPEND statement, as shown in the following example:

```
create Temp3 from cov[colname=VarName];
append from cov;
close Temp3;
```

You can also use the APPEND statement with the [EDIT statement](#). See the documentation for the EDIT statement for examples.

APPLY Function

APPLY(*modname*, *argument1* < , *argument2*, . . . , *argument14* >);

The APPLY function applies a user-defined module to each element of the argument matrix or matrices and returns a matrix of results.

The arguments to the APPLY statement are as follows:

- modname* specifies the name of an existing function module. You can specify the module name as a literal string or as matrix that contains the module name.
- argument* specifies an argument passed to the module. You must have at least one argument. You can specify up to 15 arguments.

The first argument to APPLY is the name of a function module. The module must take scalar arguments and must already be defined before the APPLY function is executed. The subsequent arguments to the APPLY function are the arguments passed to the module. They all must have the same dimension.

If the function module takes n scalar arguments, *argument1* through *argumentn* should be passed to APPLY where $1 \leq n \leq 14$. The APPLY function calls the module one time for each element in its input arguments. The result has the same dimension as the input arguments, and each element of the result corresponds to the module applied to the corresponding elements of the argument matrices. The APPLY function can work on

numeric in addition to character arguments. For example, the following statements define module ABC and then call the APPLY function, with matrix **a** as an argument:

```
start abc(x);
  r = x + 100;
  return (r);
finish abc;

a = {6  7  8,
     9 10 11};
s = apply("ABC", a);
print s;
```

The result is shown in [Figure 23.42](#).

Figure 23.42 Result of a Module Applied to Each Argument in a Matrix

s		
106	107	108
109	110	111

The module can also alter the contents of the arguments. In the following example, the statements define the module ABSDIFF and call the APPLY function:

```
/* compute abs(x-y); permute elements of x and y so that x[i] >= y[i] */
start AbsDiff(x, y);
  if x<y then do; /* swap x and y */
    t = x;
    x = y;
    y = t;
  end;
  return( x-y );
finish;

a = {-1 0 1};
b = {-2 0 2};
mod = "AbsDiff";
r = apply(mod, a, b);
print a, b, r;
```

Notice that the third element of the **a** and **b** arguments are exchanged, as shown in [Figure 23.43](#).

Figure 23.43 Result of a Module Applied to Each Argument in a Matrix

a		
-1	0	2
b		
-2	0	1

Figure 23.43 *continued*

			r		
		1	0	1	

ARMACOV Call

CALL ARMACOV(*auto, cross, convol, phi, theta, num*);

The ARMACOV subroutine computes an autocovariance sequence for an autoregressive moving average (ARMA) model. The input arguments to the ARMACOV subroutine are as follows:

<i>phi</i>	refers to a $1 \times (p + 1)$ matrix that contains the autoregressive parameters. The first element is assumed to have the value 1.
<i>theta</i>	refers to a $1 \times (q + 1)$ matrix that contains the moving average parameters. The first element is assumed to have the value 1.
<i>num</i>	refers to a scalar that contains n , the number of autocovariances to be computed, which must be a positive number.

The ARMACOV subroutine returns the following values:

<i>auto</i>	specifies a variable to contain the returned $1 \times n$ matrix that contains the autocovariances of the specified ARMA model, assuming unit variance for the innovation sequence.
<i>cross</i>	specifies a variable to contain the returned $1 \times (q + 1)$ matrix that contains the covariances of the moving-average term with lagged values of the process.
<i>convol</i>	specifies a variable to contain the returned $1 \times (q + 1)$ matrix that contains the autocovariance sequence of the moving-average term.

The ARMACOV subroutine computes the autocovariance sequence that corresponds to a given autoregressive moving-average (ARMA) time series model. An arbitrary number of terms in the sequence can be requested. Two related covariance sequences are also returned.

The model notation for the ARMACOV and [ARMALIK](#) subroutines is the same. The ARMA(p, q) model is denoted

$$\sum_{j=0}^p \phi_j y_{t-j} = \sum_{i=0}^q \theta_i \epsilon_{t-i}$$

with $\theta_0 = \phi_0 = 1$. The notation is the same as that of Box and Jenkins (1976) except that the model parameters are opposite in sign. The innovations $\{\epsilon_t\}$ satisfy $E(\epsilon_t) = 0$ and $E(\epsilon_t \epsilon_{t-k}) = 1$ if $k = 0$, and are zero otherwise. The formula for the k th element of the *convol* argument is

$$\sum_{i=k-1}^q \theta_i \theta_{i-k+1}$$

for $k = 1, 2, \dots, q + 1$. The formula for the k th element of the *cross* argument is

$$\sum_{i=k-1}^q \theta_i \psi_{i-k+1}$$

for $k = 1, 2, \dots, q + 1$, where ψ_i is the i th impulse response value. The ψ_i sequence, if desired, can be computed with the **RATIO** function. It can be shown that ψ_k is the same as $E(Y_{t-k}\epsilon_t^2)/\sigma$, which is used by Box and Jenkins (1976) in their formulation of the autocovariances. The k th autocovariance, denoted γ_k and returned as the $k + 1$ element of the *auto* argument ($k = 0, 1, \dots, n - 1$), is defined implicitly for $k > 0$ by

$$\sum_{i=0}^p \gamma_{k-i} \phi_i = \eta_k$$

where η_k is the k th element of the *cross* argument. See Box and Jenkins (1976) or McLeod (1975) for more information.

Consider the model

$$y_t = 0.5y_{t-1} + e_t + 0.8e_{t-1}$$

To compute the autocovariance function at lags zero through four for this model, use the following statements:

```
/* an ARMA(1,1) model */
phi   = {1 -0.5};
theta = {1 0.8};
call armacov(auto, cross, convol, phi, theta, 5);
print auto, cross convol;
```

The result is shown in Figure 23.44.

Figure 23.44 Result of the ARMACOV Subroutine

auto				
3.2533333	2.4266667	1.2133333	0.6066667	0.3033333
cross		convol		
2.04	0.8	1.64	0.8	

ARMALIK Call

CALL ARMALIK(*lnl*, *resid*, *std*, *x*, *phi*, *theta*);

The ARMALIK subroutine computes the log likelihood and residuals for an autoregressive moving average

(ARMA) model. The input arguments to the ARMALIK subroutine are as follows:

<i>x</i>	is an $n \times 1$ or $1 \times n$ matrix that contains values of the time series (assuming mean zero).
<i>phi</i>	is a $1 \times (p + 1)$ matrix that contains the autoregressive parameter values. The first element is assumed to have the value 1.
<i>theta</i>	is a $1 \times (q + 1)$ matrix that contains the moving average parameter values. The first element is assumed to have the value 1.

The ARMALIK subroutine returns the following values:

<i>lnl</i>	specifies a 3×1 matrix that contains the log likelihood concentrated with respect to the innovation variance; the estimate of the innovation variance (the unconditional sum of squares divided by n); and the log of the determinant of the variance matrix, which is standardized to unit variance for the innovations.
<i>resid</i>	specifies an $n \times 1$ matrix that contains the standardized residuals. These values are uncorrelated with a constant variance if the specified ARMA model is the correct one.
<i>std</i>	specifies an $n \times 1$ matrix that contains the scale factors used to standardize the residuals. The actual residuals from the one-step-ahead predictions that use the past values can be computed as std # resid .

The ARMALIK subroutine computes the concentrated log-likelihood function for an ARMA model. The unconditional sum of squares is readily available, as are the one-step-ahead prediction residuals. Factors that can be used to generate confidence limits associated with prediction from a finite past sample are also returned.

The notational conventions for the ARMALIK subroutine are the same as those used by the ARMACOV subroutine. See the description of the [ARMACOV call](#) for the model employed. In addition, the condition $\sum_{i=0}^q \theta_{iz}^i \neq 0$ for $|z| < 1$ should be satisfied to guard against floating-point overflow.

If the column vector \mathbf{x} contains n values of a time series and the variance matrix is denoted $\Sigma = \sigma^2 \mathbf{V}$, where σ^2 is the variance of the innovations, then, up to additive constants, the log likelihood, concentrated with respect to σ^2 , is

$$-\frac{n}{2} \log (\mathbf{x}' \mathbf{V}^{-1} \mathbf{x}) - \frac{1}{2} \log |\mathbf{V}|$$

The matrix \mathbf{V} is a function of the specified ARMA model parameters. If \mathbf{L} is the lower Cholesky root of \mathbf{V} (that is, $\mathbf{V} = \mathbf{L} \mathbf{L}'$), then the standardized residuals are computed as $\text{resid} = \mathbf{L}^{-1} \mathbf{x}$. The elements of *std* are the diagonal elements of \mathbf{L} . The variance estimate is $\mathbf{x}' \mathbf{V}^{-1} \mathbf{x} / n$, and the log determinant is $\log |\mathbf{V}|$. See Ansley (1979) for further details. Consider the following model:

$$y_t - y_{t-1} + 0.25y_{t-2} = e_t + 0.5e_{t-1}$$

To compute the log likelihood for this model, use the following statements:

```
phi = {1 -1 0.25} ;
theta = {1 0.5} ;
x = {1 2 3 4 5} ;
call armalik(lnl, resid, std, x, phi, theta);
print lnl resid std;
```

Figure 23.45 Results from an ARMALIK Call

	lnl	resid	std
	-0.822608	0.4057513	2.4645637
	0.8721154	0.9198158	1.2330147
	2.3293833	0.8417343	1.0419028
		1.0854175	1.0098042
		1.2096421	1.0024125

ARMASIM Function

ARMASIM(*phi*, *theta*, *mu*, *sigma*, *n* <, *seed*>);

The ARMASIM function simulates a univariate series from a autoregressive moving average (ARMA) model.

The arguments to the ARMASIM function are as follows:

<i>phi</i>	is a $1 \times (p + 1)$ matrix that contains the autoregressive parameters. The first element is assumed to have the value 1.
<i>theta</i>	is a $1 \times (q + 1)$ matrix that contains the moving average parameters. The first element is assumed to have the value 1.
<i>mu</i>	is a scalar that contains the overall mean of the series.
<i>sigma</i>	is a scalar that contains the standard deviation of the innovation series.
<i>n</i>	is a scalar that contains <i>n</i> , the length of the series. The value of <i>n</i> must be greater than 0.
<i>seed</i>	is a scalar that contains the random number seed. At the first execution of the function, the seed variable is used as follows:

- If *seed* > 0, the input seed is used for generating the series.
- If *seed* = 0, the system clock is used to generate the seed.
- If *seed* < 0, the value $-seed$ is used for generating the series.

If the seed is not supplied, the system clock is used to generate the seed.

On subsequent calls to the function, the seed variable is used as follows:

- If *seed* > 0, the seed remains unchanged.
- In other cases, after each execution of the function, the current seed is updated internally.

The ARMASIM function generates a series of length *n* from a given autoregressive moving average (ARMA) time series model and returns the series in an $n \times 1$ matrix. The notational conventions for the ARMASIM function are the same as those used by the ARMACOV subroutine. See the description of the [ARMACOV call](#) for the model employed. The ARMASIM function uses an exact simulation algorithm as described in Woodfield (1988). A sequence $Y_0, Y_1, \dots, Y_{p+q-1}$ of starting values is produced by using an

expanded covariance matrix, and then the remaining values are generated by using the following recursion form of the model:

$$Y_t = -\sum_{i=1}^p \phi_i Y_{t-i} + \epsilon_t + \sum_{i=1}^q \theta_i \epsilon_{t-i} \quad t = p+q, p+q+1, \dots, n-1$$

The random number generator RANNOR is used to generate the noise component of the model. Note that the following statement returns n standard normal pseudorandom deviates:

```
y = armasim(1, 1, 0, 1, n, seed);
```

For example, consider the following model:

$$y_t = 0.5y_{t-1} + e_t + 0.8e_{t-1}$$

To generate a time series of length 10 from this model, use the following statements to produce the result shown in [Figure 23.46](#):

```
phi = {1 -0.5};
theta = {1 0.8};
y = armasim(phi, theta, 0, 1, 10, -1234321);
print y;
```

Figure 23.46 Simulated Time Series

y
2.3253578
0.975835
-0.376358
-0.878433
-2.515351
-3.083021
-1.996886
-1.839975
-0.214027
1.4786717

BIN Function

```
BIN(x, cutpoints <, closed> );
```

The BIN function divides numeric values into a set of disjoint intervals called bins. The BIN function returns a matrix that is the same shape as x and that indicates which elements of x are contained in each bin. The arguments are as follows:

x specifies a numerical vector or matrix.

<i>cutpoints</i>	specifies the intervals into which to bin the data. This argument can have a vector or a scalar value. A vector defines the endpoints of the intervals; a scalar value specifies the number of evenly spaced intervals into which the range of the data is divided.				
<i>closed</i>	is an optional argument that specifies whether the bins are open on the right or left sides. The following values are valid: <table> <tr> <td>"Left"</td><td>specifies that the bins are closed on the left and open on the right. The last interval is closed on both sides. This is the default value.</td></tr> <tr> <td>"Right"</td><td>specifies that the intervals are open on the left and closed on the right. The first interval is closed on both sides.</td></tr> </table>	"Left"	specifies that the bins are closed on the left and open on the right. The last interval is closed on both sides. This is the default value.	"Right"	specifies that the intervals are open on the left and closed on the right. The first interval is closed on both sides.
"Left"	specifies that the bins are closed on the left and open on the right. The last interval is closed on both sides. This is the default value.				
"Right"	specifies that the intervals are open on the left and closed on the right. The first interval is closed on both sides.				

If *cutpoints* is a vector, then it must be ordered so that the first element is the smallest and the last element is the largest. The ordered values define the intervals that are used to bin the values. For example, the following statements bin *x* into the intervals $I_1 = [0, 1)$, $I_2 = [1, 1.8)$, $I_3 = [1.8, 2)$, and $I_4 = [2, 4]$, and return the bin numbers for each element of *x*:

```
x = {0, 0.5, 1, 1.5, 2, 2.5, 3, 0.5, 1.5, 3, 3, 1};
cutpoints = {0 1 1.8 2 4};
b = bin(x, cutpoints);
print x b;
```

Figure 23.47 Bins for Each Observation

<i>x</i>	<i>b</i>
0	1
0.5	1
1	2
1.5	2
2	4
2.5	4
3	4
0.5	1
1.5	2
3	4
3	4
1	2

You can use the special missing values `.M` and `.I` to specify unbounded intervals. A missing value of `.M` in the first element is interpreted as $-\infty$, and a missing value of `.I` in the last element is interpreted as $+\infty$. For example, the following statements are all valid specifications of the *cutpoints* argument:

```
c = {.M -2 -1 0 1 2};
c = {.M -2 -1 0 1 2 .I};
c = {-2 -1 0 1 2 .I};
```

If *cutpoints* is a positive integer, *n*, then the interval $\min(x)$, $\max(x)$ is divided into *n* intervals of width $\Delta = (\max(x) - \min(x))/n$ and the data are binned into these intervals. For example, the following statements bin the elements of *x* into one of three intervals $[0, 1)$, $[1, 2)$, or $[2, 3]$:

```
bin = bin(x, 3);
```

```
print x bin;
```

Figure 23.48 Bins That Are Associated with Each Value

x	bin
0	1
0.5	1
1	2
1.5	2
2	3
2.5	3
3	3
0.5	1
1.5	2
3	3
3	3
1	2

Notice in [Figure 23.48](#) that the value 3 is placed into the third interval because the last interval is closed on the right.

The BIN function returns missing values for data values that are not contained in any bin. Missing values are also returned for missing values in the data.

You can use the BIN function in conjunction with the TABULATE function to count the number of observations in each interval. The following statements sample from the standard normal distribution and count the number of observations in a set of evenly spaced intervals:

```
z = rannor(j(1000, 1, 1));
set = do(-3.5, 3.5, 1);
b = bin(z, set);
call tabulate(levels, count, b);

/* label counts by the center of each interval */
intervals = char(do(-3, 3, 1), 2);
print count[colname=intervals];
```

Figure 23.49 Bins Counts for Evenly Spaced Intervals

count						
-3	-2	-1	0	1	2	3
6	65	241	385	235	59	9

BLOCK Function

```
BLOCK(matrix1 <, matrix2, ..., matrix15> );
```

The BLOCK function forms a block-diagonal matrix. The blocks are defined by the arguments to the

function. Up to 15 matrices can be specified. The matrices are combined diagonally to form a new matrix.

For example, if **A**, **B**, and **C** are any matrices, then the block matrix formed from these matrices has the following form:

$$\begin{bmatrix} A & 0 & 0 \\ 0 & B & 0 \\ 0 & 0 & C \end{bmatrix}$$

The following statements produce a block-diagonal matrix composed of three blocks, shown in [Figure 23.50](#):

```
a = 1;
b = {2 2,
     3 3};
c = {4 4 4,
     5 5 5};
d = block(a, b, c);
print d;
```

Figure 23.50 Block Matrix

d					
1	0	0	0	0	0
0	2	2	0	0	0
0	3	3	0	0	0
0	0	0	4	4	4
0	0	0	5	5	5

BRANKS Function

BRANKS(*matrix*);

The **BRANKS** function computes the tied ranks and the bivariate ranks for an $n \times 2$ matrix and returns an $n \times 3$ matrix of these ranks. The tied ranks of the first column of *matrix* are contained in the first column of the result matrix; the tied ranks of the second column of *matrix* are contained in the second column of the result matrix; and the bivariate ranks of *matrix* are contained in the third column of the result matrix.

The tied rank of an element x_j of a vector is defined as

$$\mathbf{R}_i = \frac{1}{2} + \sum_j u(x_i - x_j)$$

where

$$u(t) = \begin{cases} 1 & \text{if } t > 0 \\ \frac{1}{2} & \text{if } t = 0 \\ 0 & \text{if } t < 0 \end{cases}$$

The bivariate rank of a pair (x_j, y_j) is defined as

$$Q_i = \frac{3}{4} + \sum_j u(x_i - x_j) u(y_i - y_j)$$

The results of the `BRANKS` function can be used to compute rank-based correlation coefficients such as the Spearman rank-order correlation and Hoeffding's D statistic.

The following statements compute the bivariate ranks of two columns of data:

```
z = { 1 2,
      2 1,
      3 3,
      3 5,
      4 4,
      5 4,
      5 4,
      4 5 };

b = branks(z);
print b;
```

Figure 23.51 Tied Ranks and Bivariate Ranks

b		
1	2	1
2	1	1
3.5	3	3
3.5	7.5	3.5
5.5	5	4
7.5	5	4.75
7.5	5	4.75
5.5	7.5	5

BSPLINE Function

BSPLINE($x, d, k <, i >$);

The `BSPLINE` function computes a B-spline basis. The arguments to the `BSPLINE` function are as follows:

- x is an $m \times 1$ or $1 \times m$ numeric vector.
- d is a nonnegative numeric scalar value that specifies the degree of the B-spline. The order of a B-spline is one greater than the degree.
- k is a numeric vector of size n that contains the B-spline knots or a scalar that denotes the number of interior knots. When $n > 1$, the elements of the knot vector must be nondecreasing, $k_{j-1} \leq k_j$ for $j = 2, \dots, n$.

i is an optional argument that specifies the number of interior knots when $n = 1$ and k contains a missing value. In this case the BSPLINE function constructs a vector of knots as follows: If $x_{(1)}$ and $x_{(m)}$ are the smallest and largest value in the x vector, then interior knots are placed at

$$x_{(1)} + j(x_{(m)} - x_{(1)})/(k + 1), \quad j = 1, \dots, k$$

In addition, d exterior knots are placed under $x_{(1)}$ and $\max(d, 1)$ exterior knots are placed over $x_{(m)}$. The exterior knots are evenly spaced and start at $x_{(1)} - 1\text{E-}12$ and $x_{(m)} + 1\text{E-}12$. In this case the BSPLINE function returns a matrix with m rows and $i + d + 1$ columns.

The BSPLINE function computes B-splines of degree d . Suppose that $B_j^d(x)$ denotes the j th B-spline of degree d in the knot sequence k_1, \dots, k_n . DeBoor (1981) defines the splines based on the following relationships:

$$B_j^0(x) = \begin{cases} 1 & k_j \leq x < k_{j+1} \\ 0 & \text{otherwise} \end{cases}$$

and for $d > 0$

$$\begin{aligned} B_j^d(x) &= w_j^d(x) B_j^{d-1}(x) + (1 - w_{j+1}^d(x)) B_{j+1}^{d-1}(x) \\ w_j^d(x) &= \frac{x - k_j}{k_{j+d} - k_j} \end{aligned}$$

Note that DeBoor (1981) expresses B-splines in terms of order rather than degree; in his notation $B_{j,d} = B_j^{d-1}$. B-splines have many interesting properties, including the following:

- $\sum_j B_j^d = 1$
- The sequence B_j^d is positive on $d + 1$ knots and zero elsewhere.
- The B-spline B_j^d is a piecewise polynomial of at most $d + 1$ pieces.
- If $k_j = k_{j+d}$, then $B_j^{d-1} = 0$.

See DeBoor (1981) for more details. The BSPLINE function defines B-splines of degree 0 as nonzero if $k_j < x \leq k_{j+1}$.

A typical knot vector for calculating B-splines consists of d exterior knots smaller than the smallest data value, and $\max\{d, 1\}$ exterior knots larger than the largest data value. The remaining knots are the interior knots.

For example, the following statements creates a B-spline basis with three interior knots. The BSPLINE function returns a matrix with $3 + d + 1 = 7$ columns, shown in [Figure 23.53](#).

```
x      = {2.5 3 4.5 5.1};      /* data range is [2.5, 5.1] */
knots  = {0 1 2 3 4 5 6 7 8}; /* three interior knots at x=3, 4, 5 */
bsp    = bspline(x, 3, knots);
print bsp[format=best7.];
```

Figure 23.52 B-Spline Basis

bsp						
0.02083	0.47917	0.47917	0.02083	0	0	0
0	0.16667	0.66667	0.16667	0	0	0
0	0	0.02083	0.47917	0.47917	0.02083	0
0	0	0	0.1215	0.65717	0.22117	0.00017

If you pass an x vector of data values, you can also rely on the BSPLINE function to compute a knot vector for you. For example, the following statements compute B-splines of degree 2 based on four equally spaced interior knots:

```
n = 15;
x = ranuni(J(n, 1, 45));
bsp2 = bspline(x, 2, ., 4);
print bsp2[format=8.3];
```

The resulting matrix is shown in [Figure 23.53](#).

Figure 23.53 B-Spline Basis with Four Interior Knots

bsp2						
0.000	0.104	0.748	0.147	0.000	0.000	0.000
0.000	0.000	0.000	0.286	0.684	0.030	0.000
0.000	0.000	0.000	0.000	0.000	0.517	0.483
0.000	0.000	0.000	0.217	0.725	0.058	0.000
0.000	0.000	0.239	0.713	0.048	0.000	0.000
0.000	0.000	0.000	0.446	0.553	0.002	0.000
0.000	0.000	0.394	0.600	0.006	0.000	0.000
0.000	0.000	0.000	0.000	0.064	0.729	0.207
0.000	0.389	0.604	0.007	0.000	0.000	0.000
0.000	0.000	0.000	0.000	0.000	0.500	0.500
0.000	0.000	0.000	0.000	0.210	0.728	0.062
0.000	0.000	0.014	0.639	0.347	0.000	0.000
0.000	0.001	0.546	0.453	0.000	0.000	0.000
0.500	0.500	0.000	0.000	0.000	0.000	0.000
0.304	0.672	0.024	0.000	0.000	0.000	0.000

BTRAN Function

BTRAN(x , n , m);

The BTRAN function computes the block transpose of a partitioned matrix. The arguments to the BTRAN function are as follows:

- x is an $(in) \times (jm)$ numeric matrix.
- n is a scalar with a value that specifies the row dimension of the submatrix blocks.

m is a scalar with a value that specifies the column dimension of the submatrix blocks.

The argument x is a partitioned matrix formed from submatrices of dimension $n \times n$. If the i th, j th submatrix of the argument x is denoted A_{ij} , then the i th, j th submatrix of the result is A_{ji} .

The value returned by the BTRAN function is a $(jn) \times (im)$ matrix, the block transpose of x , where the blocks are $n \times m$.

For example, the following statements compute the block transpose of a matrix:

```

a11 = {1 1,           /* a 3 x 2 matrix */
      1 1,
      1 1};
a12 = 1 + a11;
a13 = 2 + a11;
a21 = 3 + a11;
a22 = 4 + a11;
a23 = 5 + a11;

x = (a11 || a12 || a13) // /* a partitioned matrix */
    (a21 || a22 || a23); /* each submatrix is a 3 x 2 block */

z = btran(x, 3, 2);      /* transpose the blocks */
print z;
```

Figure 23.54 Block Transpose of a Partitioned Matrix

z			
1	1	4	4
1	1	4	4
1	1	4	4
2	2	5	5
2	2	5	5
2	2	5	5
3	3	6	6
3	3	6	6
3	3	6	6

BYTE Function

BYTE(*matrix*);

The BYTE function returns values in a computer's character set. The input to the function is a numeric matrix, each element of which specifies the position of a character in the computer's character set. These numeric elements should generally be in the range 0 to 255. The BYTE function returns a character matrix with the same shape as the numeric argument.

For example, in the ASCII character set, the following two statements are equivalent:

```
a1 = byte(47);
```

```
a2 = "/";      /* the slash character */
print a1 a2;
```

Figure 23.55 Specifying the Slash Character

	a1	a2
	/	/

The lowercase English letters can be generated with the following statement, shown in [Figure 23.56](#):

```
y = byte(97:122);
print y;
```

Figure 23.56 Lowercase English Letters

	y
a b c d e f g h i j k l m n o p q r s t u v w x y z	

The BYTE function simplifies the use of special characters and control sequences that cannot be entered directly into SAS/IML programs by using the keyboard. Consult the character set tables for your computer to determine the printable and control characters that are available and their ordinal positions.

CALL Statement

CALL *name* < (*arguments*) > ;

The CALL statement enables you to call a built-in or user-defined subroutine.

The arguments to the CALL statement are as follows:

name is the name of a built-in subroutine or a user-defined module.

arguments are arguments to the module or subroutine.

The CALL statement executes a subroutine. The order of resolution for the CALL statement is as follows:

1. built-in SAS/IML subroutine
2. user-defined module

This resolution order is important only if you have defined a module with the same name as a built-in subroutine.

See also the section on the [RUN statement](#).

CHANGE Call

CALL CHANGE(*matrix*, *old*, *new* <, *numchange* >);

The CHANGE subroutine searches for and replaces text in a character matrix. The arguments to the CHANGE call are as follows:

matrix is a character matrix.
old is the string to be changed.
new is the string to replace the *old* string.
numchange is the number of times to make the change.

The CHANGE subroutine changes the first *numchange* occurrences of the substring *old* in each element of the character array *matrix* to the form *new*. If *numchange* is not specified, the routine defaults to 1. If *numchange* is 0, the routine changes all occurrences of *old*. If no occurrences are found, the matrix is not changed.

For example, consider the following statements:

```
a = "It was a dark and stormy night.";
call change(a, "night", "day");
print a;
```

The result of these statements is shown in [Figure 23.57](#).

Figure 23.57 New String

<p>a</p> <p>It was a dark and stormy day.</p>
--

In the *old* operand, the following characters are reserved:

% \$ [] { } < > - ? * # @ ' (backquote) ^

CHAR Function

CHAR(*matrix* <, *w* > <, *d* >);

The CHAR function produces a character representation of a numeric matrix. Essentially, the CHAR function is equivalent to applying a *w.d* format to each element of a numeric matrix.

The arguments to the CHAR function are as follows:

matrix is a numeric matrix or literal.

w is the field width.
d is the number of decimal positions.

The CHAR function takes a numeric matrix as an argument and, optionally, a field width *w* and a number of decimal positions *d*. The CHAR function produces a character matrix with the same dimensions as the argument matrix, and with elements that are character representations of the corresponding numeric elements.

If the *w* argument is not supplied, the system default field width is used. If the *d* argument is not supplied, the best representation is used. See also the description of the NUM function, which converts a character matrix into a numeric matrix.

For example, the following statements produce the output shown in Figure 23.58:

```
a = {-1.1 0 3.1415 4};
reset print;          /* display values and type of matrices */
m = char(a, 4, 1);
```

Figure 23.58 Character Matrix

m	1 row	4 cols	(character, size 4)
		-1.1 0.0 3.1 4.0	

CHOOSE Function

CHOOSE(*condition*, *result-for-true*, *result-for-false*);

The CHOOSE function examines each element of the first argument for being true (nonzero and not missing) or false (zero or missing). For each true element, it returns the corresponding element in the second argument. For each false element, it returns the corresponding element in the third argument.

The arguments to the CHOOSE function are as follows:

condition is checked for being true or false for each element.
result-for-true is returned when *condition* is true.
result-for-false is returned when *condition* is false.

Each argument must be conformable with the others (or be a scalar value).

For example, suppose that you want to choose between *x* and *y* according to whether *x*#*y* is odd or even, respectively. You can use the following statements to execute this task, as shown in Figure 23.59:

```
x = {1, 2, 3, 4, 5};
y = {101, 205, 133, 806, 500};
r = choose(mod(x#y,2)=1, x, y);
print x y r;
```


Figure 23.59 Result of the CHOOSE Function

	x	y	r
	1	101	1
	2	205	205
	3	133	3
	4	806	806
	5	500	500

As another example, the following statements replace all missing values in the matrix **z** with zeros, as shown in Figure 23.60:

```
z = {1 2 ., 100 . -90, . 5 8};
newZ = choose(z=., 0, z);
print z, newZ;
```

Figure 23.60 Replacement of Missing Values

z		
1	2	.
100	.	-90
.	5	8
newZ		
1	2	0
100	0	-90
0	5	8

CLOSE Statement

CLOSE < SAS-data-set > ;

The CLOSE statement is used to close one or more SAS data sets opened with the [USE](#), [EDIT](#), or [CREATE](#) statement.

The optional argument specifies the name of one or more SAS data sets. The data sets can be specified with a one-level name (for example, **A**) or a two-level name (for example, **Sasuser.A**). For more information about specifying SAS data sets, refer to Chapter 7, “[Working with SAS Data Sets](#).”

You can use the [SHOW DATASETS](#) statement to find the names of open data sets.

SAS/IML software automatically closes all open data sets when a [QUIT](#) statement is executed.

The following statements provide examples of using the CLOSE statement:

```
use Sashelp.Class;
read all var _NUM_ into x[colname=VarName];
```

```
corr = corr(x);
create ClassCorr from corr[rowname=VarName colname=VarName];
append from corr[rowname=VarName];

show datasets;
close Sashelp.Class ClassCorr;
```

Figure 23.61 Open Data Sets

LIBNAME	MEMNAME	OPEN MODE	STATUS
-----	-----	-----	-----
SASHELP	CLASS	Input	
WORK	CLASSCORR	Update	Current Input/Output

It is good programming practice to close data sets when you are finished using them.

CLOSEFILE Statement

CLOSEFILE *files* ;

The CLOSEFILE statement is used to close files opened by the INFILE or FILE statement.

The statement arguments specify the name of one or more file specifications. You can specify names (for defined filenames), literals, or expressions in parentheses (for pathnames). Each file specification should be the same as when the file was opened.

To find out what files are open, use the [SHOW FILES](#) statement. For further information, see [Chapter 8](#). See also the description of the [SAVE statement](#).

SAS/IML software automatically closes all files when a QUIT statement is executed.

The following example opens and closes an external file named *MyData.txt* that resides in the current directory. (If you run PROC IML through a SAS Display Manager Session (DMS), you can change the current directory by selecting **Tools ► Options ► Change Current Folder** from the main menu.)

```
filename MyFile 'MyData.txt';
infile MyFile;
show files;
closefile MyFile;
```

Figure 23.62 Open External File

FILE NAME	MODE	EOF	OPTIONS
-----	-----	-----	-----
FILENAME:MYFILE	Current Input	, no eof,	lrecl=512 STOPOVER

Alternatively, you can specify the full path of the file, as shown in the following statements:

```
src = "C:\My Data\MyData.txt";
infile (src);
show files;
closefile (src);
```

Figure 23.63 Open File Specified by a Full Path

FILE NAME	MODE	EOF	OPTIONS
-----	-----	-----	-----
C:\My Data\MyData.txt	Current Input	, no eof,	lrecl=512 STOPOVER

COMPORT Call

CALL COMPORT(*q*, *r*, *p*, *piv*, *lindep*, *a* < , *b* > < , *sing* >);

The COMPORT subroutine provides the complete orthogonal decomposition by Householder transformations of a matrix **A**.

The subroutine returns the following values:

- q* is a matrix. If *b* is not specified, *q* is the $m \times m$ orthogonal matrix **Q** that is the product of the $\min(m, n)$ separate Householder transformations. If *b* is specified, *q* is the $m \times p$ matrix **Q'****B** that has the transposed Householder transformations **Q'** applied to the *p* columns of the argument matrix **B**.
- r* is the $n \times n$ upper triangular matrix **R** that contains the $r \times r$ nonsingular upper triangular matrix **L'** of the complete orthogonal decomposition, where $r \leq n$ is the rank of **A**. The full $m \times n$ upper triangular matrix **R** of the orthogonal decomposition of matrix **A** can be obtained by vertical concatenation of the $(m - n) \times n$ zero matrix to the result *r*.
- p* is an $n \times n$ matrix that is the product **P****Π** of a permutation matrix **Π** with an orthogonal matrix **P**. The permutation matrix is determined by the vector *piv*.
- piv* is an $n \times 1$ vector of permutations of the columns of **A**. That is, the QR decomposition is computed, not of **A**, but of the matrix with columns $[\mathbf{A}_{piv[1]} \dots \mathbf{A}_{piv[n]}]$. The vector *piv* corresponds to an $n \times n$ permutation matrix, **Π**, of the pivoted QR decomposition in the first step of orthogonal decomposition.
- lindep* specifies the number of linearly dependent columns in the matrix **A** detected by applying the *r* Householder transformation in the order specified by the argument *piv*. That is, *lindep* is $n - r$.

The input arguments to the COMPORT subroutine are as follows:

- a* specifies the $m \times n$ matrix **A**, with $m \geq n$, which is to be decomposed into the product of the $m \times m$ orthogonal matrix **Q**, the $n \times n$ upper triangular matrix **R**, and the $n \times n$ orthogonal

matrix \mathbf{P} ,

$$\mathbf{A} = \mathbf{Q} \begin{bmatrix} \mathbf{R} \\ \mathbf{0} \end{bmatrix} \mathbf{\Pi}' \mathbf{P}' \mathbf{\Pi}$$

b specifies an optional $m \times p$ matrix \mathbf{B} that is to be left-multiplied by the transposed $m \times m$ matrix \mathbf{Q}' .

sing is an optional scalar that specifies a singularity criterion.

The complete orthogonal decomposition of the singular matrix \mathbf{A} can be used to compute the Moore-Penrose inverse \mathbf{A}^- , $r = \text{rank}(\mathbf{A}) < n$, or to compute the minimum Euclidean-norm solution of the rank-deficient least squares problem $\|\mathbf{A}\mathbf{x} - \mathbf{b}\|_2^2$.

1. Use the QR decomposition of \mathbf{A} with column pivoting,

$$\mathbf{A} = \mathbf{Q} \begin{bmatrix} \mathbf{R} \\ \mathbf{0} \end{bmatrix} \mathbf{\Pi}' = [\mathbf{Y} \quad \mathbf{Z}] \begin{bmatrix} \mathbf{R}_1 & \mathbf{R}_2 \\ \mathbf{0} & \mathbf{0} \end{bmatrix} \mathbf{\Pi}'$$

where $\mathbf{R} = [\mathbf{R}_1 \quad \mathbf{R}_2] \in \mathcal{R}^{r \times t}$ is upper trapezoidal, $\mathbf{R}_1 \in \mathcal{R}^{r \times r}$ is upper triangular and invertible, $\mathbf{R}_2 \in \mathcal{R}^{r \times s}$, $\mathbf{Q} = [\mathbf{Y} \quad \mathbf{Z}]$ is orthogonal, $\mathbf{Y} \in \mathcal{R}^{t \times r}$, $\mathbf{Z} \in \mathcal{R}^{t \times s}$, and $\mathbf{\Pi}$ permutes the columns of \mathbf{A} .

2. Use the transpose \mathbf{L}_{12} of the upper trapezoidal matrix $\mathbf{R} = [\mathbf{R}_1 \quad \mathbf{R}_2]$,

$$\mathbf{L}_{12} = \begin{bmatrix} \mathbf{L}_1 \\ \mathbf{L}_2 \end{bmatrix} = \mathbf{R}' \in \mathcal{R}^{t \times r}$$

with $\text{rank}(\mathbf{L}_{12}) = \text{rank}(\mathbf{L}_1) = r$, $\mathbf{L}_1 \in \mathcal{R}^{r \times r}$ lower triangular, $\mathbf{L}_2 \in \mathcal{R}^{s \times r}$. The lower trapezoidal matrix $\mathbf{L}_{12} \in \mathcal{R}^{t \times r}$ is premultiplied with r Householder transformations $\mathbf{P}_1, \dots, \mathbf{P}_r$,

$$\mathbf{P}_r \dots \mathbf{P}_1 \begin{bmatrix} \mathbf{L}_1 \\ \mathbf{L}_2 \end{bmatrix} = \begin{bmatrix} \mathbf{L} \\ \mathbf{0} \end{bmatrix}$$

each zeroing out one of the r columns of \mathbf{L}_2 and producing the nonsingular lower triangular matrix $\mathbf{L} \in \mathcal{R}^{r \times r}$. Therefore, you obtain

$$\mathbf{A} = \mathbf{Q} \begin{bmatrix} \mathbf{L}' & \mathbf{0} \\ \mathbf{0} & \mathbf{0} \end{bmatrix} \mathbf{\Pi}' \mathbf{P}' = \mathbf{Y} [\mathbf{L}' \quad \mathbf{0}] \mathbf{\Pi}' \mathbf{P}'$$

with $\mathbf{P} = \mathbf{\Pi} \mathbf{P}_r \dots \mathbf{P}_1 \in \mathcal{R}^{t \times t}$ and upper triangular \mathbf{L}' . This second step is described in Golub and Van Loan (1989).

3. Compute the Moore-Penrose inverse \mathbf{A}^- explicitly:

$$\mathbf{A}^- = \mathbf{P} \mathbf{\Pi} \begin{bmatrix} (\mathbf{L}')^{-1} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} \end{bmatrix} \mathbf{Q}' = \mathbf{P} \mathbf{\Pi} \begin{bmatrix} (\mathbf{L}')^{-1} \\ \mathbf{0} \end{bmatrix} \mathbf{Y}'$$

- (a) Obtain \mathbf{Y} in $\mathbf{Q} = [\mathbf{Y} \quad \mathbf{Z}]$ explicitly by applying the r Householder transformations obtained in the first step to $\begin{bmatrix} \mathbf{I}_r \\ \mathbf{0} \end{bmatrix}$.
- (b) Solve the $r \times r$ lower triangular system $(\mathbf{L}')^{-1} \mathbf{Y}'$ with t right-hand sides by using backward substitution, which yields an $r \times t$ intermediate matrix.

- (c) Left-apply the r Householder transformations in \mathbf{P} on the $r \times t$ intermediate matrix $\begin{bmatrix} (\mathbf{L}')^{-1}\mathbf{Y}' \\ \mathbf{0} \end{bmatrix}$, which results in the symmetric matrix $\mathbf{A}^- \in \mathcal{R}^{t \times t}$.

The **GINV** function computes the Moore-Penrose inverse \mathbf{A}^- by using the singular value decomposition of \mathbf{A} . Using complete orthogonal decomposition to compute \mathbf{A}^- usually requires far fewer floating-point operations. However, it can be slightly more sensitive to rounding errors, which can disturb the detection of the true rank of \mathbf{A} , than the singular value decomposition.

The following example demonstrates some uses of the COMPORT subroutine:

```
/* Only four linearly independent columns */
A = {1 0 1 0 0,
      1 0 0 1 0,
      1 0 0 0 1,
      0 1 1 0 0,
      0 1 0 1 0,
      0 1 0 0 1 };
m = nrow(A);
n = ncol(A);

call comport(q,r,p,piv,lindep,A);
fullR = r // j(m-n, n, 0);
perm = i(n);
perm[piv,] = i(n);

/* recover A from factorization */
A2 = q*fullR*p`*perm`;
reset fuzz;
print A2;

/* compute Moore-Penrose generalized inverse */
rankA = n - lindep;
subR = R[1:rankA, 1:rankA];
fullRinv = j(n, n, 0);
fullRinv[1:rankA, 1:rankA] = inv(subR);
Ainv = perm*p*fullRinv*q[,1:n]`;
print Ainv;

/* verify generalized inverse */
eps = 1e-12;
if any(A*Ainv*A-A > eps) |
  any(Ainv*A*Ainv-Ainv > eps) |
  any((A*Ainv)`-A*Ainv > eps) |
  any((Ainv*A)`-Ainv*A > eps) then
  msg = "Pseudoinverse conditions not satisfied";
else
  msg = "Pseudoinverse conditions satisfied";
print msg;
```

Figure 23.64 Results from a Complete Orthogonal Factorization

A2					
1	0	1	0	0	
1	0	0	1	0	
1	0	0	0	1	
0	1	1	0	0	
0	1	0	1	0	
0	1	0	0	1	

Ainv					
0.2666667	0.2666667	0.2666667	-0.0666667	-0.0666667	-0.0666667
-0.0666667	-0.0666667	-0.0666667	0.2666667	0.2666667	0.2666667
0.4	-0.1	-0.1	0.4	-0.1	-0.1
-0.1	0.4	-0.1	-0.1	0.4	-0.1
-0.1	-0.1	0.4	-0.1	-0.1	0.4

msg					
Pseudoinverse conditions satisfied					

CONCAT Function

CONCAT(*argument1*, *argument2* <, ..., *argument15*>);

The CONCAT function produces a character matrix that contains elements that are the concatenations of corresponding elements from each argument. The CONCAT function accepts up to 15 arguments, where each argument is a character matrix or a scalar.

All nonscalar arguments must have the same dimensions. Any scalar arguments are used repeatedly to concatenate to all elements of the other arguments. The element length of the result equals the sum of the element lengths of the arguments. Trailing blanks of one matrix argument appear before elements of the next matrix argument in the result matrix.

For example, suppose you specify the following matrices:

```
b = {"AB" "C ",
      "DE" "FG"};
c = {"H " "IJ",
      " K" "LM"};
```

The following statement produces a new 2×2 character matrix, **a**:

```
a = concat(b, c);
print a;
```

Figure 23.65 Elementwise Concatenation of Strings

a	
ABH	C IJ
DE	K FGLM

Quotation marks (") are needed only if you want to embed blanks or maintain uppercase and lowercase characters. You can also use the [ADD](#) operator to concatenate character operands.

CONTENTS Function

CONTENTS(< libref> < , SAS-data-set>);

The CONTENTS function returns a column vector that contains the variable names for a SAS data set. The vector contains n rows, where n is the number of variables in the data set. The variable list is returned in the order in which the variables occur in the data set.

You can specify the SAS data set with a one-level name (for example, A) or with a libref and a SAS data set name (for example, Sashelp.Class). If you specify a one-level name, SAS/IML software uses the default SAS data library (as specified in the DEFLIB= option in the [RESET statement](#).) If no arguments are specified, the current open input data set is used.

The following statements use the CONTENTS function to obtain the names of variables in SAS data sets:

```
x = 1:5;
create temp from x;
append from x;
tempVars = contents();           /* use current open input data set */
close temp;

classVars = contents("sashelp", "class"); /* contents of data set in */
                                           /* SASHELP library          */
print tempVars classVars;
```

Figure 23.66 Names of Variables in SAS Data Sets

tempVars classVars	
COL1	Name
COL2	Sex
COL3	Age
COL4	Height
COL5	Weight

See also the description of the [SHOW CONTENTS statement](#).

CONVEXIT Function

CONVEXIT(*times*, *flows*, *ytm*);

The CONVEXIT function computes and returns a scalar that contains the convexity of a noncontingent cash flow. The arguments to the CONVEXIT function are as follows:

times is an n -dimensional column vector of times. Elements should be nonnegative.
flows is an n -dimensional column vector of cash flows.
ytm is the per-period yield-to-maturity of the cash-flow stream. This is a scalar and should be positive.

Convexity is essentially a measure of how duration, the sensitivity of price to yield, changes as interest rates change:

$$C = \frac{1}{P} \frac{d^2 P}{dy^2}$$

Under certain assumptions, the convexity of cash flows that are not yield-sensitive is given by

$$C = \frac{\sum_{k=1}^K t_k(t_k + 1) \frac{c(k)}{(1+y)^{t_k}}}{P(1+y)^2}$$

where P is the present value, y is the effective per-period yield-to-maturity, K is the number of cash flows, and the k th cash flow is $c(k)$ t_k periods from the present.

The following statements compute the convexity of a noncontingent cash flow.

```
timesn = T(do(1, 100, 1));
flows = repeat(10, 100);
ytm = 0.1;
convexit = convexit(timesn, flows, ytm);
print convexit;
```

Figure 23.67 Convexity of a Noncontingent Cash Flow

convexit
199.26229

CORR Function

CORR($x <$, *method* <, *excludemiss* >);

The CORR function computes a sample correlation matrix for data. The arguments are as follows:

<i>x</i>	specifies an $n \times p$ numerical matrix of data. The CORR function computes a $p \times p$ correlation matrix of the data.								
<i>method</i>	specifies the method used to compute the correlation matrix. The following strings are valid: <table border="0"> <tr> <td>"Pearson"</td><td>specifies the computation of Pearson product-moment correlations. The correlations range from -1 to 1. This is the default value.</td></tr> <tr> <td>"Hoeffding"</td><td>specifies the computation of Hoeffding's D statistics, scaled to range between -0.5 and 1.</td></tr> <tr> <td>"Kendall"</td><td>specifies the computation of Kendall's tau-b coefficients based on the number of concordant and discordant pairs of observations. Kendall's tau-b ranges from -1 to 1.</td></tr> <tr> <td>"Spearman"</td><td>specifies the computation of Spearman correlation coefficients based on the ranks of the variables. The correlations range from -1 to 1.</td></tr> </table>	"Pearson"	specifies the computation of Pearson product-moment correlations. The correlations range from -1 to 1 . This is the default value.	"Hoeffding"	specifies the computation of Hoeffding's D statistics, scaled to range between -0.5 and 1 .	"Kendall"	specifies the computation of Kendall's tau- b coefficients based on the number of concordant and discordant pairs of observations. Kendall's tau- b ranges from -1 to 1 .	"Spearman"	specifies the computation of Spearman correlation coefficients based on the ranks of the variables. The correlations range from -1 to 1 .
"Pearson"	specifies the computation of Pearson product-moment correlations. The correlations range from -1 to 1 . This is the default value.								
"Hoeffding"	specifies the computation of Hoeffding's D statistics, scaled to range between -0.5 and 1 .								
"Kendall"	specifies the computation of Kendall's tau- b coefficients based on the number of concordant and discordant pairs of observations. Kendall's tau- b ranges from -1 to 1 .								
"Spearman"	specifies the computation of Spearman correlation coefficients based on the ranks of the variables. The correlations range from -1 to 1 .								
<i>excludemiss</i>	specifies how missing values are handled. The following values are valid: <table border="0"> <tr> <td>"listwise"</td><td>specifies that observations with missing values are excluded from the analysis. This is the default value.</td></tr> <tr> <td>"pairwise"</td><td>specifies that all nonmissing pairs of values for each pair of variables are included in the statistical computations.</td></tr> </table>	"listwise"	specifies that observations with missing values are excluded from the analysis. This is the default value.	"pairwise"	specifies that all nonmissing pairs of values for each pair of variables are included in the statistical computations.				
"listwise"	specifies that observations with missing values are excluded from the analysis. This is the default value.								
"pairwise"	specifies that all nonmissing pairs of values for each pair of variables are included in the statistical computations.								

The *method* and *excludemiss* arguments are not case-sensitive. The first four characters are used to determine the value. For example, "LIST" and "listwise" specify the same option.

The CORR function computes a sample correlation matrix for data, as shown in the following example:

```
x = {5 1 10,
      6 2 3,
      6 8 5,
      6 7 9,
      7 2 13};
corr = corr(x);
spearman = corr(x, "spearman");
print corr, spearman;
```

Figure 23.68 Correlation Matrices

corr			
	1	0.1091089	0.265165
0.1091089		1	-0.289319
0.265165	-0.289319		1
spearman			
	1	0.3441236	0.2236068
0.3441236		1	-0.410391
0.2236068	-0.410391		1

The CORR function behaves similarly to the CORR procedure. In particular, the documentation for the CORR procedure in the *Base SAS Procedures Guide: Statistical Procedures* includes details about the various correlation statistics.

The CORR function also handles missing values in the same way as the CORR procedure. In particular, be aware that specifying *excludemiss*="pairwise" might result in a correlation matrix that is not nonnegative definite.

You can use the ROWNAME= and COLNAME= options in the MATTRIB statement or the PRINT statement to associate names of variables to rows and columns of the correlation matrix. For example, if the names of the variables in the previous example are X1, X2, and X3, then the following statements associate those names with the matrix returned by the CORR function:

```
varnames = {"X1" "X2" "X3"};
mattrib corr      rowname=varnames colname=varnames
              spearman rowname=varnames colname=varnames;
print corr, spearman;
```

Figure 23.69 Correlation Matrices with Named Rows and Columns

corr				
	X1		X2	X3
X1	1	0.1091089	0.265165	
X2	0.1091089		1	-0.289319
X3	0.265165	-0.289319		1
spearman				
	X1		X2	X3
X1	1	0.3441236	0.2236068	
X2	0.3441236		1	-0.410391
X3	0.2236068	-0.410391		1

Prior to SAS/IML 9.22, there was a module named CORR in the IMLMLIB library. This module has been removed.

COUNTMISS Function

COUNTMISS(*x* <, *method* >);

The COUNTMISS function counts the number of missing values in a matrix. The arguments are as follows:

- x* specifies an $n \times p$ numerical or character matrix. The COUNTMISS function counts the number of missing values in this matrix.
- method* specifies the method used to count the missing values. This argument is optional. The following are valid values:

"all"	specifies that all missing values are counted. This is the default value. The function returns a 1×1 matrix.
"row"	specifies that the function return an $n \times 1$ matrix whose i th element is the number of missing values in the i th row of x .
"col"	specifies that the function return a $1 \times p$ matrix whose j th element is the number of missing values in the j th row of x .

The *method* argument is not case-sensitive. The first three characters are used to determine the value.

For example, the following statements count missing values for the matrix **x**:

```
x = {1 2 3,
      . 0 2,
      1 . .,
      1 0 . };
totalMiss = countmiss(x);
rowMiss = countmiss(x, "ROW");
colMiss = countmiss(x, "COL");
print totalMiss, rowMiss, colMiss;
```

Figure 23.70 Counts of Missing Values

totalMiss		
4		
rowMiss		
0		
1		
2		
1		
colMiss		
1	1	2

COUNTN Function

COUNTN(x <, *method* >);

The COUNTN function counts the number of nonmissing values in a matrix. The arguments are as follows:

x	specifies an $n \times p$ numerical or character matrix. The COUNTN function counts the number of nonmissing values in this matrix.
<i>method</i>	specifies the method used to count the nonmissing values. This argument is optional. The following are valid values:

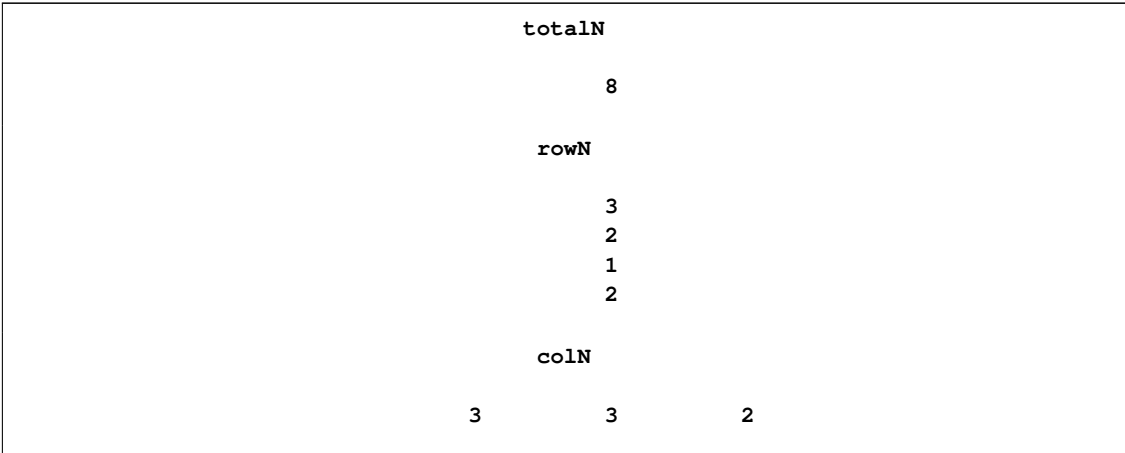
"all"	specifies that all nonmissing values are counted. This is the default value. The function returns a 1×1 matrix.
"row"	specifies that the function return an $n \times 1$ matrix whose i th element is the number of nonmissing values in the i th row of x .
"col"	specifies that the function return a $1 \times p$ matrix whose j th element is the number of nonmissing values in the j th row of x .

The *method* argument is not case-sensitive. The first three characters are used to determine the value.

For example, the following statements count nonmissing values for a matrix **x**:

```
x = {1 2 3,  
      . 0 2,  
      1 . .,  
      1 0 . };  
totalN = countn(x);  
rowN = countn(x, "ROW");  
colN = countn(x, "COL");  
print totalN, rowN, colN;
```

Figure 23.71 Counts of Nonmissing Values



COUNTUNIQUE Function

```
COUNTUNIQUE(x <, method>);
```

The COUNTUNIQUE function counts the number of unique values in a matrix. The arguments are as follows:

<i>x</i>	specifies an $n \times p$ numerical or character matrix. The COUNTUNIQUE function counts the number of unique values in this matrix.
<i>method</i>	specifies the method used to count the missing values. This argument is optional. The following are valid values:

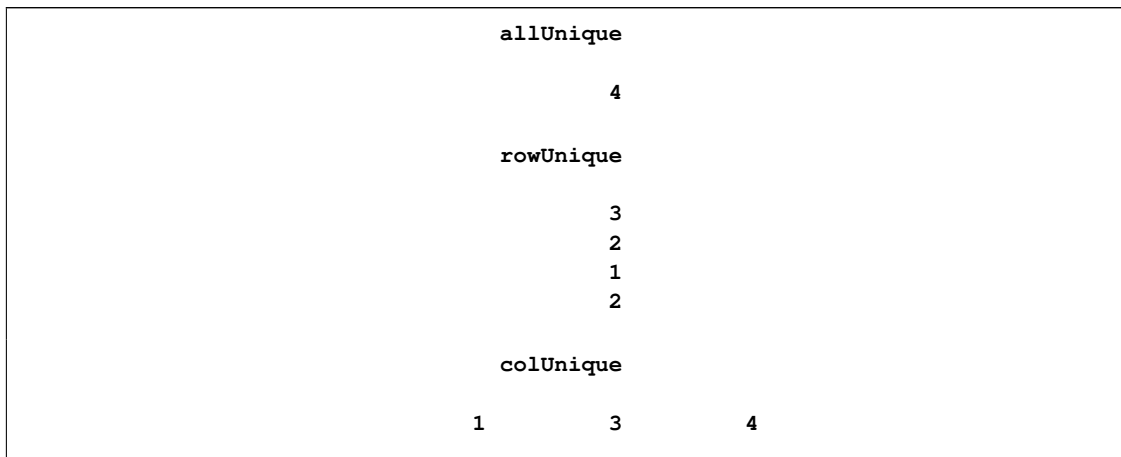
"all"	specifies that the function counts all unique values in the matrix. This is the default value. The function returns a 1×1 matrix.
"row"	specifies that the function counts the unique values in each row. The function returns an $n \times 1$ matrix whose i th element is the number of unique values in the i th row of x .
"col"	specifies that the function counts the unique values in each column. The function returns a $1 \times p$ matrix whose j th element is the number of unique values in the j th column of x .

The *method* argument is not case-sensitive. The first three characters are used to determine the value.

For example, the following statements count unique values for the matrix x :

```
x={1 2 3,
    1 1 2,
    1 1 1,
    1 0 0};
allUnique = countunique(x);
rowUnique = countunique(x, "ROW");
colUnique = countunique(x, "COL");
print allUnique, rowUnique, colUnique;
```

Figure 23.72 Counts of Unique Values



COV Function

COV(x <, *excludemiss* >);

The COV function computes a sample variance-covariance matrix for data. The arguments are as follows:

x	specifies an $n \times p$ numerical matrix of data. The COV function computes a $p \times p$ variance-covariance matrix of the data.
<i>excludemiss</i>	specifies how missing values are handled. The following values are valid:

"listwise"	specifies that observations with missing values are excluded from the analysis. This is the default value.
"pairwise"	specifies that all nonmissing pairs of values for each pair of variables are included in the statistical computations.

The *excludemiss* argument is not case-sensitive. The first four characters are used to determine the value. For example, "LIST" and "listwise" specify the same option.

The COV function computes a sample variance-covariance matrix for data, as the following example shows:

```
x = {5 1 10,  
      6 2 3,  
      6 8 5,  
      6 7 9,  
      7 2 13};  
cov = cov(x);  
print cov;
```

Figure 23.73 Variance-Covariance Matrix

cov		
0.5	0.25	0.75
0.25	10.5	-3.75
0.75	-3.75	16

The COV function handles missing values in the same way as the CORR procedure. For additional details, see the documentation for the CORR procedure (especially the NOMISS option) in the *Base SAS Procedures Guide: Statistical Procedures*.

It might be useful to use the ROWNAME= and COLNAME= options in the MATTRIB statement or the PRINT statement to associate names of variables to rows and columns of the correlation matrix, as shown in the example for the [CORR function](#).

COVLAG Function

COVLAG(*x*, *k*);

The COVLAG function computes a sequence of lagged crossproduct matrices. This function is useful for computing sample autocovariance sequences for scalar or vector time series.

The arguments to the COVLAG function are as follows:

- x* is an $n \times nv$ matrix of time series values; *n* is the number of observations, and *nv* is the dimension of the random vector.
- k* is a scalar, the absolute value of which specifies the number of lags desired. If *k* is positive, a mean correction is made. If *k* is negative, no mean correction is made.

The value returned by the COVLAG function is an $nv \times (k * nv)$ matrix. The i th $nv \times nv$ block of the matrix is the sum

$$\frac{1}{n} \sum_{j=i}^n x_j' x_{j-i+1} \quad \text{if } k < 0$$

where x_j is the j th row of x . If $k > 0$, then the i th $nv \times nv$ block of the matrix is

$$\frac{1}{n} \sum_{j=i}^n (x_j - \bar{x})' (x_{j-i+1} - \bar{x})$$

where \bar{x} is a row vector of the column means of x .

For example, the following statements produce a lagged crossproduct matrix:

```
x = T(do(-9, 9, 2));
cov = covlag(x, 4);
print cov;
```

Figure 23.74 Lagged Crossproduct Matrix

cov			
33	23.1	13.6	4.9

CREATE Statement

CREATE *SAS-data-set* < **VAR** *operand* > ;

CREATE *SAS-data-set* **FROM** *matrix-name* < [*COLNAME=column-name*
ROWNAME=row-name] > ;

The CREATE statement creates a new SAS data set and makes it both the current input and output data sets. The variables in the new SAS data set are either the variables listed in the VAR clause or variables created from the columns of the FROM matrix. The FROM clause and the VAR clause should not be specified together.

The arguments to the CREATE statement are as follows:

- SAS-data-set* is the name of a SAS data set. It can be specified with a one-level name (for example, A) or a two-level name (for example, Sasuser.A).
- operand* specifies a set of existing SAS/IML matrices that contain data. The names of the matrices become the names of the data set variables.
- matrix-name* specifies a matrix that contains the data. Each column of the matrix produces a variable in the data set.
- column-name* is a character matrix or quoted literal that contains names of the data set variables.

row-name is a character matrix or quoted literal that contains text to associate with each observation in the data set.

You can specify a set of variables to use with the VAR clause. The *operand* argument can be specified in one of the following ways:

- a literal that contains variable names
- the name of a matrix that contains variable names
- an expression in parentheses that yields variable names
- one of the keywords in the following list:

<u>ALL</u>	specifies that all variables in scope should be written to the data set.
<u>CHAR</u>	specifies that all character variables in scope should be written to the data set.
<u>NUM</u>	specifies that all numeric variables in scope should be written to the data set.

The following example demonstrates ways that you can use the VAR clause:

```
x1 = T(1:5);
x2 = T(5:1);
y = {-1,0,1,0,1};
z = {a,b,c,d,e};
create temp var {x1 y z};      /* a literal matrix of names      */
append;
close temp;

varNames = {"x1" "y" "z"};
create temp var varNames;     /* a matrix that contains names */
append;
close temp;
free varNames;

create temp var ("x1":"x2"); /* an expression              */
append;
close temp;

create temp var _all_;        /* all variables in scope      */
append;
close temp;
```

You can specify a COLNAME= and a ROWNAME= matrix in the FROM clause. The COLNAME= matrix gives names to variables in the SAS data set being created. The COLNAME= operand specifies the name of a character matrix. The first *ncol* values from this matrix provide the variable names in the data set being created, where *ncol* is the number of columns in the FROM matrix. The CREATE statement uses the first *ncol* elements of the COLNAME= matrix in row-major order.

The ROWNAME= operand adds a variable to the data set that contains labels. The operand must be a character matrix. The length of the resulting data set variable is the length of a matrix element of the operand. The same ROWNAME= matrix should be used in any subsequent APPEND statements for this data set.

The variable types and lengths correspond to the attributes of the matrices specified in the VAR clause or the matrix in the FROM clause. The default type is numeric when the name is undefined. If you do not specify the name of a variable, then all variables in scope are used.

To add observations to your data set, you must use the [APPEND](#) statement.

For example, the following statements create a new SAS data named Population that contains two numeric and two character variables:

```
State   = {"NC",      "NC",    "FL",    "FL"};
County  = {"Chatham", "Wake",  "Orange", "Seminole"};
Pop2000 = {49329,    627846,  896344,  365196};
Pop2009 = {64772,    897214, 1086480,  413204};
create Population var {"State" "County" "Pop2000" "Pop2009"};
append;
close Population;
```

The data come from vectors with the same names. You must initialize the character variables (State and County) prior to calling the CREATE statement. The State variable has length 2 and the County variable has length 8. The Pop2000 and Pop2009 variables are numeric.

In the next example, you use the FROM clause with the COLNAME= option to create a SAS data set named MyData. The new data set has variables named with the COLNAME= operand. The data are in the FROM matrix **x**, and there are two observations because **x** has two rows of data. The COLNAME= operand gives descriptive names to the data set variables, as shown in the following statements:

```
x = {1 2 3, 4 5 6};
varNames = "x1":"x3";
/* create data set MYDATA with variables X1, X2, X3 */
create MyData from x [colname=varNames];
append from x;
close MyData;
```

If you associate a format with a matrix by using the [MATTRIB](#) statement, then the CREATE statement assigns that format to the corresponding variable in the data set, as shown in the following example:

```
proc iml;
date = { '20MAR2010'd, '20MAR2011'd, '20MAR2012'd,
         '20MAR2013'd, '20MAR2014'd, '20MAR2015'd };
mattrib date format=WORDDATE.;

/* time of equinox, GMT (Greenwich Mean Time) */
time = { '17:32't,      '23:21't,      '05:14't,
         '11:02't,      '16:57't,      '22:45't };
mattrib time format=TIMEAMPM.;

create MarchEquinox var {"Date" "Time"};
append;
close MarchEquinox;

proc print data=MarchEquinox;
run;
```

Figure 23.75 Data Set That Contains Formats

Obs	Date	Time
1	March 20, 2010	5:32:00 PM
2	March 20, 2011	11:21:00 PM
3	March 20, 2012	5:14:00 AM
4	March 20, 2013	11:02:00 AM
5	March 20, 2014	4:57:00 PM
6	March 20, 2015	10:45:00 PM

CSHAPE Function

CSHAPE(*matrix*, *nrow*, *ncol*, *size* <, *padchar*>);

The CSHAPE function changes the shape of a character matrix by redefining the matrix dimensions.

The arguments to the CSHAPE function are as follows:

matrix is a character matrix or quoted literal.
nrow is the number of rows.
ncol is the number of columns.
size is the element length.
padchar is an optional padding character.

The dimension of the matrix created by the CSHAPE function is specified by *nrow* (the number of rows), *ncol* (the number of columns), and *size* (the element length). A padding character is specified by *padchar*.

The CSHAPE function works by looking at the source matrix as if the characters of the source elements had been concatenated in row-major order. The source characters are then regrouped into elements of length *size*. These elements are assigned to the result matrix, once again in row-major order.

If there are not enough characters for the result matrix, the source of the remaining characters depends on whether padding was specified with *padchar*. If no padding was specified, the characters in the source matrix are cycled through again. If a padding character was specified, the remaining characters are all the padding character.

If one of the size arguments (*nrow*, *ncol*, or *size*) is zero, the CSHAPE function computes the dimension of the output matrix by dividing the number of elements of the input matrix by the product of the nonzero arguments.

For example, the following statement produces a 2×2 matrix:

```
a = cshape("abcd", 2, 2, 1);
print a;
```

Figure 23.76 Reshaped Character Matrix

```

a
a b
c d

```

The following statement rearranges the 12 characters in the input matrix into a 2×2 matrix with three characters in each element:

```

m = {"ab" "cd",
     "ef" "gh",
     "ij" "kl"};
b = cshape(m, 2, 2, 3);
print b;

```

Figure 23.77 Reshaped Character Matrix

```

b
abc def
ghi jkl

```

The following statement uses the *size* argument to specify the length of the result matrix. Notice that the characters in the *matrix* argument are reused in order to form a 2×2 matrix with three characters in each element.

```

c = cshape("abcde", 2, 2, 3);
print c;

```

Figure 23.78 Reusing Characters

```

c
abc dea
bcd eab

```

The next example is similar, except that the optional *padchar* argument is used to specify what character to use after the characters in the *matrix* argument are each used once:

```

d = cshape("abcde", 2, 2, 3, "*");
print d;

```

Figure 23.79 Using a Pad Character

```

d
abc de*
*** ***

```

See also the description of the [SHAPE function](#), which is used with numeric data.

CUSUM Function

CUSUM(*matrix*);

The CUSUM function computes cumulative sums. The argument to this function is a numeric matrix or literal.

The CUSUM function returns a matrix of the same dimension as the argument matrix. The result contains the cumulative sums obtained by adding the nonmissing elements of the argument in row-major order.

For example, the following statements compute cumulative sums:

```
a = cusum({1 2 4 5});
b = cusum({5 6, 3 4});
print a, b;
```

Figure 23.80 Cumulative Sums

	a			
	1	3	7	12
	b			
		5	11	
		14	18	

CUPROD Function

CUPROD(*matrix*);

The CUPROD function computes cumulative products. The argument to this function is a numeric matrix or literal.

The CUPROD function returns a matrix of the same dimension as the argument matrix. The result contains the cumulative products obtained by multiplying the nonmissing elements of the argument in row-major order.

For example, the following statements compute cumulative products:

```
a = cuprod({1 2 4 5});
b = cuprod({5 6, . 4});
print a, b;
```

Figure 23.81 Output from the CUPROD Function

a			
1	2	8	40
b			
	5	30	
	30	120	

CVEXHULL Function

CVEXHULL(*matrix*);

The CVEXHULL function finds a convex hull of a set of planar points.

The *matrix* argument is an $n \times 2$ matrix of (x, y) points.

The CVEXHULL function returns an $n \times 1$ matrix of indices. The indices of points in the convex hull in counterclockwise order are returned as the first part of the result matrix, and the negative of the indices of the internal points are returned as the remaining elements of the result matrix. Any points that lie on the convex hull but lie on a line segment joining two other points on the convex hull are not included as part of the convex hull.

The result matrix can be split into positive and negative parts by using the [LOC function](#). For example, the following statements find the index vector for the convex hull and print the associated points:

```
points = {0 2, 0.5 2, 1 2, 0.5 1, 0 0, 0.5 0, 1 0,
          2 -1, 2 0, 2 1, 3 0, 4 1, 4 0, 4 -1,
          5 2, 5 1, 5 0, 6 0 };
indices = cvexhull( points );
hullIndices = indices[loc(indices>0)];
convexHull = points[hullIndices, ];
print convexHull;
```

Figure 23.82 Convex Hull of a Planar Set of Points

convexHull	
0	2
0	0
2	-1
4	-1
6	0
5	2

DATASETS Function

DATASETS(< libref >);

The DATASETS function returns a character matrix that contains the names of the SAS data sets in the specified SAS data library. The result is a character matrix with n rows and one column, where n is the number of data sets in the library. If no argument is specified, SAS/IML software uses the default libname. (See the DEFLIB= option in the description of the [RESET statement](#).)

For more information about specifying a SAS data library, see [Chapter 7](#).

Recall that SAS distributes sample data sets in the Sashelp library. The following statements list the names of the first few data sets in the library:

```
lib = "sashelp";
a = datasets(lib);
First5 = a[1:5];
print First5;
```

Figure 23.83 Several Data Sets in the Sashelp Library

First5
ACCEPTS
ADOMSG
ADSMMSG
AFMSG
AIR

DELETE Call

CALL DELETE(< libname >, < member-name >);

The DELETE call deletes one or more SAS data sets. The arguments to the DELETE subroutine are as follows:

libname is a character matrix or quoted literal that contains the name of one or more SAS data libraries.

member-names is a character matrix or quoted literal that contains the names of one or more data sets.

The DELETE subroutine deletes SAS data sets in a specified library. If you omit the *libname* argument, the default SAS data library is used. (See the DEFLIB= option in the description of the [RESET statement](#).)

The following statements use the DATA step to create several data sets and then delete them by using the DELETE subroutine in SAS/IML software:

```
data a b c d e;          /* create data sets in WORK */
  x=1;
run;
```

```

proc iml;
call delete(work,a);          /* deletes WORK.A */

reset deflib=work;           /* sets default libname to WORK */
call delete(b);              /* deletes WORK.B */

members = {"c" "d"};
call delete(members);        /* deletes WORK.C and WORK.D */

ds = datasets("work");      /* returns all data sets in WORK */
call delete("work",ds[1]);   /* deletes first data set */

```

DELETE Statement

DELETE <range> <WHERE(expression)> ;

The DELETE statement marks observations (also called records) in the current output data set for deletion. To actually delete the records and renumber the remaining observations, use the [PURGE statement](#).

The arguments to the DELETE statement are as follows:

range specifies a range of observations.
expression is an expression that is evaluated for being true or false.

You can specify *range* by using a keyword or by using the POINT operand to specify an observation number. The following keywords are valid values for *range*:

ALL	specifies all observations.
CURRENT	specifies the current observation.
NEXT <number>	specifies the next observation or the next <i>number</i> of observations.
AFTER	specifies all observations after the current one.
POINT <i>value</i>	specifies observations by number, where <i>value</i> is one of the following:

Value	Example
a single record number	<code>delete point 5</code>
a literal that contains several record numbers	<code>delete point {2 5 10}</code>
the name of a matrix that contains record numbers	<code>p=5; delete point p;</code>
an expression in parentheses	<code>delete point (p+1);</code>

The default value for *range* is **CURRENT**. If the current data set has an index in use (see the [INDEX statement](#), the **POINT** keyword is invalid.


```

delete point 3;          /* marks obs 3          */
delete all where(age<21); /* marks obs where age<21 */
purge;                  /* deletes all marked obs */
close MyData;

proc print data=MyData;
run;

```

Figure 23.84 Observations That Remain after Deletion

Obs	Sex	Age
1	M	28
2	F	32
3	F	24

Notice that observations marked for deletion by using the DELETE statement are not physically removed from the data set until a **PURGE statement** is executed.

DESIGN Function

DESIGN(*column-vector*);

The DESIGN function creates a design matrix of zeros and ones from the column vector specified by *column-vector*. Each unique value of the column vector generates a column of the design matrix. The columns are arranged in the sort order of the original values. If x_i is the i th sorted value in the column vector, \mathbf{x} , then the i th column of the design matrix contains ones in rows for which \mathbf{x} has the value x_i , and contains zeros elsewhere.

For example, the following statements produce a design matrix for a column vector that contains three unique values. The first column corresponds to the ‘A’ level, the second column corresponds to the ‘B’ level, and the third column corresponds to the ‘C’ level.

```

x = {C, A, B, B, A, A};
m = design(x);

cols = unique(x);
print m[colname=cols];

```

Figure 23.85 Design Matrix for a Vector with Three Unique Values

	m		
	A	B	C
	0	0	1
	1	0	0
	0	1	0
	0	1	0
	1	0	0
	1	0	0

The design matrix that is returned by the DESIGN function corresponds to the GLM parameterization of classification variables as documented in the section “Parameterization of Model Effects” in the *SAS/STAT User’s Guide*. See also the documentation for the [DESIGNF function](#).

DESIGNF Function

DESIGNF(*column-vector*);

The DESIGNF function creates a design matrix of zeros and ones from the column vector specified by *column-vector*. The DESIGNF function is similar to the [DESIGN function](#). The difference is that the matrix returned by the DESIGNF function is one column smaller than the matrix returned by the DESIGN function. The result of the DESIGNF function is obtained by subtracting the last column of the DESIGN function matrix from the other columns.

For example, the following statements produce a design matrix for a column vector that contains three unique values:

```
x = {C, A, B, B, A, A};
m = designf(x);

cols = unique(x);
print m[colname=cols];
```

Figure 23.86 Design Matrix for Vector with Three Unique Values

	m	
	A	B
	-1	-1
	1	0
	0	1
	0	1
	1	0
	1	0

The matrix that is returned by the DESIGNF function can be used to produce full-rank designs. The ma-

trix corresponds to the EFFECT parameterization of classification variables as documented in the section “Parameterization of Model Effects” in the *SAS/STAT User’s Guide*.

DET Function

DET(*square-matrix*);

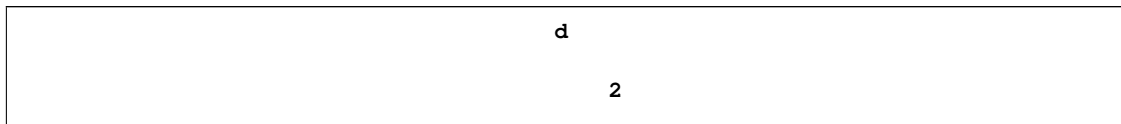
The DET function computes the determinant of a square matrix. The determinant, the product of the eigenvalues, is a scalar numeric value. If the determinant of a matrix is zero, then the matrix is singular. A singular matrix does not have an inverse.

The DET function performs an LU decomposition and collects the product of the diagonals (Forsythe, Malcom, and Moler 1967). For a matrix with n rows, the DET function allocates a temporary n^2 array in order to compute the determinant.

The following statements compute the determinant of a matrix:

```
a = {1 1 1,
      1 2 4,
      1 3 9};
d = det(a);
print d;
```

Figure 23.87 Determinant of a Matrix



The DET function uses a criterion to determine whether the input matrix is singular. See the [INV function](#) for details.

DIAG Function

DIAG(*matrix*);

The DIAG function creates a diagonal matrix. The *matrix* argument can be either a numeric square matrix or a vector.

If *matrix* is a square matrix, the DIAG function creates a matrix with diagonal elements equal to the corresponding diagonal elements. All off-diagonal elements in the new matrix are zeros.

If *matrix* is a vector, the DIAG function creates a matrix with diagonal elements that are the values in the vector. All off-diagonal elements are zeros.

For example, the following statements produce a diagonal matrix by extracting the diagonal elements of a square matrix:

```
a = {4 3,
      2 1};
c = diag(a);
print c;
```

Figure 23.88 Diagonal Matrix Obtained from a Full Matrix

c	
4	0
0	1

The following statements produce a diagonal matrix by using the elements of a vector:

```
b = {1 2 3};
d = diag(b);
print d;
```

Figure 23.89 Diagonal Matrix Obtained from a Vector

d		
1	0	0
0	2	0
0	0	3

DIF Function

DIF(*x* <, *lags* >);

The DIF function computes the differences between data values and one or more lagged (shifted) values for time series data. The arguments are as follows:

- x* specifies a $n \times 1$ numerical matrix of time series data.
- lags* specifies integer lags. The *lags* argument can be an integer matrix with d elements. If so, the DIF function returns an $n \times d$ matrix where the i th column represents the difference between the time series and the lagged data for the i th lag.

The values of the *lags* argument are usually positive integers. A positive lag shifts the time series data backwards in time. A lag of 0 represents the original time series. A negative value for the *lags* argument shifts the time series data forward in time; this is sometimes called a *lead* effect.

For example, the following statements compute the difference between the time series and the lagged data:

```
x = {1,3,4,7,9};
dif = dif(x, {0 1 3});
print dif;
```

Figure 23.90 Differences between Data and Lagged Data

dif		
0	.	.
0	2	.
0	1	.
0	3	6
0	2	6

DISPLAY Statement

DISPLAY <group-spec group-options <, ..., group-spec group-options>> ;

The DISPLAY statement displays fields in windows. The arguments to the DISPLAY statement are as follows:

<i>group-spec</i>	specifies a group. It can be specified as either a compound name of the form <i>window-name.groupname</i> or a window name followed by a group of the form <i>window-name (field-specs)</i> , where <i>field-specs</i> is as defined for the WINDOW statement .
<i>group-options</i>	can be any of the following:
NOINPUT	displays the group with all fields protected so that no data can be entered in the fields.
REPEAT	repeats the group for each element of the matrices specified as field operands.
BELL	rings the bell, sounds the alarm, or causes the speaker in your workstation to beep when the window is displayed.

The DISPLAY statement directs PROC IML to gather data into fields defined in the window for purposes of display, data entry, or menu selection. The DISPLAY statement always refers to a window that has been previously opened by a [WINDOW statement](#). The statement is described completely in [Chapter 16](#).

The DISPLAY statement is described in detail in Chapter 16, “[Window and Display Features](#).” Following are several examples that demonstrate the use of the DISPLAY statement:

```
display;
display w(i);
display w ("BELL") bell;
display w.g1 noinput;
display w (i protect=yes
           color="blue"
           j color="yellow");
```



```

x=0;
y=1;
if x<y then
  do;
    z1 = abs(x+y);
    z2 = abs(x-y);
  end;

```

The statements between the DO and END statements (called the DO group) are executed only if $\mathbf{x} < \mathbf{y}$. That is, they are executed only if all elements of \mathbf{x} are less than the corresponding elements of \mathbf{y} . If any element of \mathbf{x} is not less than the corresponding element of \mathbf{y} , the statements in the DO group are skipped and the statement that follows the END statement is executed.

It is good practice to indent the statements in a DO group as shown in the preceding example. However, the DO and END statements do not need to be on separate lines. A popular indenting style is to write the DO statement on the same line as the THEN or ELSE clause, as shown in following statements:

```

if x<y then do;
  z1 = abs(x+y);
  z2 = abs(x-y);
end;
else do;
  z1 = abs(x-y);
  z2 = abs(x+y);
end;

```

DO groups can be nested. There is no limit imposed on the number of nested DO groups. The following statements show an example of nested DO groups:

```

if x<y then do;
  if z1>z2 then do;
    z = z1 - z2;
    w = x # y;
  end;
end;

```

DO Statement, Iterative

DO *variable* = *start* **TO** *stop* < **BY** *increment* > ;

The iterative DO statement executes a group of statements several times.

The arguments to the DO statement are as follows:

<i>variable</i>	is the name of a variable that indexes the loop. This variable is sometimes called an <i>index variable</i> or a <i>looping variable</i> .
<i>start</i>	is the starting value for <i>variable</i> .
<i>stop</i>	is the stopping value for <i>variable</i> .
<i>increment</i>	is an increment value.

The *start*, *stop*, and *increment* values should be scalars or expressions that yield scalars.

When the DO group has this form, the statements between the DO and END statements are executed iteratively. The number of times the statements are executed depends on the evaluation of the expressions given in the DO statement.

The index variable starts with the *start* value and is incremented by the *increment* value after each iteration. The iterations continue provided that the index variable is less than or equal to the *stop* value. If a negative increment is used, then iterations continue provided that the index variable is greater than or equal to the *stop* value. The *start*, *stop*, and *increment* expressions are evaluated only once before the looping starts.

For example, the following statements print the value of *i* three times, as shown in [Figure 23.92](#):

```
do i = 1 to 5 by 2;
    print "The value of i is:" i;
end;
```

Figure 23.92 Arithmetic Sequences

	<i>i</i>
The value of <i>i</i> is:	1
	<i>i</i>
The value of <i>i</i> is:	3
	<i>i</i>
The value of <i>i</i> is:	5

DO DATA Statement

DO DATA < *variable* = *start* **TO** *stop* > ;

The DO DATA statement repeats a loop until an end-of-file condition occurs.

The arguments to the DO DATA statement are as follows:

<i>variable</i>	is the name of a variable that indexes the loop.
<i>start</i>	is the starting value for the looping variable.
<i>stop</i>	is the stopping value for the looping variable.

The DO DATA statement is used for repetitive DO loops that need to be exited upon the occurrence of an end of file for an [INPUT](#), [READ](#), or other I/O statement. This form is common for loops that read data from either a sequential file or a SAS data set.

When an end of file is reached inside the DO DATA group, the program immediately jumps from the group and starts executing the statement that follows the [END statement](#). DO DATA groups can be nested, where

each end of file causes a jump from the most local DO DATA group. The DO DATA loop simulates the end-of-file behavior of the SAS DATA step. You should avoid using **GOTO** and **LINK** statements to jump out of a DO DATA group.

The following statements read data from an external file. The example reads the first 100 lines or until the end of file, whichever occurs first.

```
do data i = 1 to 100;
    input name $8.;
end;
```

If you are reading data from a SAS data set, then you can use the following statements:

```
do data;                /* read next obs until eof is reached */
    read next var{x}; /* read only variable X                */
end;
```

DO Statement with an UNTIL Clause

DO UNTIL (*expression*) ;

DO *variable* = *start* **TO** *stop* <**BY** *increment*> **UNTIL**(*expression*) ;

The DO UNTIL statement conditionally executes statements iteratively.

The arguments to the DO UNTIL statement are as follows:

<i>expression</i>	is an expression that is evaluated at the bottom of the loop for being true or false.
<i>variable</i>	is the name of a variable that indexes the loop.
<i>start</i>	is the starting value for the looping variable.
<i>stop</i>	is the stopping value for the looping variable.
<i>increment</i>	is an increment value.

Using an UNTIL expression enables you to conditionally execute a set of statements iteratively. The UNTIL expression is evaluated at the bottom of the loop, and the statements inside the loop are executed repeatedly as long as the expression yields a zero or missing value. In the following example, the body of the loop executes until the value of X exceeds 100:

```
x = 1;
do until (x>100);
    x = x + 1;
end;
print x;
```

Figure 23.93 Result of a DO-UNTIL Statement

x
101

DO Statement with a WHILE Clause

DO WHILE (*expression*) ;

DO *variable* = *start* **TO** *stop* < **BY** *increment* > **WHILE**(*expression*) ;

The DO WHILE statement executes statements iteratively while a condition is true.

The arguments to the DO WHILE statement are as follows:

expression is an expression that is evaluated at the top of the loop for being true or false.
variable is the name of a variable that indexes the loop.
start is the starting value for the looping variable.
stop is the stopping value for the looping variable.
increment is an increment value.

Using a WHILE expression enables you to conditionally execute a set of statements iteratively. The WHILE expression is evaluated at the top of the loop, and the statements inside the loop are executed repeatedly as long as the expression yields a nonzero or nonmissing value.

Note that the incrementing is done before the WHILE expression is tested. The following example demonstrates the incrementing:

```
x = 1;  
do while (x<100);  
  x = x + 1;  
end;  
print x;
```

Figure 23.94 Result of a DO-WHILE Statement

x
100

The next example increments the starting value by 2:

```
y = 1;  
do i = 1 to 100 by 2 while(y<200);  
  y = y # i;  
end;  
print i y;
```

Figure 23.95 Result of an Iterative DO-WHILE Statement

i	y
11	945

DURATION Function

DURATION(*times*, *flows*, *ytm*);

The DURATION function returns a scalar value that represents the modified duration of a noncontingent cash flow. The arguments are as follows:

- times* is an n -dimensional column vector of times. The i th time corresponds to the time (often in years) until the i th cash flow occurs. Elements should be nonnegative.
- flows* is an n -dimensional column vector of cash flows.
- ytm* is the per-period yield-to-maturity of the cash-flow stream. This is a scalar and should be positive.

Duration of a security is generally defined as

$$D = -\frac{\frac{dP}{P}}{dy}$$

In other words, it is the relative change in price for a unit change in yield. Since prices move in the opposite direction to yields, the sign change preserves positivity for convenience. With cash flows that are not yield-sensitive and the assumption of parallel shifts to a flat term structure, duration is given by

$$D_{\text{mod}} = \frac{\sum_{k=1}^K t_k \frac{c(k)}{(1+y)^{t_k}}}{P(1+y)}$$

where P is the present value, y is the per-period effective yield-to-maturity, K is the number of cash flows, and the k th cash flow is $c(k)$, t_k periods from the present. This measure is referred to as *modified duration* to differentiate it from the *Macauley duration*:

$$D_{\text{Mac}} = \frac{\sum_{k=1}^K t_k \frac{c(k)}{(1+y)^{t_k}}}{P}$$

This expression also reveals the reason for the name duration, since it is a present-value-weighted average of the duration (that is, timing) of all the cash flows and is hence an “average time-to-maturity” of the bond.

For example, consider the following statements:

```
times = 1;
flow = 10;
ytm = 0.1;
duration = duration(times, flow, ytm);
print duration;
```

Figure 23.96 Duration of a Cash Flow

duration
0.9090909

ECHELON Function

ECHELON(*matrix*);

The ECHELON function uses elementary row operations to reduce a matrix to row-echelon normal form, as in the following example (Graybill 1969):

```
a = {3  6  9,  
     1  2  5,  
     2  4 10 };  
e = echelon(a);  
print e;
```

Figure 23.97 Result of the ECHELON Function

e		
1	2	0
0	0	1
0	0	0

If the argument is a square matrix, then the row-echelon normal form can be obtained from the Hermite normal form by rearranging rows that are all zeros. See the [HERMITE function](#) for details about the Hermite normal form.

EDIT Statement

EDIT *SAS-data-set* < **VAR** *operand* > < **WHERE**(*expression*) > < **NOBS** *name* > ;

The EDIT statement opens a SAS data set for reading and updating. If the data set has already been opened, the EDIT statement makes it the current input and output data sets.

The arguments to the EDIT statement are as follows:

<i>SAS-data-set</i>	can be specified with a one-level name (for example, A) or a two-level name (for example, Sasuser.A). For more information about specifying SAS data sets, see the chapter on SAS data sets in <i>SAS Language Reference: Concepts</i> .
<i>operand</i>	selects a set of variables.
<i>expression</i>	selects observations conditionally.
<i>name</i>	names a variable to contain the number of observations.

You can specify a set of variables to use with the VAR clause, where *operand* can be specified as one of the following:

- a literal that contains variable names

- the name of a matrix that contains variable names
- an expression in parentheses that yields variable names
- one of the keywords described in the following list:

<u>ALL</u>	for all variables
<u>CHAR</u>	for all character variables
<u>NUM</u>	for all numeric variables

The following examples demonstrate each possible way you can use the VAR clause:

```
var {x1 x5 x9};           /* a literal matrix of names      */
var x;                    /* a matrix that contains the names */
var ("x1":"x9");          /* an expression                  */
var _all_;                 /* a keyword                      */
```

The WHERE clause conditionally selects observations within the range specification, according to conditions given in the clause.

The general form of the WHERE clause is

WHERE (*variable comparison-op operand*) ;

The arguments to the WHERE clause are as follows:

variable is a variable in the SAS data set.

comparison-op is any one of the following comparison operators:

<	less than
<=	less than or equal to
=	equal to
>	greater than
>=	greater than or equal to
^=	not equal to
?	contains a given string
^?	does not contain a given string
=:	begins with a given string
=*	sounds like or is spelled like a given string

operand is a literal value, a matrix name, or an expression in parentheses.

WHERE comparison arguments can be matrices. For the following operators, the WHERE clause succeeds if *all* the elements in the matrix satisfy the condition:

^= ^? < <= > >=

For the following operators, the WHERE clause succeeds if *any* of the elements in the matrix satisfy the condition:

`= ? =: =*`

Logical expressions can be specified within the WHERE clause by using the AND (&) and OR (!) operators. The general form is

`clause & clause` (for an AND clause)
`clause | clause` (for an OR clause)

where *clause* can be a comparison, a parenthesized clause, or a logical expression clause that is evaluated by using operator precedence.

NOTE: The expression on the left-hand side refers to values of the data set variables, and the expression on the right-hand side refers to matrix values.

The EDIT statement can define a set of variables and the selection criteria that are used to control access to data set observations. The NOBS clause returns the total number of observations in the data set in the variable *name*.

The VAR and WHERE clauses are optional and can be specified in any order. The NOBS clause is also optional.

See [Chapter 7](#) for more information about editing SAS data sets.

To control the variables you want to edit and conditionally select observations for editing, use the VAR and WHERE clauses. For example, to read and update observations for which the *Age* variable is greater than 30, use the following statements:

```
proc iml;
/* create sample data set */
sex = { M,  M,  M,  F,  F,  F};
age = {34, 28, 38, 32, 24, 18};
create MyData var {"Sex" "Age"};
append;
close MyData;

edit MyData where (Age>30);
list all;
close MyData;
```

Figure 23.98 Result of the LIST Statement

OBS	Sex	Age
1	M	34.0000
3	M	38.0000
4	F	32.0000

To edit the data set *Work.MyData* and obtain the number of observations in the data set, use the following statements:

```
edit Work.MyData nobs NumObs;
close Work.MyData;
```

```
print NumObs;
```

Figure 23.99 Number of Observations in a Data Set

NumObs
6

Another example of using the EDIT statement is presented in the documentation for the [DELETE statement](#).

EIGEN Call

CALL EIGEN(*evals*, *evecs*, *A*) <VECL=*vl*>;

The EIGEN subroutine computes eigenvalues and eigenvectors an arbitrary square numeric matrix.

The *A* argument is the input argument to the EIGEN subroutine. The EIGEN call returns the following values:

<i>evals</i>	names a matrix to contain the eigenvalues of <i>A</i> .
<i>evecs</i>	names a matrix to contain the right eigenvectors of <i>A</i> .
<i>vl</i>	is an optional $n \times n$ matrix that contains the left eigenvectors of <i>A</i> in the same manner that <i>evecs</i> contains the right eigenvectors.

The EIGEN subroutine computes *evals*, a matrix that contains the eigenvalues of *A*. If *A* is symmetric, *evals* is the $n \times 1$ vector that contains the n real eigenvalues of *A*. If *A* is not symmetric (as determined by the criteria in the symmetry test described later), *evals* is an $n \times 2$ matrix. The first column of *evals* contains the real parts, $\text{Re}(\lambda)$, and the second column contains the imaginary parts, $\text{Im}(\lambda)$. Each row represents one eigenvalue, $\text{Re}(\lambda) + i\text{Im}(\lambda)$.

If *A* is symmetric, the eigenvalues are arranged in descending order. Otherwise, the eigenvalues are sorted first by their real parts, then by the magnitude of their imaginary parts. Complex conjugate eigenvalues, $\text{Re}(\lambda) \pm i\text{Im}(\lambda)$, are stored in standard order; that is, the eigenvalue of the pair with a positive imaginary part is followed by the eigenvalue of the pair with the negative imaginary part.

The EIGEN subroutine also computes *evecs*, a matrix that contains the orthonormal column eigenvectors that correspond to *evals*. If *A* is symmetric, then the first column of *evecs* is the eigenvector that corresponds to the largest eigenvalue, and so forth. If *A* is not symmetric, then *evecs* is an $n \times n$ matrix that contains the right eigenvectors of *A*. If the eigenvalue in row *i* of *evals* is real, then column *i* of *evecs* contains the corresponding real eigenvector. If rows *i* and *i* + 1 of *evals* contain complex conjugate eigenvalues $\text{Re}(\lambda) \pm i\text{Im}(\lambda)$, then columns *i* and *i* + 1 of *evecs* contain the real part, **u**, and imaginary part, **v**, of the two corresponding eigenvectors $\mathbf{u} \pm i\mathbf{v}$.

The following paragraphs present some properties of eigenvalues and eigenvectors. Let **A** be a general $n \times n$ matrix. The eigenvalues of **A** are the roots of the characteristic polynomial, which is defined as $p(z) = \det(z\mathbf{I} - \mathbf{A})$. The spectrum, denoted by $\lambda(A)$, is the set of eigenvalues of the matrix *A*. If $\lambda(\mathbf{A}) = \{\lambda_1, \dots, \lambda_n\}$, then $\det(\mathbf{A}) = \lambda_1 \lambda_2 \cdots \lambda_n$.

The trace of \mathbf{A} is defined by

$$\text{tr}(\mathbf{A}) = \sum_{i=1}^n a_{ii}$$

and $\text{tr}(\mathbf{A}) = \lambda_1 + \dots + \lambda_n$.

An eigenvector is a nonzero vector, \mathbf{x} , that satisfies $\mathbf{A}\mathbf{x} = \lambda\mathbf{x}$ for $\lambda \in \lambda(\mathbf{A})$. Right eigenvectors satisfy $\mathbf{A}\mathbf{x} = \lambda\mathbf{x}$, and left eigenvectors satisfy $\mathbf{x}^H \mathbf{A} = \lambda \mathbf{x}^H$, where \mathbf{x}^H is the complex conjugate transpose of \mathbf{x} . Taking the conjugate transpose of both sides shows that left eigenvectors also satisfy $\mathbf{A}'\mathbf{x} = \bar{\lambda}\mathbf{x}$.

The following are properties of the unsymmetric *real* eigenvalue problem, in which the real matrix \mathbf{A} is square but not necessarily symmetric:

- The eigenvalues of an unsymmetric matrix \mathbf{A} can be complex. If \mathbf{A} has a complex eigenvalue, $\text{Re}(\lambda) + i\text{Im}(\lambda)$, then the conjugate complex value $\text{Re}(\lambda) - i\text{Im}(\lambda)$ is also an eigenvalue of \mathbf{A} .
- The right and left eigenvectors that correspond to a real eigenvalue of \mathbf{A} are real. The right and left eigenvectors that correspond to conjugate complex eigenvalues of \mathbf{A} are also conjugate complex.
- The left eigenvectors of \mathbf{A} are the same as the complex conjugate right eigenvectors of \mathbf{A}' .

The three routines, EIGEN, EIGVAL, and EIGVEC, use the following test of symmetry for a square argument matrix \mathbf{A} :

1. Select the entry of \mathbf{A} with the largest magnitude:

$$a_{max} = \max_{i,j=1,\dots,n} |a_{i,j}|$$

2. Multiply the value of a_{max} by the square root of the machine precision, ϵ . The value of ϵ is the largest value stored in double precision that, when added to 1 in double precision, still results in 1.
3. The matrix \mathbf{A} is considered *unsymmetric* if there exists at least one pair of symmetric entries that differs in more than $a_{max}\sqrt{\epsilon}$:

$$|a_{i,j} - a_{j,i}| > a_{max}\sqrt{\epsilon}$$

If \mathbf{A} is a *symmetric* matrix and \mathbf{M} and \mathbf{E} are the eigenvalues and eigenvectors, respectively, of \mathbf{A} , then the matrices have the following properties:

$$\begin{aligned} \mathbf{A} * \mathbf{E} &= \mathbf{E} * \text{diag}(\mathbf{M}) \\ \mathbf{E}' * \mathbf{E} &= \mathbf{I} \end{aligned}$$

These properties imply the following:

$$\mathbf{E}' = \text{inv}(\mathbf{E})$$

$$\mathbf{A} = \mathbf{E} * \text{diag}(\mathbf{M}) * \mathbf{E}'$$

The QL method is used to compute the eigenvalues (Wilkinson and Reinsch 1971).

In statistical applications, nonsymmetric matrices for which eigenvalues are desired are usually of the form $\mathbf{E}^{-1}\mathbf{H}$, where \mathbf{E} and \mathbf{H} are symmetric. The eigenvalues \mathbf{L} and eigenvectors \mathbf{V} of $\mathbf{E}^{-1}\mathbf{H}$ can be obtained by using the **GENEIG subroutine**, or by using the following statements:

```
F = root(einv);
A = F*H*F`;
call eigen(L, W, A);
V = F`*W;
```

The computation can be checked by forming the residuals, \mathbf{r} , as shown in the following statement:

```
r = einv*H*V - V*diag(L);
```

The values in \mathbf{r} should be of the order of rounding error.

The following statements compute the eigenvalues and left and right eigenvectors of a nonsymmetric matrix with four real and four complex eigenvalues:

```
A = {-1  2  0      0      0      0      0  0,
     -2 -1  0      0      0      0      0  0,
       0  0 0.2379 0.5145 0.1201 0.1275 0  0,
       0  0 0.1943 0.4954 0.1230 0.1873 0  0,
       0  0 0.1827 0.4955 0.1350 0.1868 0  0,
       0  0 0.1084 0.4218 0.1045 0.3653 0  0,
       0  0  0      0      0      0      2  2,
       0  0  0      0      0      0     -2  0 };
call eigen(val, rvec, A) vec1="lvec";
print val;
```

The sorted eigenvalues of the **A** matrix are shown in [Figure 23.100](#).

Figure 23.100 Complex Eigenvalues of a Nonsymmetric Matrix

val	
1	1.7320508
1	-1.732051
1	0
0.2087788	0
0.0222025	0
0.0026187	0
-1	2
-1	-2

You can verify the correctness of the left and right eigenvector computation by using the following statements:

```
/* verify that the right eigenvectors are correct */
vec = rvec;
do j = 1 to ncol(vec);
  /* if eigenvalue is real */
  if val[j,2] = 0. then do;
```

```

    v = A * vec[,j] - val[j,1] * vec[,j];
    if any( abs(v) > 1e-12 ) then
        badVectors = badVectors || j;
    end;
/* if eigenvalue is complex with positive imaginary part */
else if val[j,2] > 0. then do;
    /* the real part */
    rp = val[j,1] * vec[,j] - val[j,2] * vec[,j+1];
    v = A * vec[,j] - rp;
    /* the imaginary part */
    ip = val[j,1] * vec[,j+1] + val[j,2] * vec[,j];
    u = A * vec[,j+1] - ip;
    if any( abs(u) > 1e-12 ) | any( abs(v) > 1e-12 ) then
        badVectors = badVectors || j || j+1;
    end;
end;
if ncol( badVectors ) > 0 then
    print "Incorrect right eigenvectors:" badVectors;
else print "All right eigenvectors are correct";

```

Similar statements can be written to verify the left eigenvectors. The statements use the fact that the left eigenvectors of A are the same as the complex conjugate right eigenvectors of A' :

```

/* verify that the left eigenvectors are correct */
vec = lvec;
do j = 1 to ncol(vec);
    /* if eigenvalue is real */
    if val[j,2] = 0. then do;
        v = A` * vec[,j] - val[j,1] * vec[,j];
        if any( abs(v) > 1e-12 ) then
            badVectors = badVectors || j;
        end;
    /* if eigenvalue is complex with positive imaginary part */
    else if val[j,2] > 0. then do;
        /* Note the use of complex conjugation */
        /* the real part */
        rp = val[j,1] * vec[,j] + val[j,2] * vec[,j+1];
        v = A` * vec[,j] - rp;
        /* the imaginary part */
        ip = val[j,1] * vec[,j+1] - val[j,2] * vec[,j];
        u = A` * vec[,j+1] - ip;
        if any( abs(u) > 1e-12 ) | any( abs(v) > 1e-12 ) then
            badVectors = badVectors || j || j+1;
        end;
    end;
if ncol( badVectors ) > 0 then
    print "Incorrect left eigenvectors:" badVectors;
else print "All left eigenvectors are correct";

```

The EIGEN call performs most of its computations in the memory allocated for returning the eigenvectors.

EIGVAL Function

EIGVAL(A);

The EIGVAL function computes the eigenvalues of a square numeric matrix, *A*. The EIGVAL function returns a column vector that contains the eigenvalues of *A*. See the description of the [EIGEN](#) subroutine for more details.

The following statements compute Example 7.1.1 from Golub and Van Loan (1989):

```
A = { 67.00  177.60  -63.20 ,
      -20.40   95.88  -87.16 ,
       22.80   67.84   12.12 };

val = eigval(A);
print val;
```

Figure 23.101 Eigenvalues

val	
75	100
75	-100
25	0

Notice that the matrix *a* is not symmetric and that the eigenvalues are complex. The first column of the *val* matrix is the real part of the three eigenvalues, and the second column is the complex part.

If a matrix is symmetric, it has real eigenvalues and real eigenvectors. The following statements produce the eigenvalues of a crossproducts matrix:

```
x = {1 1, 1 2, 1 3, 1 4};
xpx = t(x) * x;          /* xpx is a symmetric matrix */
rval = eigval(xpx);
print rval;
```

Figure 23.102 Real Eigenvalues of a Symmetric Matrix

rval	
33.401219	
0.5987805	

EIGVEC Function

EIGVEC(A);

The EIGVEC function computes the (right) eigenvectors of a square numeric matrix, A . You can obtain the left eigenvectors by first transposing A . See the description of the [EIGEN](#) subroutine for more details.

The following example calculates the eigenvectors of a symmetric matrix:

```
x = {1 1, 1 2, 1 3, 1 4};
xpx = t(x) * x;          /* xpx is a symmetric matrix */
eval = eigvec(xpx);
print eval;
```

Figure 23.103 Eigenvectors of a Symmetric Matrix

eval	
0.3220062	0.9467376
0.9467376	-0.322006

ELEMENT Function

ELEMENT(x , y);

The ELEMENT function returns a matrix that is the same shape as x . The return value indicates which elements of x are elements of y . In particular, if $\mathbf{A} = \text{element}(\mathbf{x}, \mathbf{y})$, then

$$A_i = \begin{cases} 1 & \text{if } x_i \in y \\ 0 & \text{otherwise} \end{cases}$$

The arguments are as follows:

x specifies a matrix of elements to test for membership.
 y specifies a set.

If the intersection between x and y is empty, then the ELEMENT function returns a zero matrix. If x is a proper subset of y , then the ELEMENT function returns a matrix of ones. In general, the ELEMENT function returns 1 for elements in the intersection of x and y , as shown in the following statements:

```
x = {0, 0.5, 1, 1.5, 2, 2.5, 3, 0.5, 1.5, 3, 3, 1};
set = {0 1 3}`;
b = element(x, set);

n = sum(b);          /* number of elements of X that are in SET */
idx = t(loc(b));     /* indices of elements of X that are in SET */
values = x[idx];     /* values of elements of X that are in SET */
print n idx values;
```

Figure 23.104 Elements That Belong to a Set

n	idx	values
6	1	0
	3	1
	7	3
	10	3
	11	3
	12	1

END Statement

END ;

The END statement ends a DO loop or DO statement. See the [DO statement](#) for details.

ENDSUBMIT Statement

ENDSUBMIT ;

You can use the ENDSUBMIT statement in conjunction with the [SUBMIT](#) statement to submit SAS statements for processing from within a SAS/IML program. All statements between the SUBMIT and the ENDSUBMIT statements are referred to as a *SUBMIT block*. The SUBMIT block is processed by the SAS language processor.

If you use the R option in the SUBMIT statement, you can submit statements to the R statistical software for processing.

The ENDSUBMIT statement must appear on a line by itself.

See Chapter 11, “[Calling Functions in the R Language](#),” and the documentation for the [SUBMIT](#) statement for details and examples.

EXECUTE Call

CALL EXECUTE(*statements*);

The EXECUTE subroutine immediately executes SAS statements. These can be SAS/IML statements or global SAS statements such as the TITLE statement. The arguments to the EXECUTE subroutine are character matrices or quoted literals that contains valid SAS statements. You can specify up to 15 arguments.

The EXECUTE subroutine pushes character arguments to the input command stream, executes them, and then returns to the calling module. The subroutine should be called from a module rather than from the

immediate environment because it uses the [RESUME statement](#) that works only from modules). The strings you push do not appear in the log.

Following are examples of valid EXECUTE subroutines:

```
/* define a module that writes data to a specified data set */
start WriteData(DSName, x);
  CreateStmt = "create " + DSName + " from x;"; /* build CREATE stmt */
  call execute(CreateStmt);                    /* run CREATE stmt */
  append from x;
  CloseStmt = "close " + DSName + ";";         /* build CLOSE stmt */
  call execute(CloseStmt);                    /* run CLOSE stmt */
finish;

y = {1 2 3, 4 5 6, 7 8 0};
run WriteData("MyData", y);                  /* call the module */

use MyData; list all; close MyData;          /* verify contents */
```

Figure 23.105 Results of Executing SAS/IML Statements

OBS	COL1	COL2	COL3
1	1.0000	2.0000	3.0000
2	4.0000	5.0000	6.0000
3	7.0000	8.0000	0

For more details about the EXECUTE subroutine, see Chapter 18, “[Using SAS/IML Software to Generate SAS/IML Statements](#).”

EXP Function

EXP(*matrix*);

The EXP function applies the exponential function to every element of the argument matrix. The exponential is the natural number e raised to the indicated power. For example, the following statements compute the exponentials of several numbers:

```
b = {1 2 3 4};
a = exp(b);
print a;
```

Figure 23.106 Exponential of Several Numbers

a
2.7182818 7.3890561 20.085537 54.59815

If you want to compute the exponential of a matrix, you can call the EXPMATRIX module in [IMLMLIB](#).

EXPORTDATASETTOR Call

CALL EXPORTDATASETTOR(*SAS-data-set*, *RDataFrame*);

You can use the EXPORTDATASETTOR subroutine to transfer data from a SAS data set to an R data frame. It is easier to read the subroutine name when it is written in mixed case: ExportDataSetToR.

The arguments to the subroutine are as follows:

SAS-data-set is a literal string or a character matrix that specifies the two-level name of a SAS data set (for example, Sashelp.Class).

RDataFrame is a literal string or a character matrix that specifies the name of an R data frame.

You can call the subroutine provided that the following statements are true:

1. The R statistical software is installed on the SAS workspace server.
2. The SAS system administrator at your site has enabled the RLANG SAS system option. (See “[The RLANG System Option](#)” on page 190.)

The following statements copy data from the Sashelp.Class data set into an R data frame called **class**:

```
proc iml;
call ExportDataSetToR("Sashelp.Class", "class");

submit / R;
names( class )
endsubmit;
```

To demonstrate that the data were successfully transferred, the **names** function in the R language is used to print the names of the variables in the R data frame. The output is shown in [Figure 23.107](#).

Figure 23.107 Output from R

[1] "Name" "Sex" "Age" "Height" "Weight"
--

You can transfer data from an R data frame into a SAS data set by using the [IMPORTDATASETFROMR](#) call. See Chapter 11, “[Calling Functions in the R Language](#),” for details about transferring data between R and SAS software.

EXPORTMATRIXTOR Call

CALL EXPORTMATRIXTOR(*IMLMatrix*, *RMatrix*);

You can use the EXPORTMATRIXTOR subroutine to transfer data from a SAS data set to an R data frame. It is easier to read the subroutine name when it is written in mixed case: ExportMatrixToR.

The arguments to the subroutine are as follows:

IMLMatrix is a SAS/IML matrix that contains the data you want to transfer.
RMatrix is a literal string or a character matrix that specifies the name of an R matrix to contain a copy of the data.

You can call the subroutine provided that the following statements are true:

1. The R statistical software is installed on the SAS workspace server.
2. The SAS system administrator at your site has enabled the RLANG SAS system option. (See “[The RLANG System Option](#)” on page 190.)

The following statements define a SAS/IML matrix and copy the data from the matrix to an R matrix called **m**:

```
proc iml;
a = {1 2 3, 4 . 6};
call ExportMatrixToR(a, "m");

submit / R;
print(m)
endsubmit;
```

To demonstrate that the data were successfully transferred, the **print** function in the R language is used to print the values of the **m** matrix. The output is shown in [Figure 23.108](#). Note that the SAS missing value in the SAS/IML matrix was automatically converted to the R missing value (**NA**).

Figure 23.108 Output from R

	A1	A2	A3
[1,]	1	2	3
[2,]	4	NA	6

You can transfer data from an R matrix frame into a SAS/IML matrix by using the **IMPORTMATRIXFROMR** call. See Chapter 11, “[Calling Functions in the R Language](#),” for details about transferring data between R and SAS software.

The names of the variables in the R data frame are the same as in the SAS data set.

FARMACOV Call

CALL FARMACOV(*cov*, *d* < , *phi* < , *theta* < , *sigma* < , *p* < , *q* < , *lag* >);

The FARMACOV subroutine computes the autocovariance function for an autoregressive fractionally integrated moving average (ARFIMA) model of the form ARFIMA(p, d, q).

The input arguments to the FARMACOV subroutine are as follows:

- d* specifies a fractional differencing order. The value of *d* must be in the open interval $(-0.5, 0.5)$ excluding zero. This input is required.
- phi* specifies an m_p -dimensional vector that contains the autoregressive coefficients, where m_p is the number of the elements in the subset of the AR order. The default is zero. All the roots of $\phi(B) = 0$ should be greater than one in absolute value, where $\phi(B)$ is the finite-order matrix polynomial in the backshift operator B , such that $B^j y_t = y_{t-j}$.
- theta* specifies an m_q -dimensional vector that contains the moving average coefficients, where m_q is the number of the elements in the subset of the MA order. The default is zero.
- p* specifies the subset of the AR order. The quantity m_p is defined as the number of elements of *phi*.
If you do not specify *p*, the default subset is $p = \{1, 2, \dots, m_p\}$.
For example, consider *phi*=0.5.
If you specify *p*=1 (the default), the FARMACOV subroutine computes the theoretical autocovariance function of an ARFIMA(1, *d*, 0) process as $y_t = 0.5 y_{t-1} + \epsilon_t$.
If you specify *p*=2, the FARMACOV subroutine computes the autocovariance function of an ARFIMA(2, *d*, 0) process as $y_t = 0.5 y_{t-2} + \epsilon_t$.
- q* specifies the subset of the MA order. The quantity m_q is defined as the number of elements of *theta*.
If you do not specify *q*, The default subset is $q = \{1, 2, \dots, m_q\}$.
The usage of *q* is the same as that of *p*.
- lag* specifies the length of lags, which must be a positive number. The default is *lag*= 12.

The FARMACOV subroutine returns the following value:

cov is a *lag*+1 vector that contains the autocovariance function of an ARFIMA(p, d, q) process.

As an example, consider the following ARFIMA(1, 0.3, 1) process:

$$(1 - 0.5B)(1 - B)^{0.3}y_t = (1 + 0.1B)\epsilon_t$$

In this process, $\epsilon_t \sim NID(0, 1.2)$. The following statements compute the autocovariance of this process:

```
d = 0.3;
phi = 0.5;
theta = -0.1;
sigma = 1.2;
```

```
call farmacov(cov, d, phi, theta, sigma) lag=5;
print cov;
```

Figure 23.109 Autocovariance of an ARFIMA Process

cov
4.2493033
3.5806774
2.9152846
2.4381017
2.1068697
1.8743199

For $d \in (-0.5, 0.5) \setminus \{0\}$, the series y_t represented as $(1 - B)^d y_t = \epsilon_t$ is a stationary and invertible ARFIMA(0, d , 0) process with the autocovariance function

$$\gamma_k = E(y_t y_{t-k}) = \frac{(-1)^k \Gamma(-2d + 1)}{\Gamma(k - d + 1) \Gamma(-k - d + 1)}$$

and the autocorrelation function

$$\rho_k = \frac{\gamma_k}{\gamma_0} = \frac{\Gamma(-d + 1) \Gamma(k + d)}{\Gamma(d) \Gamma(k - d + 1)} \sim \frac{\Gamma(-d + 1)}{\Gamma(d)} k^{2d-1}, \quad k \rightarrow \infty$$

Notice that ρ_k decays hyperbolically as the lag increases, rather than showing the exponential decay of the autocorrelation function of a stationary ARMA(p , q) process.

For $d \in (0.5, 0.5) \setminus \{0\}$, the series y_t is a stationary and invertible ARFIMA(p , d , q) process represented as

$$\phi(B)(1 - B)^d y_t = \theta(B)\epsilon_t$$

where $\phi(B) = 1 - \phi_1 B - \phi_2 B^2 - \dots - \phi_p B^p$ and $\theta(B) = 1 - \theta_1 B - \theta_2 B^2 - \dots - \theta_q B^q$ and ϵ_t is a white noise process; all the roots of the characteristic AR and MA polynomial lie outside the unit circle.

Let $x_t = \theta(B)^{-1} \phi(B) y_t$, so that x_t follows an ARFIMA(0, d , 0) process; let $z_t = (1 - B)^d y_t$, so that z_t follows an ARMA(p , q) process; let γ_k^x be the autocovariance function of $\{x_t\}$ and γ_k^z be the autocovariance function of $\{z_t\}$.

Then the autocovariance function of $\{y_t\}$ is as follows:

$$\gamma_k = \sum_{j=-\infty}^{j=\infty} \gamma_j^z \gamma_{k-j}^x$$

The explicit form of the autocovariance function of $\{y_t\}$ is given by Sowell (1992).

FARMAFIT Call

CALL FARMAFIT(*d*, *phi*, *theta*, *sigma*, *series* <, *p*> <, *q*> <, *opt*>);

The FARMAFIT subroutine estimates the parameters of an ARFIMA(p, d, q) model.

The input arguments to the FARMAFIT subroutine are as follows:

- series* specifies a time series (assuming mean zero).
- p* specifies the set or subset of the AR order. If you do not specify *p*, the default is $p = 0$.
 If you specify $p=3$, the FARMAFIT subroutine estimates the coefficient of the lagged variable y_{t-3} .
 If you specify $p=\{1, 2, 3\}$, the FARMAFIT subroutine estimates the coefficients of lagged variables y_{t-1} , y_{t-2} , and y_{t-3} .
- q* specifies the subset of the MA order. If you do not specify *q*, the default value is 0.
 If you specify $q=2$, the FARMAFIT subroutine estimates the coefficient of the lagged variable ϵ_{t-2} .
 If you specify $q=\{1, 2\}$, the FARMAFIT subroutine estimates the coefficients of lagged variables ϵ_{t-1} and ϵ_{t-2} .
- opt* specifies the method of computing the log-likelihood function.
- 0 requests the conditional sum of squares function. This is the default.
- 1 requests the exact log-likelihood function. This option requires that the time series be stationary and invertible.

The FARMAFIT subroutine returns the following values:

- d* is a scalar that contains a fractional differencing order.
- phi* is a vector that contains the autoregressive coefficients.
- theta* is a vector that contains the moving average coefficients.
- sigma* is a scalar that contains a variance of the innovation series.

As an example, consider the following ARFIMA(1, 0.3, 1) model:

$$(1 - 0.5B)(1 - B)^{0.3}y_t = (1 + 0.1B)\epsilon_t$$

In this model, $\epsilon_t \sim NID(0, 1)$. The following statements estimate the parameters of this model:

```
d = 0.3;
phi = 0.5;
theta = -0.1;
call farmasim(yt, d, phi, theta) seed=1234;
call farmafit(d, ar, ma, sigma, yt) p=1 q=1;
print d ar ma sigma;
```

Figure 23.110 Parameter Estimates for a ARFIMA Model

d	ar	ma	sigma
0.3950157	0.5676217	-0.012339	1.2992989

The FARMFIT subroutine estimates the parameters d , $\phi(B)$, $\theta(B)$, and σ_ϵ^2 of an ARFIMA(p, d, q) model. The log-likelihood function is solved by iterative numerical procedures such as the quasi-Newton optimization. The starting value d is obtained by the approach of Geweke and Porter-Hudak (1983); the starting values of the AR and MA parameters are obtained from the least squares estimates.

FARMALIK Call

CALL FARMALIK(*lnl*, *series*, *d* <, *phi* > <, *theta* > <, *sigma* > <, *p* > <, *q* > <, *opt* >);

The FARMALIK subroutine evaluates the log-likelihood function of an ARFIMA(p, d, q) model for a given time series.

The input arguments to the FARMALIK subroutine are as follows:

<i>series</i>	specifies a time series (assuming mean zero).
<i>d</i>	specifies a fractional differencing order. This argument is required; the value of d should be in the open interval $(-1, 1)$ excluding zero.
<i>phi</i>	specifies an m_p -dimensional vector that contains the autoregressive coefficients, where m_p is the number of the elements in the subset of the AR order. The default is zero.
<i>theta</i>	specifies an m_q -dimensional vector that contains the moving average coefficients, where m_q is the number of the elements in the subset of the MA order. The default is zero.
<i>sigma</i>	specifies a variance of the innovation series. The default is one.
<i>p</i>	specifies the subset of the AR order. See the FARMACOV subroutine for additional details.
<i>q</i>	specifies the subset of the MA order. See the FARMACOV subroutine for additional details.
<i>opt</i>	specifies the method of computing the log-likelihood function. The following are valid values:
0	requests the conditional sum of squares function. This is the default.
1	requests the exact log-likelihood function. This option requires that the time series be stationary and invertible.

The FARMALIK subroutine returns the following value:

<i>lnl</i>	is a three-dimensional vector. If <i>opt</i> = 0 is specified, the conditional sum of squares function is evaluated and the result returns in lnl[1] . Otherwise, lnl[1] contains the log-likelihood function of the model; lnl[2] contains the sum of the log determinant of the innovation variance; and lnl[3] contains the weighted sum of squares of residuals. The log-likelihood function is computed as $-0.5 \times (\mathbf{lnl}[2] + \mathbf{lnl}[3])$.
------------	---

As an example, consider the following ARFIMA(1, 0.3, 1) model:

$$(1 - 0.5B)(1 - B)^{0.3}y_t = (1 + 0.1B)\epsilon_t$$

In this model, $\epsilon_t \sim NID(0, 1.2)$. The following statements compute the log-likelihood function of this model:

```

d = 0.3;
phi = 0.5;
theta = -0.1;
sigma = 1.2;
call farmasim(yt, d, phi, theta, sigma) seed=1234;
call farmalik(lnl, yt, d, phi, theta, sigma);
print (lnl[1])[label="Conditional Sum of Squares"];

```

Figure 23.111 Log-Likelihood for an ARFIMA Model

Conditional Sum of Squares
-16.67587

The FARMALIK subroutine computes a log-likelihood function of the ARFIMA(p, d, q) model. The exact log-likelihood function was proposed by Sowell (1992); the conditional sum of squares function was proposed by Chung (1996).

The exact log-likelihood function only considers a stationary and invertible ARFIMA(p, d, q) process with $d \in (-0.5, 0.5) \setminus \{0\}$ represented as

$$\phi(B)(1 - B)^d y_t = \theta(B)\epsilon_t$$

where $\epsilon_t \sim NID(0, \sigma^2)$.

Let $Y_T = [y_1, y_2, \dots, y_T]'$ and the log-likelihood function is as follows without a constant term:

$$\ell = -\frac{1}{2}(\log |\Sigma| + Y_T' \Sigma^{-1} Y_T)$$

where $\Sigma = [\gamma_{i-j}]$ for $i, j = 1, 2, \dots, T$.

The conditional sum of squares function does not require the normality assumption. The initial observations y_0, y_{-1}, \dots and $\epsilon_0, \epsilon_{-1}, \dots$ are set to zero.

Let y_t be an ARFIMA(p, d, q) process represented as

$$\phi(B)(1 - B)^d y_t = \theta(B)\epsilon_t$$

Then the conditional sum of squares function is

$$\ell = -\frac{T}{2} \log \left(\frac{1}{T} \sum_{t=1}^T \epsilon_t^2 \right)$$

FARMASIM Call

CALL FARMASIM(series, d <, phi> <, theta> <, mu> <, sigma> <, n> <, p> <, q> <, initial> <, seed>);

The FARMASIM subroutine generates an ARFIMA(p, d, q) process. The input arguments to the FARMASIM subroutine are as follows:

- d* specifies a fractional differencing order. This argument is required; the value of *d* should be in the open interval $(-1, 1)$ excluding zero.
- phi* specifies an m_p -dimensional vector that contains the autoregressive coefficients, where m_p is the number of the elements in the subset of the AR order. The default is zero.
- theta* specifies an m_q -dimensional vector that contains the moving average coefficients, where m_q is the number of the elements in the subset of the MA order. The default is zero.
- mu* specifies a mean value. The default is zero.
- sigma* specifies a variance of the innovation series. The default is one.
- n* specifies the length of the series. The value of *n* should be greater than or equal to the AR order. The default is $n = 100$ is used.
- p* specifies the subset of the AR order. See the FARMACOV subroutine for additional details.
- q* specifies the subset of the MA order. See the FARMACOV subroutine for additional details.
- initial* specifies the initial values of random variables. The initial value is used for the nonstationary process. If *initial* = a_0 , then y_{-p+1}, \dots, y_0 take the same value a_0 . If the *initial* option is not specified, the initial values are set to zero.
- seed* is a scalar that contains the random number seed. At the first execution of the subroutine, the seed variable is used as follows:
- If *seed* > 0, the input seed is used for generating the series.
 - If *seed* = 0, the system clock is used to generate the seed.
 - If *seed* < 0, the value $(-1) \times (\text{seed})$ is used for generating the series.
 - If the seed is not supplied, the system clock is used to generate the seed.
- On subsequent calls of the subroutine in the DO-loop-like environment, the seed variable is used as follows: If *seed* > 0, the seed remains unchanged. In other cases, after each execution of the subroutine, the current seed is updated internally.

The FARMASIM subroutine returns the following value:

series is an *n* vector that contains the generated ARFIMA(*p*, *d*, *q*) process.

As an example, consider the following ARFIMA(1, 0.3, 1) process:

$$(1 - 0.5B)(1 - B)^{0.3}(y_t - 10) = (1 + 0.1B)\epsilon_t$$

In this process, $\epsilon_t \sim NID(0, 1.2)$. The following statements generate this process:

```
d = 0.3;
phi = 0.5;
theta = -0.1;
mu = 10;
sigma = 1.2;
call farmasim(yt, d, phi, theta, mu, sigma, 10) seed=1234;
print yt;
```

Figure 23.112 Data Simulated from a ARFIMA Process

y_t
12.17358
13.954495
15.817231
15.94882
12.25926
13.641022
13.399623
11.930759
10.049435
9.1445036

The FARMASIM subroutine generates a time series of length n from an ARFIMA(p, d, q) model. If the process is stationary and invertible, the initial values y_{-p+1}, \dots, y_0 are produced by using covariance matrices obtained from FARMACOV. If the process is nonstationary, the time series is recursively generated by using the user-defined initial value or the zero initial value.

To generate an ARFIMA(p, d, q) process with $d \in [0.5, 1)$, x_t is first generated for $d' \in (-0.5, 0)$, where $d' = d - 1$ and then y_t is generated by $y_t = y_{t-1} + x_t$.

To generate an ARFIMA(p, d, q) process with $d \in (-1, -0.5]$, a two-step approximation based on a truncation of the expansion $(1 - B)^d$ is used; the first step is to generate an ARFIMA(0, d , 0) process $x_t = (1 - B)^{-d} \epsilon_t$, with truncated moving average weights; the second step is to generate $y_t = \phi(B)^{-1} \theta(B) x_t$.

FDIF Call

CALL FDIF(*out*, *series*, *d*);

The FDIF subroutine computes a fractionally differenced process. The input arguments to the FDIF subroutine are as follows:

series specifies a time series with n length.

d specifies a fractional differencing order. This argument is required; the value of d should be in the open interval $(-1, 1)$ excluding zero.

The FDIF subroutine returns the following value:

out is an n vector that contains the fractionally differenced process.

As an example, consider an ARFIMA(1, 0.3, 1) process

$$(1 - 0.5B)(1 - B)^{0.3}y_t = (1 + 0.1B)\epsilon_t$$

Let $z_t = (1 - B)^{0.3}y_t$; that is, z_t follows an ARMA(1,1). The following statements compute the filtered series z_t :

```

d = 0.3;
phi = 0.5;
theta = -0.1;
call farmasim(yt, d, phi, theta) n=10 seed=1234;
call fdif(zt, yt, d);
print zt;

```

Figure 23.113 A Fractionally Differenced Process

zt
.
3.0146839
4.0190575
3.3402864
-0.41881
1.6149336
1.1998534
-0.137789
-1.475051
-1.670366

FFT Function

FFT(x);

The FFT function computes the finite Fourier transform. The argument x is a $1 \times n$ or $n \times 1$ numeric vector. The FFT function returns the cosine and sine coefficients for the expansion of a vector into a sum of cosine and sine functions. This is an $np \times 2$ matrix, where

$$np = \text{floor}\left(\frac{n}{2} + 1\right)$$

The elements of the first column of the returned matrix are the cosine coefficients; that is, the i th element of the first column is

$$\sum_{j=1}^n x_j \cos\left(\frac{2\pi}{n}(i-1)(j-1)\right)$$

for $i = 1, \dots, np$, where the elements of x are denoted as x_j . The elements of the second column of the returned matrix are the sine coefficients; that is, the i th element of the second column is

$$\sum_{j=1}^n x_j \sin\left(\frac{2\pi}{n}(i-1)(j-1)\right)$$

for $i = 1, \dots, np$.

NOTE: For most efficient use of the FFT function, n should be a power of 2. If n is a power of 2, a fast Fourier transform is used (Singleton 1969); otherwise, a Chirp-Z algorithm is used (Monro and Branch 1976).

The FFT function can be used to compute the periodogram of a time series. In conjunction with the inverse finite Fourier transform routine `IFFT`, the FFT function can be used to efficiently compute convolutions of large vectors (Gentleman and Sande 1966; Nussbaumer 1982).

As an example, suppose you measure a signal at constant time intervals. You believe the signal consists of a small number of Fourier components (that is, sines and cosines) corrupted by noise. The following examples uses the FFT function to transform the signal into the frequency domain. The example then prints the frequencies with the largest amplitudes in the signal. According to this analysis, the signal is primarily composed of a constant signal, a signal with frequency 4 (for example, $A \cos(4t) + B \sin(4t)$), a signal with frequency 1, and a signal with frequency 3. The amplitudes of the remaining Fourier components, are all substantially smaller.

```
Signal = {
  1.96  1.45  0.86  0.46  0.39  0.54 -1.65  0.60  0.43  0.20
-1.15  1.10  0.42  3.22  2.02  3.41  3.46  3.51  4.33  4.38
  3.92  4.35  2.60  3.95  4.72  4.84  1.62  0.97  0.96  1.10
  2.53  1.09  2.84  2.51  2.38  2.40  2.76  3.42  3.78  4.08
  3.84  5.62  4.33  6.66  5.27  3.14  3.82  5.74  3.45  1.07
  0.31  2.07  0.49 -1.85  0.61  0.35 -0.89 -0.92  0.33  2.31
  1.13  2.28  3.73  3.78  2.63  4.15  5.27  3.62  5.99  3.79
  4.00  3.18  3.03  3.52  2.08  1.70 -1.50 -1.35 -0.34 -1.52
-2.37 -2.84 -1.68 -2.22 -2.49 -3.28 -2.12 -0.81  0.84  1.91
  2.10  2.24  1.24  3.24  2.89  3.14  4.21  2.65  4.67  3.87
}`;

z = fft(Signal);
Amplitude = z[,1]##2 + z[,2]##2;

/* find index into Amplitude so that idx[1] is the largest
   value, idx[2] is the second largest value, etc. */
call sortndx(idx,Amplitude,1,1);

/* print the 10 most dominant frequencies */
Amplitude = Amplitude[idx[1:10],];
print (idx[1:10]-1)[label="Freqs"] Amplitude[format=10.2];
```

Figure 23.114 Frequencies and Amplitudes of a Signal

Freqs	Amplitude
0	38757.80
4	13678.28
1	4077.99
3	2726.76
26	324.23
44	269.48
12	224.09
20	217.35
11	202.30
23	201.05

Based on these results, you might choose to filter the signal to keep only the most dominant Fourier com-

ponents. One way to accomplish this is to eliminate any frequencies with small amplitudes. When the truncated frequencies are transformed back by using [IFFT](#), you obtain a filtered version of the original signal. The following statements perform these tasks:

```
/* based on amplitudes, keep only first few dominant frequencies */
NumFreqs = 4;
FreqsToDrop = idx[ (NumFreqs+1) :nrow(idx) ];
z[FreqsToDrop,] = 0;

FilteredSignal = ifft(z) / nrow(Signal);
```

FILE Statement

FILE *filename* <RECFM=*N*> <LRECL=*operand*> ;

The FILE statement opens an external file for output.

The arguments to the FILE statement are as follows:

<i>filename</i>	is a name (for defined filenames), a quoted literal, or an expression in parentheses (for pathnames).
RECFM=N	specifies that the file be written as a pure binary file without record-separator characters.
LRECL= <i>operand</i>	specifies the record length of the output file. The default record length is 512.

You can use the FILE statement to open a file for output, or if the file is already open, to make it the current output file so that subsequent [PUT statements](#) write to it. The FILE statement is similar in syntax and operation to the [INFILE statement](#). The FILE statement is described in detail in [Chapter 8](#).

The *filename* argument is either a predefined filename or a quoted string or character expression in parentheses referring to the pathname. You can refer to an input or output file two ways: by a pathname or by a filename. The pathname is the name as known to the operating system. The filename is a SAS reference to the file established directly through a connection made with the FILENAME statement. You can specify a file in either way in the FILE and [INFILE](#) statements. To specify a filename as the operand, just give the name. The name must be one already connected to a pathname by a previously issued FILENAME statement. However, two special filenames are recognized by the SAS/IML language: [LOG](#) and [PRINT](#). These refer to the standard output streams for all SAS sessions. To specify a pathname, enclose it in quotes or specify an expression in parentheses that yields the pathname.

When the pathname is specified, the operand is limited to 64 characters.

Note that RECFM=U is equivalent to RECFM=N. If an output file is subsequently read by a SAS DATA step, RECFM=N must be specified in the DATA step to guarantee that the file is read properly.

Following are several valid uses of FILE statement:

```
file "student.dat";           /* by literal pathname */

filename out "student.dat";   /* specify filename OUT */
```

```

file out;                /* refer to by filename */

file print;              /* standard print output */
file log;                /* output to log          */

file "student.dat" recfm=n; /* for a binary file      */

```

FIND Statement

FIND *<range>* **<WHERE**(*expression*) **> INTO** *matrix-name* ;

The FIND statement finds the observation numbers in *range* that satisfy the conditions of the WHERE clause. The FIND statement places these observation numbers in the numeric matrix whose name follows the INTO keyword.

The arguments to the FIND statement are as follows:

range specifies a range of observations.
expression is an expression that is evaluated for being true or false.
matrix-name names a matrix to contain the observation numbers.

You can use any of the following keywords to specify the *range* of observations:

ALL all observations
CURRENT the current observation
NEXT *<number>* the next observation or the next *number* of observations
AFTER all observations after the current one
POINT *value* observations specified by number, where *value* is one of the following:

Value	Example
A single record number	point 5
A literal that contains several record numbers	point {2 5 10}
The name of a matrix that contains record numbers	point p
An expression in parentheses	point (p+1)

If the current data set has an index in use (see the [INDEX statement](#)), the POINT option is invalid.

The WHERE clause conditionally selects observations, within the range specification, according to conditions given in the clause. The general form of the WHERE clause is

WHERE (*variable comparison-op operand*) ;

The arguments to the WHERE clause are as follows:

<i>variable</i>	is a variable in the SAS data set.
<i>comparison-op</i>	is one of the following comparison operators:
<	less than
<=	less than or equal to
=	equal to
>	greater than
>=	greater than or equal to
^=	not equal to
?	contains a given string
^?	does not contain a given string
=:	begins with a given string
=*	sounds like or is spelled like a given string
<i>operand</i>	is a literal value, a matrix name, or an expression in parentheses.

WHERE comparison arguments can be matrices. For the following operators, the WHERE clause succeeds if *all* the elements in the matrix satisfy the condition:

`^= ^? < <= > >=`

For the following operators, the WHERE clause succeeds if *any* of the elements in the matrix satisfy the condition:

`= ? =: =*`

Logical expressions can be specified within the WHERE clause by using the AND (&) and OR (|) operators. The general form is

clause & *clause* (for an AND clause)
clause | *clause* (for an OR clause)

where *clause* can be a comparison, a parenthesized clause, or a logical expression clause that is evaluated by using operator precedence.

NOTE: The expression on the left-hand side refers to values of the data set variables, and the expression on the right-hand side refers to matrix values.

Following are some valid examples of the FIND statement:

```
find all where(name="Smith") into p;
find next where(age>30) into p2;
```

The column vectors **p** and **p2** contain the observation numbers that satisfy the WHERE clause in the given range. The default range is all observations.

FINISH Statement

FINISH < module-name > ;

The FINISH statement signals the end of a module and the end of module definition mode. Optionally, the FINISH statement can take the module name as its argument. See the description of the START statement and consult [Chapter 6](#) for further information about defining modules.

Some examples follow:

```
start myAdd(a,b);
    return (a+b);
finish;

start mySubtract(a,b);
    return (a-b);
finish mySubtract;

r = myAdd(5, 3);
s = mySubtract(5, 3);
print r s;
```

Figure 23.115 Results of Calling Modules

	r	s
	8	2

FORCE Statement

The FORCE statement is an alias for the [SAVE statement](#).

FORWARD Function

FORWARD(*times*, *spot_rates*);

The FORWARD function computes a column vector of (per-period) forward rates, given vectors of spot rates and times. The arguments to the function are as follows:

- times* is an $n \times 1$ column vector of times in consistent units. Elements should be nonnegative.
- spot_rates* is an $n \times 1$ column vector of corresponding (per-period) spot rates. Elements should be positive.

The FORWARD function transforms the given spot rates as

$$f_1 = s_1$$

$$f_i = \left(\frac{(1 + s_i)^{t_i}}{(1 + s_{i-1})^{t_{i-1}}} \right)^{\frac{1}{t_i - t_{i-1}}} - 1; \quad i = 2, \dots, n$$

For example, the following statements compute forward rates:

```
time = T(do(1, 5, 1));
spot = T(do(0.05, 0.09, 0.01));
forward = forward(time, spot);
print forward;
```

Figure 23.116 Forward Rates

forward
0.05
0.0700952
0.0902839
0.1105642
0.1309345

FREE Statement

FREE *matrices* ;

FREE /<keep-matrices> ;

The FREE statement releases memory associated with matrices. The matrices specified in the FREE statement lose their values; the memory becomes available for other uses. After the FREE statement executes, the matrix does not have a value and the **NROW** and **NCOL** functions return 0. Any printing attributes (assigned by the **MATTRIB** statement) are not released.

The FREE statement is used mostly in large applications or under tight memory constraints to make room for more data (matrices) in the workspace.

For example, the following statement frees the matrices **a**, **b**, and **c**:

```
free a b c;
```

If you want to free all matrices, specify a slash (/) after the keyword FREE. If you want to free all matrices except a few, then list the ones you do not want to free after the slash. For example, the following statement frees all matrices except **d** and **e**:

```
free / d e;
```

For more information, see the discussion of workspace storage in [Chapter 22](#).

FULL Function

FULL(x <, $nrow$ > <, $ncol$ >);

The FULL function converts a matrix stored in a sparse format into a matrix stored in a dense format. See the [SPARSE function](#) for a description of how sparse matrices are stored.

The arguments are as follows:

- x specifies a $k \times 3$ numerical matrix that contains a sparse representation of an $n \times p$ matrix.
- $nrow$ specifies the number of rows in the dense matrix. If this argument is not specified, then the number of rows is determined by the maximum value of the second column of x .
- $ncol$ specifies the number of columns in the dense matrix. If this argument is not specified, then the number of columns is determined by the maximum value of the third column of x .

The matrix returned by the FULL function is an $n \times p$ matrix with k nonzero values determined by the x matrix, as shown in the following example:

```
s = {3    1    1,
      1.1  2    1,
      4    2    2,
      1    3    2,
      10   3    3,
      3.2  4    2,
      3    4    4 };
x = full(s);
print x;
```

Figure 23.117 Matrix Converted from Sparse to Dense Storage

x			
3	0	0	0
1.1	4	0	0
0	1	10	0
0	3.2	0	3

In the previous example, the **s** matrix specifies a lower triangular matrix. However, the **s** matrix might represent a symmetric matrix rather than a lower triangular matrix, but only the lower triangular entries were stored. (For example, the **s** matrix might have been created by the SPARSE function by using the “SYM” option; see the [SPARSE function](#) documentation.) If that is the case, you can use the following statement to recover the symmetric matrix representation of **s**:

```
xSym = (x+x`) - diag(x);
print xSym;
```

Figure 23.118 Symmetric Matrix Converted from Sparse Symmetric Storage

xSym			
3	1.1	0	0
1.1	4	1	3.2
0	1	10	0
0	3.2	0	3

By default, the size of the matrix returned by the FULL function is determined by the maximum row and column entry in the first argument. You can override this behavior by specifying values for the number of rows and columns returned by the FULL function, as shown in the following statements:

```
z = full(s, 5, 6);  
print z;
```

Figure 23.119 Matrix with Zeros in Last Row or Column

z					
3	0	0	0	0	0
1.1	4	0	0	0	0
0	1	10	0	0	0
0	3.2	0	3	0	0
0	0	0	0	0	0

GAEND Call

```
CALL GAEND(id);
```

The GAEND subroutine ends a genetic algorithm optimization and frees memory resources. The arguments to the GAEND call are as follows:

id is the identifier for the genetic algorithm optimization problem, which was returned by the [GASETUP function](#).

The GAEND call ends the genetic algorithm calculations associated with *id* and frees up all associated memory.

See the [GASETUP function](#) for an example.

GAGETMEM Call

```
CALL GAGETMEM(members, values, id<, index>);
```


The GAGETMEM subroutine gets members of the current solution population for a genetic algorithm optimization.

The GAGETMEM call returns the following values as output arguments:

<i>members</i>	names a matrix that contains the members of the current solution population specified by the <i>index</i> parameter.
<i>values</i>	names a matrix that contains objective function values, with a value at each row that corresponds to the solution in <i>members</i> .

The input arguments to the GAGETMEM call are as follows:

<i>id</i>	is the identifier for the genetic algorithm optimization problem, which was returned by the GASETUP function .
<i>index</i>	is a matrix of indices of the requested solution population members. If <i>index</i> is not specified, the entire population is returned.

The GAGETMEM call is used to retrieve members of the solution population and their objective function values. If the *elite* parameter of the [GASETSEL call](#) is nonzero, then the first *elite* members of the population have the most optimal objective function values of the population, and those *elite* members are sorted in ascending order of objective function value for a minimization problem and in descending order for a maximization problem.

If a single member is requested, that member is returned as-is in *members*. If more than one member is requested in a GAGETMEM call, each row of *members* has one solution, shaped into a row vector. If solutions are not of fixed length, then the number of columns of *members* equals the number of elements of the largest solution and rows that represent solutions with fewer elements have the extra elements filled in with missing values.

See the [GASETUP function](#) for an example.

GAGETVAL Call

CALL GAGETVAL(*values*, *id*<, *index*>);

The GAGETVAL subroutine gets objective function values for members of the population in a genetic algorithm optimization. The GAGETVAL call returns the following output argument:

<i>values</i>	names a matrix that contains objective function values for solutions in the current population that are specified by <i>index</i> . If <i>index</i> is not present, then values for all solutions in the population are returned. Each row in <i>values</i> corresponds to one solution.
---------------	--

The input arguments to the GAGETVAL call are as follows:

<i>id</i>	is the identifier for the genetic algorithm optimization problem, which was returned by the GASETUP function .
-----------	--

index is a matrix of indices of the requested objective function values. If *index* is not specified, then all objective function values are returned.

The GAGETVAL call is used to retrieve objective function values of the current solution population. If the *elite* parameter of the GASETSEL call is nonzero, then the first *elite* members of the population have the most optimal objective function values of the population, and those *elite* members are sorted in ascending order of objective function value for a minimization problem or in descending order for a maximization problem.

See the GASETUP function for an example.

GAINIT Call

CALL GAINIT(*id*, *popsiz*e < , *bounds* > < , *modname* >);

The GAINIT subroutine creates and initializes a solution population for a genetic algorithm optimization. The input arguments to the GAINIT call are as follows:

<i>id</i>	is the identifier for the genetic algorithm optimization problem, which was returned by the GASETUP function.
<i>popsiz</i> e	is the number of solution matrices to create and initialize.
<i>bounds</i>	is an optional parameter matrix that specifies the lower and upper bounds for each element of a solution matrix. It is used only for integer and real fixed-length vector problem encoding.
<i>modname</i>	is the name of a user-written module to be called from GAINIT when it generates the initial members of the solution population.

The GAINIT call creates the members and computes the objective values for an initial solution population for a genetic algorithm optimization. If the problem encoding is specified as a sequence in the corresponding GASETUP function call and no *modname* parameter is specified, then GAINIT creates an initial population of vectors of randomly ordered integer values ranging from 1 to the *size* parameter of the GASETUP function call. Otherwise, you control how the population is created and initialized with the *bounds* and *modname* parameters.

If real or integer fixed-length vector encoding is specified in the corresponding GASETUP function call, then the *bounds* parameter can be supplied as a $2 \times n$ matrix, where the dimension n equals the *size* parameter of the GASETUP function call: the first row gives the lower bounds of the corresponding vector elements and the second row gives the upper bounds. The solutions that result from all crossover and mutation operators are checked to ensure they are within the upper and lower bounds, and any solution components that violate the bounds are reset to the bound. However, if user-written modules are provided for these operators, the modules are expected to do the bounds checking internally. If no *modname* parameter is specified, the initial population is generated by random variation of the solution components between the lower and upper bounds.

For all problem encodings, if the *modname* parameter is specified, it is expected to be the name of a user-written subroutine module with one parameter. The module should generate and return an individual solution in that parameter. The GAINIT call invokes that module *popsiz*e times, once for each member

of the initial solution population. The *modname* parameter is required if the *encoding* parameter of the corresponding **GASETUP** function call was 0 or if the *bounds* parameter is not specified for real or integer fixed-length vector encoding.

See the **GASETUP** function for an example.

GAREEVAL Call

CALL GAREEVAL(*id*);

The GAREEVAL subroutine reevaluates the objective function values for a solution population of a genetic algorithm optimization. The input arguments to the GAREEVAL call are as follows:

id is the identifier for the genetic algorithm optimization problem, which was returned by the **GASETUP** function.

The GAREEVAL call computes the objective values for a solution population of a genetic algorithm optimization. Since the **GAINIT** call and the **GAREGEN** call also evaluate the objective function values, it is usually not necessary to call GAREEVAL. It is provided to handle the situation of a user modifying an objective function independently—for example, adjusting a global variable to relax or tighten a penalty constraint. In such a case, GAREEVAL should be called before the next **GAREGEN** call.

GAREGEN Call

CALL GAREGEN(*id*);

The GAREGEN subroutine replaces the current solution population by applying selection, crossover, and mutation for a genetic algorithm optimization problem. The input arguments to the GAREGEN call are as follows:

id is the identifier for the genetic algorithm optimization problem, which was returned by the **GASETUP** function.

The GAREGEN call applies the genetic algorithm to create a new solution population from the current population. As the first step, if the *elite* parameter of the corresponding **GASETSEL** call is nonzero, the best *elite* members of the current population are copied into the new population, sorted by objective value with the best objective value first. If a crossover operator has been specified in a corresponding **GASETCRO** call or a default crossover operator is in effect, the remaining members of the population are determined by selecting members of the current population, applying the crossover operator to generate offspring, and mutating the offspring according to the mutation probability and mutation operator. Either the mutation probability and operator are specified in the corresponding **GASETMUT** call or, if no such call is made, a default value of 0.05 is assigned to the mutation probability and a default mutation operator is assigned based on the problem encoding (see the **GASETMUT** call). The offspring are then transferred to the new population. If the no-crossover option is specified in the **GASETCRO** call, then only mutation is applied to

the non-elite members of the current population to form the new population. After the new population is formed, it becomes the current solution population, and the objective function specified in the **GASETOBJ** call is evaluated for each member.

See the **GASETUP** function for an example.

GASETCRO Call

CALL GASETCRO(*id*, *crossprob*, *type* < , *parm* >);

The GASETCRO subroutine sets the crossover operator for a genetic algorithm optimization. The input arguments to the GASETCRO call are as follows:

<i>id</i>	is the identifier for the genetic algorithm optimization problem, which was returned by the GASETUP function.
<i>crossprob</i>	is the crossover probability, which has a range from zero to one. It specifies the probability that selected members of the current generation undergo crossover to produce new offspring for the next generation.
<i>type</i>	specifies the kind of crossover operator to be used. <i>type</i> is used in conjunction with <i>parm</i> to specify either a user-written module for the crossover operator or one of several other operators, as explained in the following list.
<i>parm</i>	is a matrix whose interpretation depends on the value of <i>type</i> , as described in the following list.

The following list specifies the valid values of the *type* parameter and the corresponding crossover operators:

- 1 specifies that no crossover operator be applied and the new population be generated by applying the mutation operator to the old population, according to the mutation probability.
- 0 specifies that a user-written module, whose name is passed in the *parm* parameter, be used as the crossover operator. This module should be a subroutine with four parameters. The module should return the new offspring solutions in the first two parameters based on the input parent solutions, which are selected by the genetic algorithm and passed into the module in the last two parameters. The module is called once for each crossover operation within the **GAREGEN** call to create a new generation of solutions.
- 1 specifies the simple operator, defined for fixed-length integer and real vector encoding. To apply this operator, a position k within the vector of length n is chosen at random, such that $1 \leq k < n$. Then for parents **p1** and **p2** the offspring are as follows:

```
c1= p1[1,1:k] || p2[1,k+1:n];
c2= p2[1,1:k] || p1[1,k+1:n];
```

For real fixed-length vector encoding, you can specify an additional parameter, a , with the *parm* parameter, where a is a scalar and $0 < a \leq 1$. It modifies the offspring as follows:

```
x2 = a * p2 + (1-a) * p1;
```

```

c1 = p1[1,1:k] || x2[1,k+1:n];

x1 = a * p1 + (1-a) * p2
c2 = p2[1,1:k] || x1[1,k+1:n];

```

Note that for $a = 1$, which is the default value, $\mathbf{x2}$ and $\mathbf{x1}$ are the same as $\mathbf{p2}$ and $\mathbf{p1}$. Small values of a reduce the difference between the offspring and parents. For integer encoding, the *parm* parameter is ignored and a is always 1.

- 2 specifies the two-point operator, defined for fixed-length integer and real vector encoding with length $n \geq 3$. To apply this operator, two positions k_1 and k_2 within the vector are chosen at random, such that $1 \leq k_1 < k_2 < n$. Element values between those positions are swapped between parents. For parents $\mathbf{p1}$ and $\mathbf{p2}$ the offspring are as follows:

```

c1 = p1[1,1:k1] || p2[1,k1+1:k2] || p1[1,k2+1:n];
c2 = p2[1,1:k1] || p1[1,k1+1:k2] || p2[1,k2+1:n];

```

For real vector encoding, you can specify an additional parameter, a , in the *parm* field, where $0 < a \leq 1$. It modifies the offspring as follows:

```

x2 = a * p2 + (1-a) * p1;
c1 = p1[1,1:k1] || x2[1,k1+1:k2] || p1[1,k2+1:n];

x1 = a * p1 + (1-a) * p2;
c2 = p2[1,1:k1] || x1[1,k1+1:k2] || p2[1,k2+1:n];

```

Note that for $a = 1$, which is the default value, $\mathbf{x2}$ and $\mathbf{x1}$ are the same as $\mathbf{p2}$ and $\mathbf{p1}$. Small values of a reduce the difference between the offspring and parents. For integer encoding, the *parm* parameter is ignored if present and a is always 1.

- 3 specifies the arithmetic operator, defined for real and integer fixed-length vector encoding. This operator computes offspring of parents $\mathbf{p1}$ and $\mathbf{p2}$ as follows:

```

c1 = a * p1 + (1-a) * p2;
c2 = a * p2 + (1-a) * p1;

```

where a is a random number between 0 and 1. For integer encoding, each component is rounded off to the nearest integer. An advantage of this operator is that it always produces feasible offspring for a convex solution space. A disadvantage is that it tends to produce offspring toward the interior of the search region, so that it can be less effective if the optimum lies on or near the search region boundary.

- 4 specifies the heuristic operator, defined for real fixed-length vector encoding. This operator computes the first offspring from the two parents $\mathbf{p1}$ and $\mathbf{p2}$ as follows:

```

c1 = a * (p2 - p1) + p2;

```

where $\mathbf{p2}$ is the parent with the better objective value and a is a random number between 0 and 1. The second offspring is computed as in the arithmetic operator, as follows:

```

c2 = (1 - a) * p1 + a * p2;

```

This operator is unusual in that it uses the objective value. It has the advantage of directing the search in a promising direction and automatically fine-tuning the search in an area where solutions are clustered. If upper and lower bound constraints are specified in the **GAINIT** call, the offspring are checked against the bounds and any component outside its bound is set equal to that bound.

- 5 specifies the partial match operator, defined for sequence encoding. This operator produces offspring by transferring a subsequence from one parent and filling the remaining positions in a way consistent with the position and ordering in the other parent. Start with two parents and randomly chosen cut-points as follows:

```
p1 = {1 2|3 4 5 6|7 8 9};
p2 = {8 7|9 3 4 1|2 5 6};
```

The first step is to cross the selected segments; a missing value (.) indicates a position that is not determined):

```
c1 = {. . 9 3 4 1 . . .};
c2 = {. . 3 4 5 6 . . .};
```

Next, define a mapping according to the two selected segments, as follows:

9 ↔ 3, 3 ↔ 4, 4 ↔ 5, 1 ↔ 6

Next, fill in the positions where there is no conflict from the corresponding parent:

```
c1 = {. 2 9 3 4 1 7 8 .};
c2 = {8 7 3 4 5 6 2 . .};
```

Last, fill in the remaining positions from the subsequence mapping. In this case, for the first child 1 → 6 and 9 → 3, and for the second child 5 → 4, 3 → 9, and 6 → 1:

```
c1 = {6 2 9 3 4 1 7 8 5};
c2 = {8 7 3 4 5 6 2 9 1};
```

This operator tends to maintain similarity of both the absolute position and relative ordering of the sequence elements, and is useful for a wide range of sequencing problems.

- 6 specifies the order operator, defined for sequence encoding. This operator produces offspring by transferring a subsequence of random length and position from one parent and filling the remaining positions according to the order from the other parent. For parents **p1** and **p2**, first choose a subsequence, as follows:

```
p1 = {1 2|3 4 5 6|7 8 9};
p2 = {8 7|9 3 4 1|2 5 6};
c1 = {. . 3 4 5 6 . . .};
c2 = {. . 9 3 4 1 . . .};
```

Starting at the second cut-point, the elements of **p2** are in the following order (cycling back to the beginning):

2 5 6 8 7 9 3 4 1

After removing 3, 4, 5, and 6, which have already been placed in **c1**, you have the following:

2 8 7 9 1

Placing these back in order, starting at the second cut-point, yields the following:

c1 = {9 1 3 4 5 6 2 8 7};

Applying this logic to **c2** yields the following:

c2 = {5 6 9 3 4 1 7 8 2};

This operator maintains the similarity of the relative order (also called the adjacency) of the sequence elements of the parents. It is especially effective for circular path-oriented optimizations, such as the traveling salesman problem.

- 7 specifies the cycle operator, defined for sequence encoding. This operator produces offspring such that the position of each element value in the offspring comes from one of the parents. For example, consider the following parents **p1** and **p2**:

p1 = {1 2 3 4 5 6 7 8 9};

p2 = {8 7 9 3 4 1 2 5 6};

For the first child, pick the first element from the first parent, as follows:

c1 = {1};

To maintain the condition that the position of each element value must come from one of the parents, the position of the '8' value must come from **p1**, because the '8' position in **p2** is already taken by the '1' in **c1**:

c1 = {1 8 .};

Now the position of '5' must come from **p1** and so on until the process returns to the first position:

c1 = {1 . 3 4 5 6 . 8 9};

At this point, choose the remaining element positions from **p2**:

c1 = {1 7 3 4 5 6 2 8 9};

For the second child, starting with the first element from the second parent, similar logic produces the following:

c2 = {8 2 9 3 4 1 7 5 6};

This operator is most useful when the absolute position of the elements is of most importance to the objective value.

A GASETCRO call is required when 0 is specified for the *encoding* parameter in the [GASETUP function](#). But for fixed-length vector and sequence encoding, a default crossover operator is used in the [GAREGEN call](#) when no GASETCRO call is made. For sequence encoding, the default is the partial match operator, unless the traveling salesman option was specified in the [GASETOBJ call](#), in which case the order operator

is the default. For integer fixed-length vector encoding, the default is the simple operator. For real fixed-length vector encoding, the default is the heuristic operator.

See the [GASETUP function](#) for an example.

GASETMUT Call

CALL GASETMUT(*id*, *mutprob* < , *type* < , *parm* >);

The GASETMUT subroutine sets the mutation operator for a genetic algorithm optimization. The input arguments to the GASETMUT call are as follows:

<i>id</i>	is the identifier for the genetic algorithm optimization problem, which was returned by the GASETUP function .
<i>mutprob</i>	is the probability for a given solution to undergo mutation, a number between 0 and 1.
<i>type</i>	specifies the kind of mutation operator to be used. <i>type</i> is used in conjunction with <i>parm</i> to specify either a user-written module for the mutation operator or one of several other operators, as explained in the following list.
<i>parm</i>	is a matrix whose interpretation depends on the value of <i>type</i> , as described in the following list.

The GASETMUT call enables you to specify the frequency of mutation and the mutation operator to be used in the genetic algorithm optimization problem. If the *type* parameter is not specified, then the GASETMUT call only alters the mutation probability, without resetting the mutation operator, and any operator set by a previous GASETMUT call remains in effect. You can specify the following mutation operators with the *type* parameter:

- 0 specifies that a user-written module, whose name is passed in the *parm* parameter, be used as the mutation operator. This module should be a subroutine with one parameter, which receives the solution to be mutated. The module is called once for each mutation operation and is expected to modify the input solution according to the desired mutation operation. Any checking of bounds specified in the [GAINIT call](#) should be done inside the module; in this case they are not checked by the SAS/IML language.
- 1 specifies the uniform mutation operator, defined for fixed-length real or integer encoding, with upper and lower bounds specified in the [GAINIT call](#). The *parm* parameter is not used with this option. To apply this operator, a position *k* is randomly chosen within the solution vector *v* and *v*[*k*] is modified to a random value between the upper and lower bounds for element *k*. This operator can prove especially useful in early stages of the optimization, since it tends to distribute solutions widely across the search space and avoid premature convergence to a local optimum. However, in later stages of an optimization with real vector encoding when the search needs to be fine-tuned to home in on an optimum, the uniform operator can hinder the optimization.
- 2 specifies the delta mutation operator, defined for integer and real fixed-length vector encoding. This operator first chooses an element of the solution at random, and then perturbs that element by a fixed amount, *delta*, which is set with the *parm* parameter. *delta* has the same dimension as the solution vectors, and each element *delta*[*k*] is set to *parm*[*k*], unless *parm* is a scalar, in which case

all elements are set equal to *parm*. For integer encoding, all *delta[k]* are truncated to integers if they are not integers in *parm*. To apply the mutation, a randomly chosen element *k* of the solution vector *v* is modified such that one of the following statements is true:

```
v[k] = v[k] + delta[k]; /* with probability 0.5 */
      or
v[k] = v[k] - delta[k];
```

If bounds are specified for the problem in the [GAINIT call](#), then *v[k]* is adjusted as necessary to fit within the bounds. This operator enables you to control the scope of the search with the *parm* matrix. One possible strategy is to start with a larger *delta* value and then reduce it with subsequent GASETMUT calls as the search progresses and begins to converge to an optimum. This operator is also useful if the optimum is known to be on or near a boundary, in which case *delta* can be set large enough to always perturb the solution element to a boundary.

- 3 specifies the swap operator, which is defined for sequence problem encoding. This operator picks two random locations in the solution vector and swaps their values. It is the default mutation operator for sequence encoding, except for when the traveling salesman option is specified in the [GASETOBJ call](#). You can also specify that multiple swaps be made for each mutation with the *parm* parameter. The number of swaps defaults to 1 if *parm* is not specified, and is equal to *parm* otherwise.
- 4 specifies the invert operator, defined for sequence encoding. This operator picks two locations at random and then reverses the order of elements between them. This operator is most often applied to the traveling salesman problem. The *parm* parameter is not used with this operator.

Mutation is generally useful in the application of the genetic algorithm to ensure that a diverse population of solutions is sampled to avoid premature convergence to a local optimum. More than one GASETMUT call can be made at any time in the progress of the algorithm. This enables flexible adaptation of the mutation process, either changing the mutation probability or changing the operator itself. You can do this to ensure a wide search at the beginning of the optimization, and then reduce the variation later to narrow the search close to an optimum.

A GASETMUT call is required when an *encoding* parameter of 0 is specified in the [GASETUP function](#). But when no GASETMUT call is made for fixed-length vector and sequence encoding, a default value of 0.05 is set for *mutprob* and a default mutation operator is used in the [GAREGEN call](#). The mutation operator defaults to the uniform operator for fixed-length vector encoding with bounds specified in the [GAINIT call](#), the delta operator with a *parm* value of 1 for fixed-length vector encoding with no bounds specified, the invert operator for sequence encoding when the traveling salesman option is chosen in the [GASETOBJ call](#), and the swap operator for all other sequence encoded problems.

See the [GASETUP function](#) for an example.

GASETOBJ Call

CALL GASETOBJ(*id*, *type* <, *parm*>);

The GASETOBJ subroutine sets the objective function for a genetic algorithm optimization. The input arguments to the GASETOBJ call are as follows:

<i>id</i>	is the identifier for the genetic algorithm optimization problem, which was returned by the GASETUP function .
<i>type</i>	specifies the type of objective function to be used.
<i>parm</i>	is a matrix whose interpretation depends on the value of <i>type</i> , as described in the following list.

You can specify that a user-written module be used to compute the value of the objective function, or you can specify a standard preset function. This is specified with the *type* and *parm* parameters. The following list specifies the valid values of the *type* parameter:

- 0 specifies that a user-written function module is to be minimized. The name of the module is supplied in the *parm* parameter. The specified module should take a single parameter that represents a given solution, and return a scalar numeric value for the objective function.
- 1 specifies that a user-written function module be maximized. The name of the module is supplied in the *parm* parameter. The specified module should take a single parameter that represents a given solution, and return a scalar numeric value for the objective function.
- 2 specifies an objective function from the traveling salesman problem, which is minimized. This option is valid only if three conditions are met: sequence encoding was specified in the [GASETUP function](#) call, the solution vector is to be interpreted as a circular route, and each element represents a location. The *parm* parameter should be a square cost matrix, such that *parm*[*i*, *j*] is the cost of going from location *i* to location *j*. The dimension of the matrix should be the same as the *size* parameter of the corresponding [GASETUP function](#) call.

The specified objective function is called once for each solution to evaluate the objective values for the [GAREGEN call](#), [GAINIT call](#), and [GAREEVAL call](#). Also, the objective values for the current solution population are reevaluated if GASETOBJ is called after a [GAINIT call](#).

See the [GASETUP function](#) for an example.

GASETSEL Call

CALL GASETSEL(*id*, *elite*, *type*, *parm*);

The GASETSEL subroutine sets the selection parameters for a genetic algorithm optimization.

The input arguments to the GASETSEL call are as follows:

<i>id</i>	is the identifier for the genetic algorithm optimization problem, which was returned by the GASETUP function .
<i>elite</i>	specifies the number of solution population members to carry over unaltered to the next generation in the GAREGEN call . If nonzero, then <i>elite</i> members with the best objective function values are carried over without crossover or mutation.
<i>type</i>	specifies the selection method to use.
<i>parm</i>	is a parameter used to control the selection pressure.

This module sets the selection parameters that are used in the [GAREGEN call](#) to select solutions for the crossover operation. You can choose between two variants of the “tournament” selection method in which a group of different solutions is picked at random from the current solution population and the solution from that group with the best objective value is selected. In the first variation, chosen by setting *type* to 0, the most optimal solution is always selected, and the *parm* parameter is used to specify the size of the group, always two or greater. The larger the group size, the greater the selective pressure. In the second variation, chosen by setting *type* to 1, the group size is set to 2 and the best solution is chosen with probability specified by *parm*. If *parm* is 1, the best solution is always picked; a *parm* value of 0.5 is equivalent to pure random selection. The *parm* value must be between 0.5 and 1. When *type* is 0, the selective pressure is greater than when *type* is 1. Higher selective pressure leads to faster convergence of the genetic algorithm, but is more likely to give premature convergence to a local optimum.

In order to ensure that the best solution of the current solution population is always carried over to the next generation, an *elite* value of 1 should be specified. Higher values of *elite* generally lead to faster convergence of the algorithm, but they increase the chances of premature convergence to a local optimum. If GASETSEL is not called, the optimization uses the default values of 1 for *elite*, 1 for *type*, and 2 for *parm*.

See the [GASETUP function](#) for an example.

GASETUP Function

GASETUP(*encoding*, *size* <, *seed* >);

The GASETUP function sets up the problem encoding for a genetic algorithm optimization problem. The GASETUP function returns a scalar number that identifies the genetic algorithm optimization problem. This number is used in subsequent calls to carry out the optimization.

The arguments to the GASETUP function are as follows:

<i>encoding</i>	is a scalar number used to specify the form or structure of the problem solutions to be optimized. A value of 0 indicates a numeric matrix of arbitrary dimensions, 1 indicates a fixed-length floating-point row vector, 2 indicates a fixed-length integer row vector, and 3 indicates a fixed-length sequence of integers, with alternate solutions distinguished by different sequence ordering.
<i>size</i>	is a numeric scalar, whose value is the vector or sequence length, if a fixed-length <i>encoding</i> is specified. For arbitrary matrix encoding (<i>encoding</i> value of 0), <i>size</i> is not used.
<i>seed</i>	is an optional initial random number seed to be used for the initialization and the selection process. If <i>seed</i> is not specified or its value is 0, an initial seed is derived from the current system time.

GASETUP is the first call that must be made to set up a genetic algorithm optimization problem. It specifies the problem encoding, the size of a population member, and an optional seed that initializes the random number generator used in the selection process. GASETUP returns an identifying number that must be passed to the other modules that specify genetic operators and control the execution of the genetic algorithm. More than one optimization can be active concurrently, and optimization problems with different problem identifiers are completely independent. When a satisfactory solution has been determined, the op-

timization problem should be terminated with a call to [GAEND](#) to free up resources associated with the genetic algorithm.

The following example demonstrates the use of several genetic algorithm subroutines:

```

/* Use a genetic algorithm to explore the solution space for the
   "traveling salesman" problem. First, define the objective
   function to minimize:
   Compute the sum of distances between sequence of cities */
start EvalFitness( pop ) global ( dist );
  fitness = j( nrow(pop),1 );
  do i = 1 to nrow(pop);
    city1 = pop[i,1];
    city2 = pop[i,ncol(pop)];
    fitness[i] = dist[ city1, city2 ];
    do j = 1 to ncol(pop)-1;
      city1 = pop[i,j];
      city2 = pop[i,j+1];
      fitness[i] = fitness[i] + dist[city1,city2];
    end;
  end;
  return ( fitness );
finish;

/* Set up parameters for the genetic algorithm */

mutationProb = 0.15; /* prob that a child will be mutated */
numElite = 2; /* copy this many to next generation */
numCities = 15; /* number of cities to visit */
numGenerations = 100; /* number of generations to evolve */
seed = 54321; /* random number seed */

/* fix population size; generate random locations for cities */
popSize = max(30,2*numCities);
locations = uniform( j(numCities,2,seed) );

/* compute distances between cities one time */
dist = j( numCities, numCities, 0 );
do i = 1 to numCities;
  do j = 1 to i-1;
    v = locations[i,]-locations[j,];
    dist[i,j] = sqrt( v[##] );
    dist[j,i] = dist[i,j];
  end;
end;

/* run the genetic algorithm */
id = gasetup( 3, numCities, seed);
call gasetobj(id, 0, "EvalFitness" );
call gasetcro(id, 1.0, 6);
call gasetmut(id, mutationProb, 3);
call gasetssel(id, numElite, 1, 0.95);
call gainit(id, popSize );

```

```

do i = 1 to numGenerations;
  if mod(i,20)=0 then do;
    call gagetval( value, id, 1 );
    print "Iteration:" i "Top value:" value;
  end;
  call garegen(id);
end;

/* report final sequence for cities */
call gagetmem(mem, value, id, 1);
print mem, value;
call gaend(id);

```

Figure 23.120 Result of a Genetic Algorithm Optimization

		i		value	
	Iteration:	20	Top value:	3.6836569	
		i		value	
	Iteration:	40	Top value:	3.5567152	
		i		value	
	Iteration:	60	Top value:	3.4562136	
		i		value	
	Iteration:	80	Top value:	3.4562136	
		i		value	
	Iteration:	100	Top value:	3.437183	
		mem			
	COL1	COL2	COL3	COL4	COL5
ROW1	6	4	12	7	13
		mem			
	COL6	COL7	COL8	COL9	COL10
ROW1	15	8	9	11	5
		mem			
	COL11	COL12	COL13	COL14	COL15
ROW1	2	14	10	3	1
		value			
		3.437183			

GBLKVP Call

CALL GBLKVP(*viewport* < , *inside* >);

The GBLKVP subroutine is a graphical call that defines a blanking viewport.

The arguments to the GBLKVP subroutine are as follows:

<i>viewport</i>	is a numeric matrix or literal that defines a viewport. This rectangular area's boundary is specified in normalized coordinates, where you specify the coordinates of the lower left corner and the upper right corner of the rectangular area in the form <i>{ minimum-x minimum-y maximum-x maximum-y }</i>
<i>inside</i>	is a numeric argument that specifies whether the graphics output is to be clipped inside or outside the blanking area. The default is to clip outside the blanking area.

The GBLKVP subroutine defines an area, called the blanking area, in which nothing is drawn until the area is released. This routine is useful for clipping areas outside the graph or for blanking out inner portions of the graph. If *inside* is set to 0 (the default), no graphics output appears outside the blanking area. Setting *inside* to 1 clips inside the blanking areas.

The blanking area (as specified by the viewport argument) is defined on the current viewport, and it is released when the viewport is changed or popped. At most one blanking area is in effect at any time. The blanking area can also be released by the [GBLKVPD subroutine](#) or another GBLKVP call. The coordinates in use for this graphics command are given in normalized coordinates because they are defined relative to the current viewport.

For example, to blank out a rectangular area with corners at the coordinates (20,20) and (80,80) relative to the currently defined viewport, use the following statement:

```
call gblkvp({20 20 80 80});
```

No graphics or text can be written outside this area until the blanking viewport is ended.

Alternatively, if you want to clip inside the rectangular area, use the *inside* parameter, as follows:

```
call gblkvp({20 20 80 80}, 1);
```

See also the description of the CLIP option in the [RESET statement](#).

GBLKVPD Call

CALL GBLKVPD ;

The GBLKVPD subroutine is a graphical call that deletes and releases the current blanking area. It enables graphics output to be drawn in the area previously blanked out by a call to the [GBLKVP subroutine](#).

To release an area previously blanked out, as in the example for the [GBLKVP subroutine](#), use the following statement.

```

/* define blanking viewport */
call gblkvp({20 20, 80 80});
/* more graphics statements... */

/* now release the blanked out area */
call gblkvpd;
/* graphics or text can now be written to the area */
/* continue graphics statements... */

```

See also the description of the CLIP option in the [RESET statement](#).

GCLOSE Call

CALL GCLOSE ;

The GCLOSE subroutine is a graphical call that closes the current graphics segment. Once a segment is closed, no other primitives can be added to it. The next call to a graph-generating function begins building a new graphics segment. However, the GCLOSE subroutine does not have to be called explicitly to terminate a segment; the [GOPEN subroutine](#) causes GCLOSE to be called.

GDELETE Call

CALL GDELETE(*segment-name*);

The GDELETE subroutine is a graphical call that searches the current catalog and deletes the first segment found with the name *segment-name*.

An example of a valid statement follows:

```

/* SEG_A is defined as a character matrix */
/* that contains the name of the segment to delete */
call gdelete(seg_a);

```

The segment can also be specified as a quoted literal, as follows:

```
call delete("plot_13");
```

GDRAW Call

CALL GDRAW(*x*, *y* <, *style*> <, *color*> <, *window*> <, *viewport*>);

The GDRAW subroutine is a graphical call that draws a polyline.

The required arguments to the GDRAW subroutine are as follows:

<i>x</i>	is a vector that contains the horizontal coordinates of points used to draw a sequence of lines.
<i>y</i>	is a vector that contains the vertical coordinates of points used to draw a sequence of lines.

The optional arguments to the GDRAW subroutine are as follows:

<i>style</i>	is a numeric matrix or literal that specifies an index that corresponds to a valid line style.
<i>color</i>	is a valid SAS color, where <i>color</i> can be specified as a quoted text string (such as 'RED'), the name of a character matrix that contains a valid color as an element, or a color number (such as 1) that refers to a color in the color list.
<i>window</i>	is a numeric matrix or literal that specifies a window. This is given in world coordinates and has the form $\{ \textit{minimum-x} \textit{ minimum-y} \textit{ maximum-x} \textit{ maximum-y} \}$
<i>viewport</i>	is a numeric matrix or literal that specifies a viewport. This is given in normalized coordinates and has the same form as the <i>window</i> argument.

The GDRAW subroutine draws a sequence of connected lines from points represented by values in *x* and *y*, which must be vectors of the same length. If *x* and *y* have *n* points, there are *n* – 1 lines. The first line is from the point (*x*₁, *y*₁) to (*x*₂, *y*₂). The lines are drawn in the same color and line style. The coordinates in use for this graphics command are world coordinates. An example that uses the GDRAW subroutine follows:

```
call gstart;
/* line from (50,50) to (75,75) */
call gdraw({50 75},{50 75});
call gshow;
```

GDRAWL Call

CALL GDRAWL(*xy1*, *xy2* <, *style* > <, *color* > <, *window* > <, *viewport* >);

The GDRAWL subroutine is a graphical call that draws individual lines.

The required arguments to the GDRAWL subroutine are as follows:

<i>xy1</i>	is a matrix of points used to draw a sequence of lines.
<i>xy2</i>	is a matrix of points used to draw a sequence of lines.

The optional arguments to the GDRAWL subroutine are as follows:

<i>style</i>	is a numeric matrix or literal that specifies an index that corresponds to a valid line style.
<i>color</i>	is a valid SAS color, where <i>color</i> can be specified as a quoted text string (such as 'RED'), the name of a character matrix that contains a valid color as an element, or a color number (such as 1) that refers to a color in the color list.

<i>window</i>	is a numeric matrix or literal that specifies a window. This is given in world coordinates and has the form $\{ \textit{minimum-x} \textit{ minimum-y} \textit{ maximum-x} \textit{ maximum-y} \}$
<i>viewport</i>	is a numeric matrix or literal that specifies a viewport. This is given in normalized coordinates and has the same form as the <i>window</i> argument.

The GDRAWL subroutine draws a sequence of lines specified by their beginning and ending points. The matrices *xy1* and *xy2* must have the same number of rows and columns. The first two columns (other columns are ignored) of *xy1* give the coordinates of the beginning points of the line segment, and the first two columns of *xy2* have coordinates of the corresponding endpoints. If *xy1* and *xy2* have *n* rows, *n* lines are drawn.

The lines are drawn in the same color and line style. The coordinates in use for this graphics command are world coordinates. An example that uses the GDRAWL call follows:

```
proc iml;
call gstart;
/* three line segments */
xy1 = { 0 0, 25 50, 50 75};
xy2 = {25 25, 50 50, 75 50};
call gdrawl(xy1, xy2);
call gshow;
```

GENEIG Call

CALL GENEIG(*eval*, *evects*, *sym-matrix1*, *sym-matrix2*);

The GENEIG subroutine computes eigenvalues and eigenvectors of a generalized eigenproblem.

The input arguments to the GENEIG subroutine are as follows:

<i>sym-matrix1</i>	is a symmetric numeric matrix.
<i>sym-matrix2</i>	is a positive definite symmetric matrix.

The subroutine returns the following output arguments:

<i>evals</i>	names a vector in which the eigenvalues are returned.
<i>evects</i>	names a matrix in which the corresponding eigenvectors are returned.

The GENEIG subroutine computes eigenvalues and eigenvectors of the generalized eigenproblem. If **A** and **B** are symmetric and **B** is positive definite, then the vector **M** and the matrix **E** solve the generalized eigenproblem provided that

$$\mathbf{A} * \mathbf{E} = \mathbf{B} * \mathbf{E} * \text{diag}(\mathbf{M})$$

The vector **M** contains the eigenvalues arranged in descending order, and the matrix **E** contains the corresponding eigenvectors in the columns.

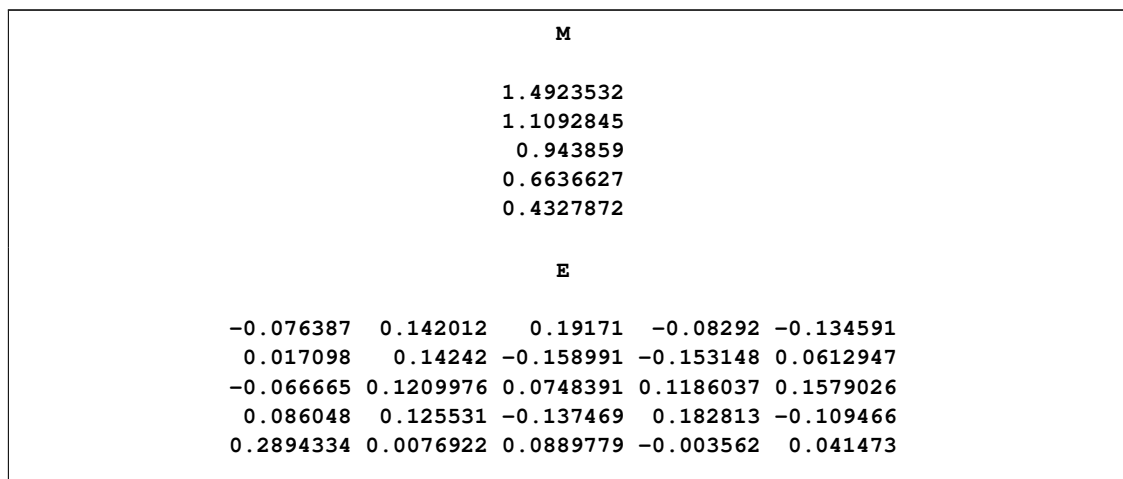
The following example is from Wilkinson and Reinsch (1971):

```
A = {10  2  3  1  1,
      2 12  1  2  1,
      3  1 11  1 -1,
      1  2  1  9  1,
      1  1 -1  1 15};
```

```
B = {12  1 -1  2  1,
      1 14  1 -1  1,
     -1  1 16 -1  1,
      2 -1 -1 12 -1,
      1  1  1 -1 11};
```

```
call geneig(M, E, A, B);
print M, E;
```

Figure 23.121 Solution of a Generalized Eigenproblem



GEOMEAN Function

GEOMEAN(*matrix*);

The **GEOMEAN** function returns a scalar that contains the geometric mean of the elements of the input matrix. The geometric mean of a set of nonnegative numbers a_1, a_2, \dots, a_n is the n th root of the product $a_1 \cdot a_2 \cdots a_n$.

The geometric mean is zero if any of the a_i are zero. The geometric mean is not defined for negative numbers. If any of the a_i are missing, they are excluded from the computation.

The geometric mean can be used to compute the average return on an investment. For example, the following data gives the annual returns on U.S. Treasury bonds from 1994 to 2004. The following statements compute the average rate of return during this time. The output, shown in [Figure 23.122](#), shows that the average rate of return was 6.43%.

```

/*      year  return% */
TBonds = { 1994 -8.04,
           1995 23.48,
           1996  1.43,
           1997  9.94,
           1998 14.92,
           1999 -8.25,
           2000 16.66,
           2001  5.57,
           2002 15.12,
           2003  0.38,
           2004  4.49 };

proportion = 1 + TBonds[,2]/100; /* convert to proportion */
aveReturn = geomean( proportion );
print aveReturn;

```

Figure 23.122 Average Rate of Return for an Investment

aveReturn
1.0643334

GGRID Call

CALL GGRID(*x*, *y* <, *style* > <, *color* > <, *window* > <, *viewport* >);

The GGRID subroutine is a graphical call that draws a grid on a graphical window. The required arguments to the GGRID subroutine are as follows:

- x* is a vector of points that contains the horizontal coordinates of the grid lines.
- y* is a vector of points that contains the vertical coordinates of the grid lines.

The optional arguments to the GGRID subroutine are as follows:

- style* is a numeric matrix or literal that specifies an index that corresponds to a valid line style.
- color* is a valid SAS color, where *color* can be specified as a quoted text string (such as 'RED'), the name of a character matrix that contains a valid color as an element, or a color number (such as 1) that refers to a color in the color list.
- window* is a numeric matrix or literal that specifies a window. This is given in world coordinates and has the form

$$\{ \textit{minimum-x} \textit{ minimum-y} \textit{ maximum-x} \textit{ maximum-y} \}$$
- viewport* is a numeric matrix or literal that specifies a viewport. This is given in normalized coordinates and has the same form as the *window* argument.

The GGRID subroutine draws a sequence of vertical and horizontal lines specified by the x and y vectors, respectively. The start and end of the vertical lines are implicitly defined by the minimum and maximum of the y vector. Likewise, the start and end of the horizontal lines are defined by the minimum and maximum of the x vector. The grid lines are drawn in the same color and line style. The coordinates in use for this graphics command are world coordinates.

For example, use the following statements to place a grid in the lower left corner of the screen:

```
call gstart;
x={10, 20, 30, 40, 50};
y=x;

/* Places a grid in the lower left corner of the screen, */
/* assuming the default window and viewport           */
call ggrid(x,y);
call gshow;
```

GINCLUDE Call

CALL GINCLUDE(*segment-name*);

The GINCLUDE subroutine is a graphical call that includes a previously defined graph in the current graph. The segment that is included is named *segment-name* and is in the same catalog as the current graph. The included segment is defined in the current viewport but not in the current window.

The implementation of the GINCLUDE subroutine makes it possible to include other segments in the current segment and reposition them in different viewports. Furthermore, a segment can be included by different graphs, thus effectively reducing storage space. Examples of valid statements follow:

```
/* segment1 is a character variable */
/* that contains the segment name   */
segment1={myplot};
call ginclude(segment1);

/* specify the segment with quoted literal */
call ginclude("myseg");
```

GINV Function

GINV(*matrix*);

The GINV function computes the Moore-Penrose generalized inverse of *matrix*. This inverse, known as the four-condition inverse, has these properties:

If $G = \text{GINV}(A)$ then

$$AGA = A \quad GAG = G \quad (AG)' = AG \quad (GA)' = GA$$

The generalized inverse is also known as the *pseudoinverse*, usually denoted by \mathbf{A}^- . It is computed by using the singular value decomposition (Wilkinson and Reinsch 1971).

See Rao and Mitra (1971) for a discussion of properties of this function.

As an example, consider the following model:

$$\mathbf{Y} = \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\epsilon}$$

Least squares regression for this model can be performed by using the quantity $\mathbf{ginv}(\mathbf{x}) * \mathbf{y}$ as the estimate of $\boldsymbol{\beta}$. This solution has minimum $\mathbf{b}'\mathbf{b}$ among all solutions that minimize $\boldsymbol{\epsilon}'\boldsymbol{\epsilon}$, where $\boldsymbol{\epsilon} = \mathbf{Y} - \mathbf{X}\mathbf{b}$.

Projection matrices can be formed by specifying $\mathbf{GINV}(\mathbf{X}) * \mathbf{X}$ (*row space*) or $\mathbf{X} * \mathbf{GINV}(\mathbf{X})$ (*column space*).

The following program demonstrates some common uses of the GINV function:

```
A = {1 0 1 0 0,
      1 0 0 1 0,
      1 0 0 0 1,
      0 1 1 0 0,
      0 1 0 1 0,
      0 1 0 0 1 };

/* find generalized inverse */
Ainv = ginv(A);

/* find LS solution: min |Ax-b|^2 */
b = { 3, 2, 4, 2, 1, 3 };
x = Ainv*b;

/* form projection matrix onto row space.
   Note P = P` and P*P = P */
P = Ainv*A;

/* find numerical rank of A */
rankA = round(trace(P));

reset fuzz;
print Ainv, rankA, x, P;
```

Figure 23.123 Common Uses of the Generalized Inverse

Ainv					
0.2666667	0.2666667	0.2666667	-0.0666667	-0.0666667	-0.0666667
-0.0666667	-0.0666667	-0.0666667	0.2666667	0.2666667	0.2666667
0.4	-0.1	-0.1	0.4	-0.1	-0.1
-0.1	0.4	-0.1	-0.1	0.4	-0.1
-0.1	-0.1	0.4	-0.1	-0.1	0.4
rankA					
4					

Figure 23.123 continued

x				
		2		
		1		
		1		
		0		
		2		
p				
0.8	-0.2	0.2	0.2	0.2
-0.2	0.8	0.2	0.2	0.2
0.2	0.2	0.8	-0.2	-0.2
0.2	0.2	-0.2	0.8	-0.2
0.2	0.2	-0.2	-0.2	0.8

If **A** is an $n \times m$ matrix, then, in addition to the memory allocated for the return matrix, the GINV function temporarily allocates an $n^2 + nm$ array for performing its computation.

GOPEN Call

CALL GOPEN(< *segment-name* > < , *replace* > < , *description* >);

The GOPEN subroutine is a graphical call that starts a new graphics segment.

The arguments to the GOPEN subroutine are as follows:

segment-name is a character matrix or quoted literal that specifies the name of a graphics segment.
replace is a numeric argument.
description is a character matrix or quoted text string with a maximum length of 40 characters.

The GOPEN subroutine starts a new graphics segment. The window and viewport are reset to the default values ({0 0 100 100}) in both cases. Any attribute modified by using a **GSET** call is reset to its default value, which is set by the attribute's corresponding GOPTIONS value.

A nonzero value for *replace* indicates that the new segment should replace the first found segment with the same name, and zero indicates otherwise. If you do not specify the *replace* flag, the flag set by a previous **GSTART** call is used. By default, the **GSTART** subroutine sets the flag to NOREPLACE.

The *description* is a text string of up to 40 characters that you want to store with the segment to describe the graph.

Two graphs cannot have the same name. If you try to create a named segment twice, the second segment is given an automatically generated name.

The following statement opens a new segment named “cosine”, replaces the existing segment of the same name, and attaches a description to the segment:

```
call gopen("cosine", 1, "Graph of Cosine Curve");
```

GOTO Statement

GOTO *label* ;

The GOTO statement causes a program to jump to a new statement in the program. When the GOTO statement is executed, the program jumps immediately to the statement with the given *label* and begin executing statements from that point. A label is a name followed by a colon that precedes an executable statement.

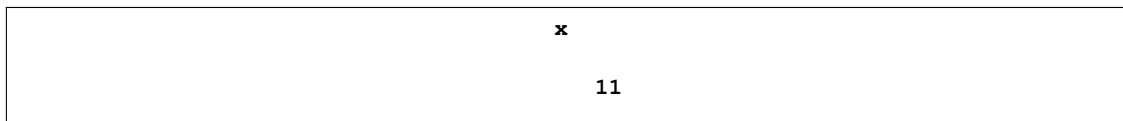
GOTO statements are often clauses of IF-THEN statements. For example, the following statements use a GOTO statement to iterate until a condition is satisfied:

```
start Iterate;
  x = 1;
  TheStart:
  if x > 10 then
    goto TheEnd;
  x = x + 1;
  goto TheStart;

  TheEnd: print x;
finish;

run Iterate;
```

Figure 23.124 Iteration by Using the GOTO Statement

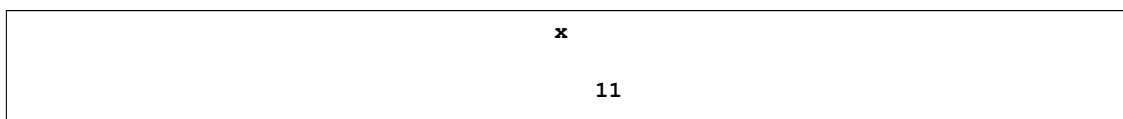


The function of GOTO statements is usually better performed by DO groups. For example, the preceding statements could be better written as follows:

```
x = 1;
do until(x > 10);
  x = x + 1;
end;

print x;
```

Figure 23.125 Avoiding the GOTO Statement



As good programming practice, you should avoid using a GOTO statement that refers to a label that precedes the GOTO statement; otherwise, an infinite loop is possible. You cannot use a GOTO statement to jump out of a module; use the [RETURN statement](#) instead.

GPIE Call

```
CALL GPIE(x, y, r < , angle1 > < , angle2 > < , color > < , outline > < , pattern > < , window > < , viewport >
);
```

The GPIE subroutine is a graphical call that draws pie slices.

The required arguments to the GPIE subroutine are as follows:

<i>x</i>	is a scalar value that contains the horizontal coordinates of the center of the pie slices. This argument can also be a vector, in which case it defines centers for multiple pie slices.
<i>y</i>	is a scalar value that contains the vertical coordinates of the center of the pie slices. This argument can also be a vector, in which case it defines centers for multiple pie slices.
<i>r</i>	is a scalar or vector that contains the radii of the pie slices.

The optional arguments to the GPIE subroutine are as follows:

<i>angle1</i>	is a scalar or vector that contains the start angles. It defaults to 0.
<i>angle2</i>	is a scalar or vector that contains the terminal angles. It defaults to 360.
<i>color</i>	is a valid SAS color, where <i>color</i> can be specified as a quoted text string (such as 'RED'), the name of a character matrix that contains a valid color as an element, or a color number (such as 1) that refers to a color in the color list.
<i>outline</i>	is an index that indicates the side of the slice to draw. The default is 3.
<i>pattern</i>	is a character matrix or quoted literal that specifies the pattern with which to fill the interior of a closed curve.
<i>window</i>	is a numeric matrix or literal that specifies a window. This is given in world coordinates and has the form <div style="text-align: center;">{ <i>minimum-x</i> <i>minimum-y</i> <i>maximum-x</i> <i>maximum-y</i> }</div>
<i>viewport</i>	is a numeric matrix or literal that specifies a viewport. This is given in normalized coordinates and has the same form as the <i>window</i> argument.

The GPIE subroutine draws one or more pie slices. The number of pie slices is the maximum dimension of the first five vectors. The angle arguments are specified in degrees. The start angle (*angle1*) defaults to 0, and the terminal angle (*angle2*) defaults to 360. The *outline* argument is an index that indicates the side of the slice to draw; it can have the following values:

- < 0 uses absolute value as the line style and draws no line segment from center to arc.
- 0 draws no line segment from center to arc.
- 1 draws an arc and line segment from the center to the starting angle point.

- 2 draws an arc and line segment from the center to the ending angle point.
- 3 draws all sides of the slice. This is the default.

The *color*, *outline*, and *pattern* arguments can have more than one element. The coordinates in use for this graphics command are world coordinates. An example that uses the GPIE subroutine follows:

```
call gstart;
center = {50 50};
r = 30;
angle1 = {0 90 180 270};
angle2 = {90 180 270 360};
/* draw a pie with 4 slices of equal size */
call gpie(center[1], center[2], r, angle1, angle2);
```

GPIEXY Call

CALL GPIEXY(*x*, *y*, *fract-radii*, *angles* <, *center* > <, *radius* > <, *window* >);

The GPIEXY subroutine is a graphical call that converts from polar to world coordinates.

The GPIEXY subroutine returns the following output arguments:

- | | |
|----------|--|
| <i>x</i> | names a vector to contain the horizontal coordinates returned by GPIEXY. |
| <i>y</i> | names a vector to contain the vertical coordinates returned by GPIEXY. |

The required input arguments to the GPIEXY subroutine are as follows:

- | | |
|--------------------|---|
| <i>fract-radii</i> | is a vector of fractions of the radius of the reference circle. |
| <i>angles</i> | is the vector of angle coordinates in degrees. |

The optional input arguments to the GPIEXY subroutine are as follows:

- | | |
|---------------|---|
| <i>center</i> | defines the reference circle. |
| <i>radius</i> | defines the reference circle. |
| <i>window</i> | is a numeric matrix or literal that specifies a window. This is given in world coordinates and has the form
<div style="text-align: center;">{ <i>minimum-x</i> <i>minimum-y</i> <i>maximum-x</i> <i>maximum-y</i> }</div> |

The GPIEXY subroutine computes the world coordinates of a sequence of points relative to a circle. The *x* and *y* arguments are vectors of new coordinates returned by the GPIEXY subroutine. Together, the vectors *fract-radii* and *angles* define the points in polar coordinates. Each pair from the *fract-radii* and *angles* vectors yields a corresponding pair in the *x* and *y* vectors. For example, suppose *fract-radii* has two elements, 0.5 and 0.33 and the corresponding two elements of *angles* are 90 and 30. The GPIEXY subroutine returns two elements in the *x* vector and two elements in the *y* vector. The first (*x*, *y*) pair locates a point halfway from the center to the reference circle on the vertical line through the center, and the second (*x*, *y*) pair locates a point one-third of the way on the line segment from the center to the reference circle, where the line segment

slants 30 degrees from the horizontal. The reference circle can be defined by an earlier [GPIE call](#) or another GPIEXY call, or it can be defined by specifying *center* and *radius*.

Graphics devices can have diverse aspect ratios; thus, a circle can appear distorted when drawn on some devices. The PROC IML graphics subsystem adjusts computations to compensate for this distortion. Thus, for any given point, the transformation from polar coordinates to world coordinates might need an equivalent adjustment. The GPIEXY subroutine ensures that the same adjustment applied in the [GPIE subroutine](#) is applied to the conversion. An example that uses the GPIEXY call follows:

```
call gstart;
center = {50 50};
r = 30;
angle1 = {0 90 180 270};
angle2 = {90 180 270 360};
call gpie(center[1], center[2], r, angle1, angle2);
/* add labels to a pie with 4 slices of equal size */
angle = (angle1+angle2)/2; /* middle of slice */
call gpiexy(x, y, 1.2, angle, center, r);

/* adjust for label size: */
x [1,] = x[1,] - 4;
x [2,] = x[2,] + 1;
x [4,] = x[4,] - 3;
call gscript(x, y, {"QTR1" "QTR2" "QTR3" "QTR4"});
call gshow;
```

GPOINT Call

CALL GPOINT(*x*, *y* <, *symbol* > <, *color* > <, *height* > <, *window* > <, *viewport* >);

The GPOINT subroutine is a graphical call that draws symbols at specified locations.

The required arguments to the GPOINT subroutine are as follows:

- x* is a vector that contains the horizontal coordinates of points.
- y* is a vector that contains the vertical coordinates of points.

The optional arguments to the GPOINT subroutine are as follows:

- symbol* is a character vector or quoted literal that specifies a valid plotting symbol or symbols.
- color* is a valid SAS color, where *color* can be specified as a quoted text string (such as 'RED'), the name of a character matrix that contains a valid color as an element, or a color number (such as 1) that refers to a color in the color list.
- height* is a numeric matrix or literal that specifies the character height.
- window* is a numeric matrix or literal that specifies a window. This is given in world coordinates and has the form

$$\{ \textit{minimum-x} \textit{ minimum-y} \textit{ maximum-x} \textit{ maximum-y} \}$$

viewport is a numeric matrix or literal that specifies a viewport. This is given in normalized coordinates and has the same form as the *window* argument.

The GPOINT subroutine marks one or more points with symbols. The *x* and *y* vectors define the locations of the markers. The *symbol* and *color* arguments can have from one to as many elements as there are well-defined points. The coordinates in use for this graphics command are world coordinates.

The following example plots the curve $y = 50 + 25 \sin(x/10)$ for $0 \leq x \leq 100$:

```
call gstart;
x = 0:100;
y = 50 + 25*sin(x/10);
call gpoint(x, y);
call gshow;
```

The following example uses the GPOINT subroutine to plot symbols at specific locations on the screen:

```
marker = {a b c d e '@' '#' '$' '%' '^' '&' '*' '-' '+' '='};
x = 5*(1:ncol(marker));
y = x;
call gpoint(x, y, marker);
call gshow;
```

See [Chapter 15](#) for further examples that use the GPOINT subroutine.

GPOLY Call

CALL GPOLY(*x*, *y* < , *style* < , *ocolor* < , *pattern* < , *color* < , *window* < , *viewport* >);

The GPOLY subroutine is a graphical call that draws and fills a polygon.

The required arguments to the GPOLY subroutine are as follows:

x is a vector that defines the horizontal coordinates of the corners of the polygon.
y is a vector that defines the vertical coordinates of the corners of the polygon.

The optional inputs to the GPOLY subroutine are as follows:

style is a numeric matrix or literal that specifies an index that corresponds to a valid line style.
ocolor is a matrix or literal that specifies a valid outline color. The *ocolor* argument can be specified as a quoted text string (such as 'RED'), the name of a character matrix that contains a valid color as an element, or a color number (such as 1) that refers to a color in the color list.
pattern is a character matrix or quoted literal that specifies the pattern to fill the interior of a closed curve.
color is a valid SAS color used in filling the polygon. The *color* argument can be specified as a quoted text string (such as 'RED'), the name of a character matrix that contains a valid color as an element, or a color number (such as 1) that refers to a color in the color list.

<i>window</i>	is a numeric matrix or literal that specifies a window. This is given in world coordinates and has the form $\{ \textit{minimum-x} \textit{ minimum-y} \textit{ maximum-x} \textit{ maximum-y} \}$
<i>viewport</i>	is a numeric matrix or literal that specifies a viewport. This is given in normalized coordinates and has the same form as the <i>window</i> argument.

The GPOLY subroutine fills an area enclosed by a polygon. The polygon is defined by the set of points given in the vectors *x* and *y*. The *color* argument is the color used in shading the polygon, and *ocolor* is the outline color. By default, the shading color and the outline color are the same, and the interior pattern is empty. The coordinates in use for this graphics command are world coordinates. An example that uses the GPOLY subroutine follows:

```
call gstart;
xd = {20 20 80 80};
yd = {35 85 85 35};
call gpoly (xd, yd, , , "X", 'red');
call gshow;
```

GPOR Call

CALL GPOR(*viewport*);

The GPOR subroutine is a graphical call that defines a viewport. The rectangular area's boundary is specified in normalized coordinates, where you specify the coordinates of the lower left corner and the upper right corner of the rectangular area in the form

$\{ \textit{minimum-x} \textit{ minimum-y} \textit{ maximum-x} \textit{ maximum-y} \}$

The GPOR subroutine changes the current viewport. The *viewport* argument defines the new viewport by using device coordinates (always 0 to 100). Changing the viewport can affect the height of the character fonts; if so, you might want to modify the HEIGHT parameter. An example of a valid statement follows:

```
call gport ({20 20 80 80});
```

The default values for viewport are 0 0 100 100.

GPORPOP Call

CALL GPORPOP ;

The GPORPOP subroutine is a graphical call that deletes the top viewport from the stack.

GPORTSTK Call

CALL GPORTSTK(*viewport*);

The GPORTSTK subroutine is a graphical call that stacks the viewport defined by the matrix *viewport* onto the current viewport; that is, the new viewport is defined relative to the current viewport. The *viewport* argument is a numeric matrix or literal defined in normalized coordinates of the form

{ *minimum-x minimum-y maximum-x maximum-y* }

This graphics command uses world coordinates. An example of a valid statement follows:

```
call gportstk({5 5 95 95});
```

GSCALE Call

CALL GSCALE(*scale*, *x*, *nincr* < , *nicenum* > < , *fixed-end* >);

The GSCALE subroutine computes a suitable scale and tick values for labeling axes.

The required arguments to the GSCALE subroutine are as follows:

<i>scale</i>	is a returned vector that contains the scaled minimum data value, the scaled maximum data value, and a grid increment.
<i>x</i>	is a numeric matrix or literal.
<i>nincr</i>	is the number of intervals desired.

The optional arguments to the GSCALE subroutine are as follows:

<i>nicenum</i>	is numeric and provides up to 10 numbers to use for scaling. By default, <i>nicenum</i> is the vector { 1,2,2.5,5 }.
<i>fixed-end</i>	is a character argument that specifies which end of the scale is held fixed. The default is 'X'.

The GSCALE subroutine obtains simple (round) numbers with uniform grid interval sizes to use in scaling a linear axis. The GSCALE subroutine implements Algorithm 463 (Lewart 1973) of the *Collected Algorithms* from the Association for Computing Machinery (ACM). The scale values are integer multiples of the interval size. They are returned in the first argument, a vector with three elements. The first element is the scaled minimum data value. The second element is the scaled maximum data value. The third element is the grid increment.

The required input parameters are *x*, a matrix of data values, and *nincr*, the number of intervals desired. If *nincr* is positive, the scaled range includes approximately *nincr* intervals. If *nincr* is negative, the scaled range includes exactly ABS(*nincr*) intervals. The *nincr* parameter cannot be zero.

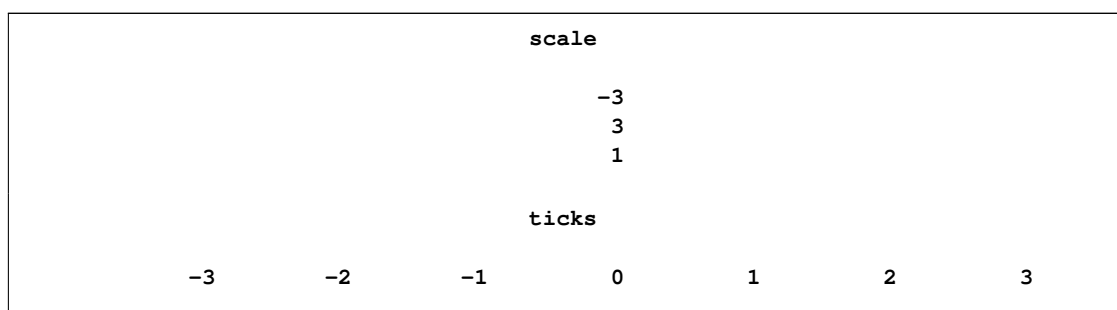
The *nicenum* and *fixed-end* arguments are optional. The *nicenum* argument provides up to 10 numbers, all between 1 and 10 (inclusive of the endpoints), to be used for scaling. The default for *nicenum* is 1, 2, 2.5,

and 5. The linear scale with this set of numbers is a scale with an interval size that is the product of an integer power of 10 and 1, 2, 2.5, or 5. Changing these numbers alters the rounding of the scaled values.

For *fixed-end*, 'U' fixes the upper end; 'L' fixes the lower end; 'X' allows both ends to vary from the data values. The default is 'X'. An example that uses the GSCALE subroutine follows:

```
x = normal( j(100,1) ); /* generate standard normal data */
call gscale(scale, x, 5); /* ask for about 5 intervals */
ticks = do(scale[1], scale[2], scale[3]);
print scale, ticks;
```

Figure 23.126 Tick Marks for Standard Normal Data



GSCRIPT Call

```
CALL GSCRIPT(x, y, text <, angle <, rotate <, height <, font <, color <, window <, view-  
port >);
```

The GSCRIPT subroutine is a graphical call that writes multiple text strings.

The required arguments to the GSCRIPT subroutine are as follows:

- x* is a scalar or vector that contains the horizontal coordinates of the lower left starting position of the text string's first character.
- y* is a scalar or vector that contains the vertical coordinates of the lower left starting position of the text string's first character.
- text* is a character vector of text strings.

The optional arguments to the GSCRIPT subroutine are as follows:

- angle* is the slant of each text string.
- rotate* is the rotation of individual characters.
- height* is a real number that specifies the character height.
- font* is a character matrix or quoted literal that specifies a valid font name.
- color* is a valid SAS color. The *color* argument can be specified as a quoted text string (such as 'RED'), the name of a character matrix that contains a valid color as an element, or a color number (such as 1) that refers to a color in the color list.

<i>window</i>	is a numeric matrix or literal that specifies a window. This is given in world coordinates and has the form $\{ \textit{minimum-x minimum-y maximum-x maximum-y} \}$
<i>viewport</i>	is a numeric matrix or literal that specifies a viewport. This is given in normalized coordinates and has the same form as the <i>window</i> argument.

The GSCRIPT subroutine writes multiple text strings with special character fonts. The *x* and *y* vectors describe the coordinates of the lower left starting position of the text string's first character. The *color* argument can have more than one element.

NOTE: Hardware characters cannot always be obtained if you change the HEIGHT or ASPECT parameters or if you use a viewport.

The coordinates in use for this graphics command are world coordinates. Examples of valid statements follow:

```
call gscript(7, y, names);
call gscript(50, 50, "plot of height vs weight");
call gscript(10, 90, "yaxis", -90, 90);
```

GSET Call

CALL GSET(*attribute* < , *value* >);

The GSET subroutine is a graphical call that sets attributes for a graphics segment.

The arguments to the GSET subroutine are as follows:

<i>attribute</i>	is a graphics attribute. This argument can be a character matrix or quoted literal.
<i>value</i>	is the value to which the attribute is set. This argument is specified as a matrix or quoted literal.

The GSET subroutine enables you to change the following attributes for the current graphics segment:

<i>aspect</i>	a numeric matrix or literal that specifies the aspect ratio (width relative to height) for characters.
<i>color</i>	a valid SAS color. The <i>color</i> argument can be specified as a quoted text string (such as 'RED'), the name of a character matrix that contains a valid color as an element, or a color number (such as 1) that refers to a color in the color list.
<i>font</i>	a character matrix or quoted literal that specifies a valid font name.
<i>height</i>	a numeric matrix or literal that specifies the character height.
<i>pattern</i>	a character matrix or quoted literal that specifies the pattern to use to fill the interior of a closed curve.
<i>style</i>	a numeric matrix or literal that specifies an index that corresponds to a valid line style.
<i>thick</i>	an integer that specifies line thickness.

To reset the PROC IML default value for any one of the attributes, omit the second argument. Attributes are reset back to the default with a call to the [GOPEN](#) or [GSTART](#) subroutine. Single or double quotes can be used around this argument. For more information about the attributes, see [Chapter 15](#).

Examples of valid statements follow:

```
call gset("pattern", "mln45");
call gset("font", "simplex");

f = "font";
s = "simplex";
call gset(f, s);
```

For example, the following statement resets *color* to its default:

```
call gset("color");
```

GSHOW Call

CALL GSHOW(<segment-name>);

The GSHOW subroutine is a graphical call that displays a window. If you do not specify *segment-name*, the GSHOW subroutine displays the current graph.

If the current graph is active at the time that the GSHOW subroutine is called, it remains active after the call; that is, graphics primitives can still be added to the segment. On the other hand, if you specify *segment-name*, the GSHOW subroutine closes any active graphics segment, searches the current catalog for a segment with the given name, and then displays that graph. Examples of valid statements follow:

```
call gshow;
call gshow("plot_a5");

seg = {myplot};
call gshow(seg);
```

See [Chapter 15](#) for examples that use the GSHOW subroutine.

GSORTH Call

CALL GSORTH(*P*, *T*, *lindep*, *A*);

The GSORTH subroutine computes the Gram-Schmidt orthonormal factorization of the $m \times n$ matrix **A**, where m is greater than or equal to n . The GSORTH subroutine implements an algorithm described by Golub (1969).

The GSORTH subroutine has a single input argument:

A is an input $m \times n$ matrix.

The output arguments to the GSORTH subroutine are as follows:

- P is an $m \times n$ column-orthonormal output matrix.
- T is an upper triangular $n \times n$ output matrix.
- lindep* is a flag with a value of 0 if columns of A are independent and a value of 1 if they are dependent. The *lindep* argument is an output scalar.

Specifically, the GSORTH subroutine computes the column-orthonormal $m \times n$ matrix \mathbf{P} and the upper triangular $n \times n$ matrix \mathbf{T} such that

$$\mathbf{A} = \mathbf{P} * \mathbf{T}$$

If the columns of \mathbf{A} are linearly independent (that is, $\text{rank}(\mathbf{A}) = n$), then \mathbf{P} is full-rank column-orthonormal: $\mathbf{P}'\mathbf{P} = \mathbf{I}_w$, \mathbf{T} is nonsingular, and the value of *lindep* (a scalar) is set to 0. If the columns of \mathbf{A} are linearly dependent (say, $\text{rank}(\mathbf{A}) = k < n$) then $n - k$ columns of \mathbf{P} are set to 0, the corresponding rows of \mathbf{T} are set to 0 (\mathbf{T} is singular), and *lindep* is set to 1. The pattern of zero columns in \mathbf{P} corresponds to the pattern of linear dependencies of the columns of \mathbf{A} when columns are considered in left-to-right order.

The following statements call the GSORTH subroutine and print the output parameters to the call:

```
x = {1 1 3 1 2,
      1 0 1 2 3,
      1 1 3 3 4,
      1 0 1 4 5,
      1 1 3 5 6,
      1 0 1 6 7};
call gsorth(P, T, lindep, x);
reset fuzz;
print P, T, lindep;
```

Figure 23.127 Results of a Gram-Schmidt Orthonormalization

P					
0.4082483	0.4082483	0	-0.5	0	
0.4082483	-0.408248	0	-0.5	0	
0.4082483	0.4082483	0	0	0	
0.4082483	-0.408248	0	0	0	
0.4082483	0.4082483	0	0.5	0	
0.4082483	-0.408248	0	0.5	0	
T					
2.4494897	1.2247449	4.8989795	8.5732141	11.022704	
0	1.2247449	2.4494897	-1.224745	-1.224745	
0	0	0	0	0	
0	0	0	4	4	
0	0	0	0	0	
lindep					
1					

If *lindep* is 1, you can permute the columns of **P** and rows of **T** so that the zero columns of **P** are rightmost—that is, $\mathbf{P} = (\mathbf{P}_1, \dots, \mathbf{P}_k, 0, \dots, 0)$, where k is the column rank of **A** and the equality $\mathbf{A} = \mathbf{P} * \mathbf{T}$ is preserved. The following statements show a permutation of columns:

```
d = loc(vecdiag(T) ^= 0) || loc(vecdiag(T) = 0);
temp = P;
P[,d] = temp;
temp = T;
T[,d] = temp;
print d, P, T;
```

Figure 23.128 Rearranging Columns

d					
1	2	4	3	5	
P					
0.4082483	0.4082483	-0.5	0	0	
0.4082483	-0.408248	-0.5	0	0	
0.4082483	0.4082483	0	0	0	
0.4082483	-0.408248	0	0	0	
0.4082483	0.4082483	0.5	0	0	
0.4082483	-0.408248	0.5	0	0	
T					
2.4494897	1.2247449	8.5732141	4.8989795	11.022704	
0	1.2247449	-1.224745	2.4494897	-1.224745	
0	0	0	0	0	
0	0	4	0	4	
0	0	0	0	0	

The GSORTH subroutine is not recommended for the construction of matrices of values of orthogonal polynomials; the [ORPOL function](#) should be used for that purpose.

GSTART Call

```
CALL GSTART( < catalog > < , replace > );
```

The GSTART subroutine initializes the graphics system the first time it is called. A catalog is opened to capture any graphics segments generated in the session. If you do not specify a catalog, PROC IML uses the temporary catalog Work.Gseg.

The arguments to the GSTART subroutine are as follows:

<i>catalog</i>	is a character matrix or quoted literal that specifies the SAS catalog for saving the graphics segments.
<i>replace</i>	is a numeric argument.

The *replace* argument is a flag; a nonzero value indicates that the new segment should replace the first found segment with the same name. The *replace* flag set by the GSTART subroutine is a global flag, as opposed to the *replace* flag set by the [GOPEN subroutine](#). When set by GSTART, this flag is applied to all subsequent segments created for this catalog, whereas with [GOPEN](#), the *replace* flag is applied only to the segment that is being created. The GSTART subroutine sets the *replace* flag to 0 when the *replace* argument is omitted. The *replace* option can be very inefficient for a catalog with many segments. In this case, it is better to create segments with different names (if necessary) than to use the *replace* option.

The GSTART subroutine must be called at least once to load the graphics subsystem. Any subsequent GSTART calls are generally to change graphics catalogs or reset the global *replace* flag.

The GSTART subroutine resets the defaults for all graphics attributes that can be changed by the [GSET subroutine](#). It does not reset GOPTIONS to their defaults unless the GOPTION corresponds to a [GSET](#) parameter. The [GOPEN subroutine](#) also resets [GSET](#) parameters.

An example of using the GSTART subroutine is provided in the documentation for the [GPOINT subroutine](#).

GSTOP Call

CALL GSTOP ;

The GSTOP subroutine deactivates the graphics system. The graphics subsystem is disabled until the [GSTART subroutine](#) is called again.

GSTRLEN Call

CALL GSTRLEN(*length*, *text* < , *height* > < , *font* > < , *window* >);

The GSTRLEN subroutine returns the lengths of text strings represented in a given font and for a given character height. The lengths are given in world coordinates. The required arguments to the GSTRLEN subroutine are as follows:

length is a matrix of lengths specified in world coordinates.

text is a matrix of text strings.

The optional arguments to the GSTRLEN subroutine are as follows:

height is a numeric matrix or literal that specifies the character height.

font is a character matrix or quoted literal that specifies a valid font name.

window is a numeric matrix or literal that specifies a window. This is given in world coordinates and has the form

{ *minimum-x minimum-y maximum-x maximum-y* }

The *length* argument is the returned matrix. It has the same shape as the matrix *text*. Thus, if *text* is an $n \times m$ matrix of text strings, then *length* is an $n \times m$ matrix of lengths in world coordinates. If you do not specify *font*, the default font is assumed. If you do not specify *height*, the default height is assumed. An example that uses the GSTRLEN subroutine follows:

```
call gstart;
/* centers text at coordinates */
ht = 2;
x = 30;
y = 90;
str = "Nonparametric Cluster Analysis";
call gstrlen(len, str, ht, "simplex");
call gscript(x-(len/2), y, str, , , ht, "simplex");
call gshow;
```

GTEXT and GVTEXT Calls

CALL GTEXT(*x*, *y*, *text* <, *color* > <, *window* > <, *viewport* >);

CALL GVTEXT(*x*, *y*, *text* <, *color* > <, *window* > <, *viewport* >);

The GTEXT subroutine places text horizontally on a graph; the GVTEXT subroutine places text vertically on a graph.

The required arguments to the GTEXT and GVTEXT subroutines are as follows:

<i>x</i>	is a scalar or vector that contains the horizontal coordinates of the lower left starting position of the text string's first character.
<i>y</i>	is a scalar or vector that contains the vertical coordinates of the lower left starting position of the text string's first character.
<i>text</i>	is a vector of text strings.

The optional arguments to the GTEXT and GVTEXT subroutines are as follows:

<i>color</i>	is a valid SAS color. The <i>color</i> argument can be specified as a quoted text string (such as 'RED'), the name of a character matrix that contains a valid color as an element, or a color number (such as 1) that refers to a color in the color list.
<i>window</i>	is a numeric matrix or literal that specifies a window. This is given in world coordinates and has the form $\{ \textit{minimum-x} \textit{ minimum-y} \textit{ maximum-x} \textit{ maximum-y} \}$
<i>viewport</i>	is a numeric matrix or literal that specifies a viewport. This is given in normalized coordinates and has the same form as the <i>window</i> argument.

The GTEXT subroutine places text horizontally on a graph; the GVTEXT subroutine places text vertically on a graph. Both subroutines use hardware characters when possible. The number of text strings drawn is the maximum dimension of the first three vectors. The *color* argument can have more than one element. Hardware characters cannot always be obtained if you use a viewport or if you change the HEIGHT or

ASPECT parameters by using the [GSET](#) subroutine or the GOPTIONS statement. The coordinates in use for this graphics command are world coordinates.

Examples of the GTEXT and GVTEXT subroutines follow:

```
call gstart;
call gopen;
call gport({0 0 50 50});
call gset("height", 3); /* set character height */
msg = "GTEXT: This will start in the center of the viewport";
call gtext(50, 50, msg);
msg = "GVTEXT: Vertical string";
call gvtext(0.35, 10, msg, 'red', {0.2 -1, 1.5 6.5}, {0 0, 100 100});
call gshow;
```

GWINDOW Call

CALL GWINDOW(*window*);

The GWINDOW subroutine sets up the window for scaling data values in subsequent graphics primitives. The argument *window* is a numeric matrix or literal that specifies a window. The rectangular area's boundary is given in world coordinates, where you specify the lower left and upper right corners in the form

{ minimum-x minimum-y maximum-x maximum-y }

The window remains until the next GWINDOW call or until the segment is closed. The coordinates in use for this graphics command are world coordinates. An example that uses the GWINDOW subroutine follows:

```
x = rannor( j(20,1) );
y = 3 + x + 0.5*rannor( j(20,1) );

call gstart;
/* define window to contain the data range plus 5% margins */
xMargin = 0.05*(max(x) - min(x));
yMargin = 0.05*(max(y) - min(y));
wd = (min(x)-xMargin) || (min(y)-yMargin) ||
      (max(x)+xMargin) || (max(y)+yMargin);
call gwindow(wd);
call gpoint(x, y);
call gshow;
```

GXAXIS and GYAXIS Calls

CALL GXAXIS(*starting-point*, *length*, *nincr* <, *nminor* <, *noticklab* <, *format* <, *height* <, *font* <, *color* <, *fixed-end* <, *window* <, *viewport* >);

CALL GYAXIS(*starting-point*, *length*, *nincr* < , *nminor* < , *noticklab* < , *format* < , *height* < , *font* < , *color* < , *fixed-end* < , *window* < , *viewport* >);

The GXAXIS subroutine is a graphical call that draws a horizontal axis. The GYAXIS subroutine draws a vertical axis.

The required arguments to the GXAXIS and GYAXIS subroutines are as follows:

<i>starting-point</i>	is the (<i>x</i> , <i>y</i>) starting point of the axis, specified in world coordinates.
<i>length</i>	is a numeric scalar that contains the length of the axis, specified in world coordinates.
<i>nincr</i>	is a numeric scalar that contains the number of major tick marks on the axis. The first tick mark corresponds to <i>starting-point</i> .

The optional arguments to the GXAXIS and GYAXIS subroutines are as follows:

<i>nminor</i>	is an integer that specifies the number of minor tick marks between major tick marks.
<i>noticklab</i>	is a flag that is nonzero if the tick marks are not labeled. The default is to label tick marks.
<i>format</i>	is a character scalar that gives a valid SAS numeric format used in formatting the tick-mark labels. The default format is 8.2.
<i>height</i>	is a numeric matrix or literal that specifies the character height. This is used for the tick-mark labels.
<i>font</i>	is a character matrix or quoted literal that specifies a valid font name. This is used for the tick-mark labels.
<i>color</i>	is a valid color. The <i>color</i> argument can be specified as a quoted text string (such as 'RED'), the name of a character matrix that contains a valid color as an element, or a color number (such as 1) that refers to a color in the color list.
<i>fixed-end</i>	holds one end of the scale fixed. 'U' fixes the upper end; 'L' fixes the lower end; 'X' allows both ends to vary from the data values. In addition, you can specify 'N', which causes the axis routines to bypass the scaling routine. The interval between tick marks is <i>length</i> divided by (<i>nincr</i> −1). The default is 'X'.
<i>window</i>	is a numeric matrix or literal that specifies a window. This is given in world coordinates and has the form <div style="text-align: center;">{ <i>minimum-x</i> <i>minimum-y</i> <i>maximum-x</i> <i>maximum-y</i> }</div>
<i>viewport</i>	is a numeric matrix or literal that specifies a viewport. This is given in normalized coordinates and has the same form as the <i>window</i> argument.

The GXAXIS and GYAXIS subroutines use the same scaling algorithm as the GSCALE subroutine. For example, if the *x* starting point is 10 and the length of the axis is 44, and if you call the GSCALE subroutine with the *x* vector that contains the two elements, 10 and 44, the scale obtained should be the same as that obtained by the GXAXIS subroutine. Sometimes, it can be helpful to use the GSCALE subroutine in conjunction with the axis subroutines to get more precise scaling and labeling.

For example, suppose you want to draw the axis for $-2 \leq X \leq 2$ and $-2 \leq Y \leq 2$. The following statements draw these axes. Each axis is four units long. The *x* axis begins at the point (−2, 0), and the *y*

axis begins at the point $(0, -2)$. The tick marks can be set at each integer value, with minor tick marks in between the major tick marks. The tick marks are labeled because the *noticklab* option has the value 0.

```
call gstart;
call gport({20 20 80 80});
call gwindow({-2 -2 2 2});
call gxaxis({-2,0}, 4, 5, 2, 0);
call gyaxis({0,-2}, 4, 5, 2, 0);
call gshow;
```

HADAMARD Function

HADAMARD($n, <, i>$);

The HADAMARD function returns a Hadamard matrix. The arguments to the HADAMARD function are as follows:

n specifies the order of the Hadamard matrix. You can specify that n is 1, 2, or a multiple of 4. Furthermore, n must satisfy at least one of the following conditions:

- $n \leq 256$
- $n - 1$ is prime
- $(n/2) - 1$ is prime and $n/2 = 2 \bmod 4$
- $n = 2^p h$ for some positive integers p and h , and h satisfies one of the preceding conditions

When any other n is specified, the HADAMARD function returns a zero.

i specifies the row number to return. When i is not specified or i is negative, the full Hadamard matrix is returned.

The HADAMARD function returns a Hadamard matrix, which is an $n \times n$ matrix that consists entirely of the values 1 and -1 . The columns of a Hadamard matrix are all orthogonal. Hadamard matrices are frequently used to make orthogonal array experimental designs for two-level factors. For example, the following statements create a 12×12 Hadamard matrix:

```
h = hadamard(12);
print h[format=2.];
```

The output is shown in [Figure 23.129](#). The first column is an intercept and the next 11 columns form an orthogonal array experimental design for 11 two-level factors in 12 runs, 2^{11} .

Figure 23.129 A Hadamard Matrix

h												
1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1
1	1	-1	1	-1	-1	-1	1	1	1	-1	1	1
1	1	1	-1	1	-1	-1	-1	1	1	1	-1	-1
1	-1	1	1	-1	1	-1	-1	-1	1	1	1	1
1	1	-1	1	1	-1	1	-1	-1	-1	-1	1	1
1	1	1	-1	1	1	-1	1	-1	-1	-1	-1	1
1	1	1	1	-1	1	1	-1	1	-1	-1	-1	-1
1	-1	1	1	1	-1	1	1	-1	1	-1	-1	-1
1	-1	-1	1	1	1	-1	1	1	-1	1	-1	-1
1	-1	-1	-1	1	1	1	-1	1	1	-1	1	1
1	1	-1	-1	-1	1	1	1	-1	1	1	-1	-1
1	-1	1	-1	-1	-1	1	1	1	-1	1	1	1

To request the seventeenth row of a Hadamard matrix of order 448, use the following statement:

```
h17 = hadamard(448, 17);
```

HALF Function

HALF(*matrix*);

The HALF function is an alias for the [ROOT function](#), which computes the Cholesky decomposition of a symmetric positive definite matrix.

HANKEL Function

HANKEL(*matrix*);

The HANKEL function generates a Hankel matrix from a vector or a block Hankel matrix from a matrix. A block Hankel matrix has the property that all matrices on the reverse diagonals are the same. The argument matrix is an $(np) \times p$ or $p \times (np)$ matrix; the value returned is the $(np) \times (np)$ result.

The Hankel function uses the first $p \times p$ submatrix \mathbf{A}_1 of the argument matrix as the blocks of the first reverse diagonal. The second $p \times p$ submatrix \mathbf{A}_2 of the argument matrix forms the second reverse diagonal. The remaining reverse diagonals are formed accordingly. After the values in the argument matrix have all been placed, the rest of the matrix is filled in with 0. If \mathbf{A} is $(np) \times p$, then the first p columns of the returned matrix, \mathbf{R} , are the same as \mathbf{A} . If \mathbf{A} is $p \times (np)$, then the first p rows of \mathbf{R} are the same as \mathbf{A} .

The HANKEL function is especially useful in time series applications that involve a set of variables that represent the present and past and a set of variables that represent the present and future. In this situation, the covariance matrix between the sets of variables is often assumed to be a block Hankel matrix. If

$$\mathbf{A} = [\mathbf{A}_1 | \mathbf{A}_2 | \mathbf{A}_3 | \cdots | \mathbf{A}_n]$$

and if \mathbf{R} is the matrix formed by the HANKEL function, then

$$\mathbf{R} = \begin{bmatrix} \mathbf{A}_1 & \mathbf{A}_2 & \mathbf{A}_3 & \cdots & \mathbf{A}_n \\ \mathbf{A}_2 & \mathbf{A}_3 & \mathbf{A}_4 & \cdots & \mathbf{0} \\ \mathbf{A}_3 & \mathbf{A}_4 & \mathbf{A}_5 & \cdots & \mathbf{0} \\ \vdots & & & & \\ \mathbf{A}_n & \mathbf{0} & \mathbf{0} & \cdots & \mathbf{0} \end{bmatrix}$$

If

$$\mathbf{A} = \begin{bmatrix} \mathbf{A}_1 \\ \mathbf{A}_2 \\ \vdots \\ \mathbf{A}_n \end{bmatrix}$$

and if \mathbf{R} is the matrix formed by the HANKEL function, then

$$\mathbf{R} = \begin{bmatrix} \mathbf{A}_1 & \mathbf{A}_2 & \mathbf{A}_3 & \cdots & \mathbf{A}_n \\ \mathbf{A}_2 & \mathbf{A}_3 & \mathbf{A}_4 & \cdots & \mathbf{0} \\ \vdots & & & & \\ \mathbf{A}_n & \mathbf{0} & \mathbf{0} & \cdots & \mathbf{0} \end{bmatrix}$$

For example, the following statements produce Hankel matrices, as shown in [Figure 23.130](#):

```
r1 = hankel({1 2 3 4 5});
r2 = hankel({1 2 ,
             3 4 ,
             5 6 ,
             7 8});
r3 = hankel({1 2 3 4 ,
             5 6 7 8});
print r1, r2, r3;
```

Figure 23.130 Hankel Matrices

r1				
1	2	3	4	5
2	3	4	5	0
3	4	5	0	0
4	5	0	0	0
5	0	0	0	0

r2			
1	2	5	6
3	4	7	8
5	6	0	0
7	8	0	0

Figure 23.130 *continued*

r3			
1	2	3	4
5	6	7	8
3	4	0	0
7	8	0	0

HARMEAN Function

HARMEAN(*matrix*);

The HARMEAN function returns a scalar that contains the harmonic mean of the elements of the input matrix. The input matrix must contain only nonnegative numbers. The harmonic mean of a set of positive numbers a_1, a_2, \dots, a_n is n divided by the sum of the reciprocals of a_i . That is, $n / \sum a_i^{-1}$.

The harmonic mean is zero if any of the a_i are zero. The harmonic mean is not defined for negative numbers. If any of the a_i are missing, they are excluded from the computation.

The harmonic mean is sometimes used to compute an average sample size in an unbalanced experimental design. For example, the following statements compute an average sample size for five samples:

```
sizes = { 8, 12, 23, 10, 8 }; /* sample sizes */
aveSize = harmean( sizes );
print aveSize;
```

Figure 23.131 Harmonic Mean

aveSize
10.486322

HDIR Function

HDIR(*matrix1*, *matrix2*);

The HDIR function computes the horizontal direct product of two numeric matrices. This operation is useful in constructing design matrices of interaction effects.

Specifically, the HDIR function performs a direct product on all rows of *matrix1* and *matrix2* and creates a new matrix by stacking these row vectors into a matrix. The *matrix1* and *matrix2* arguments must have the same number of rows, which is also the same number of rows in the result matrix. The number of columns in the result matrix is equal to the product of the number of columns in *matrix1* and *matrix2*.

For example, the following statements produce the matrix **c**, shown in [Figure 23.132](#):

```

a = {1 2,
      2 4,
      3 6};
b = {0 2,
      1 1,
      0 -1};
c = hdir(a, b);
print c;

```

Figure 23.132 Horizontal Direct Product

c			
0	2	0	4
2	2	4	4
0	-3	0	-6

The HDIR function is useful for constructing crossed and nested effects from main-effect design matrices in ANOVA models.

HERMITE Function

HERMITE(*matrix*);

The HERMITE function uses elementary row operations to compute the Hermite normal form of a matrix. For square matrices this normal form is upper triangular and idempotent.

If the argument is square and nonsingular, the result is the identity matrix. In general the result satisfies the following four conditions (Graybill 1969):

- It is upper triangular.
- It has only values of 0 and 1 on the diagonal.
- If a row has a 0 on the diagonal, then every element in that row is 0.
- If a row has a 1 on the diagonal, then every off-diagonal element is 0 in the column in which the 1 appears.

The following statements compute an example from Graybill (1969):

```

a = {3 6 9,
      1 2 5,
      2 4 10};
h = hermite(a);
print h;

```

Figure 23.133 Hermite Matrix

h		
1	2	0
0	0	0
0	0	1

If the argument is a square matrix, then the Hermite normal form can be transformed into the row-echelon form by rearranging rows in which all values are 0.

HOMOGEN Function

HOMOGEN(*matrix*);

The HOMOGEN function solves the homogeneous system of linear equations $\mathbf{A} * \mathbf{X} = \mathbf{0}$ for \mathbf{X} . For at least one solution vector \mathbf{X} to exist, the $m \times n$ matrix \mathbf{A} , $m \geq n$, has to be of rank $r < n$. The HOMOGEN function computes an $n \times (n - r)$ column orthonormal matrix \mathbf{X} with the properties that $\mathbf{A} * \mathbf{X} = \mathbf{0}$ and $\mathbf{X}'\mathbf{X} = \mathbf{I}$. In other words, the columns of \mathbf{X} form an orthonormal basis for the nullspace of \mathbf{A} .

If $\mathbf{A}'\mathbf{A}$ is ill-conditioned, rounding-error problems can occur in determining the correct rank of \mathbf{A} and in determining the correct number of solutions \mathbf{X} .

The following statements compute an example from Wilkinson and Reinsch (1971):

```
a = {22  10  2  3  7,
      14  7  10  0  8,
      -1 13 -1 -11 3,
      -3 -2 13 -2  4,
      9  8  1 -2  4,
      9  1 -7  5 -1,
      2 -6  6  5  1,
      4  5  0 -2  2};
x = homogen(a);
print x;
```

Figure 23.134 Solutions to a Homogeneous System

x	
-0.419095	0
0.4405091	0.4185481
-0.052005	0.3487901
0.6760591	0.244153
0.4129773	-0.802217

In addition, you can use the HOMOGEN function to determine the rank of an $m \times n$ matrix \mathbf{A} where $m \geq n$ by counting the number of columns in the matrix \mathbf{X} .

If A is an $n \times m$ matrix, then, in addition to the memory allocated for the return matrix, the HOMOGEN function temporarily allocates an $n^2 + nm$ array for performing its computation.

I Function

I(dim);

The I function creates an identity matrix with *dim* rows and columns. The diagonal elements of an identity matrix are ones; all other elements are zeros. The value of *dim* must be an integer greater than or equal to 1. Noninteger operands are truncated to their integer part.

For example, the following statements compute a 3×3 identity matrix:

```
a = I(3);
print a;
```

Figure 23.135 An Identity Matrix

a		
1	0	0
0	1	0
0	0	1

IF-THEN/ELSE Statement

IF expression THEN statement1 ;

ELSE statement2 ;

The IF-THEN/ELSE statement conditionally executes statements. The ELSE statement is optional.

The arguments to the IF-THEN/ELSE statement are as follows:

expression is an expression that is evaluated for being true or false.

statement1 is a statement executed when *expression* is true.

statement2 Is a statement executed when *expression* is false.

The IF statement contains an expression to be evaluated, the keyword THEN, and an action to be taken when the result of the evaluation is true.

The ELSE statement optionally follows the IF statement and gives an action to be taken when the IF expression is false. The expression to be evaluated is often a comparison. For example:

```
a = {0, 5, 1, 10};
if max(a) < 20 then
```

```

    p = 0;
else
    p = 1;

```

The IF statement results in the evaluation of the condition `max(a) < 20`. If the largest value found in the matrix `a` is less than 20, the scalar value `p` is set to 0. Otherwise, `p` is set to 1. See the description of the [MAX function](#) for details.

When the condition to be evaluated is a matrix expression, the result of the evaluation is another matrix. If all values of the result matrix are nonzero and nonmissing, the condition is true; if any element in the result matrix is 0 or missing, the condition is false. This evaluation is equivalent to using the [ALL function](#).

For example, consider the following statements:

```

a = { 1 2, 3 4};
b = {-1 0, 0 1};
if a>b then do;
    /* statements */
end;

```

This code produces the same result as the following statements:

```

if all(a>b) then do;
    /* statements */
end;

```

IF statements can be nested within the clauses of other IF or ELSE statements. There is no limit on the number of nesting levels. Consider the following example:

```

if a>b then
    if a>abs(b) then do;
        /* statements */
    end;
end;

```

Consider the following statements:

```

if a^=b then do;
    /* statements */
end;
if ^(a=b) then do;
    /* statements */
end;

```

The two IF statements are equivalent. In each case, the THEN clause is executed only when all corresponding elements of `a` and `b` are unequal.

Evaluation of the following statement requires only one element of `a` and `b` to be unequal in order for the expression to be true:

```

if any(a^=b) then do;
    /* statements */
end;

```

IFFT Function

IFFT(*f*);

The IFFT function computes the inverse finite Fourier transform of a matrix *f*, where *f* is an $np \times 2$ numeric matrix.

The IFFT function expands a set of sine and cosine coefficients into a sequence equal to the sum of the coefficients times the sine and cosine functions. The argument *f* is an $np \times 2$ matrix; the value returned is an $n \times 1$ vector.

If the element in the last row and second column of *f* is exactly 0, then *n* is $2np - 2$; otherwise, *n* is $2np - 1$.

The inverse finite Fourier transform of a two column matrix **F**, denoted by the vector **x**, is

$$x_i = F_{1,1} + 2 \sum_{j=2}^{np} \left(F_{j,1} \cos \left(\frac{2\pi}{n} (j-1)(i-1) \right) + F_{j,2} \sin \left(\frac{2\pi}{n} (j-1)(i-1) \right) \right) + q_i$$

for $i = 1, \dots, n$, where $q_i = (-1)^i F_{np,1}$ if *n* is even, or $q = 0$ if *n* is odd.

For the most efficient use of the IFFT function, *n* should be a power of 2. If *n* is a power of 2, a fast Fourier transform is used (Singleton 1969); otherwise, a Chirp-Z algorithm is used (Monro and Branch 1976).

The expression IFFT(FFT(X)) returns *n* times **x**, where *n* is the dimension of **x**. If *f* is not the Fourier transform of a real sequence, then the vector generated by the IFFT function is not a true inverse Fourier transform. However, applications exist in which the FFT and IFFT functions can be used for operations on multidimensional or complex data (Gentleman and Sande 1966; Nussbaumer 1982).

As an example, the convolution of two vectors **x** ($n \times 1$) and **y** ($m \times 1$) can be accomplished by using the following module:

```
start conv(u,v);
/* w = conv(u,v) convolves vectors u and v.
 * Algebraically, convolution is the same operation as
 * multiplying the polynomials whose coefficients are the
 * elements of u and v. Straight convolution is too slow,
 * so use the FFT.
 *
 * Both of u and v are column vectors.
 */
m = nrow(u);
n = nrow(v);

wn = m + n - 1;
/* find p so that 2##(p-1) < wn <= 2##p */
p = ceil( log(wn) / log(2) );
nice = 2##p;

a = fft( u // j(nice-m,1,0) );
b = fft( v // j(nice-n,1,0) );
/* complex multiplication of a and b */
wReal = a[,1]#b[,1] - a[,2]#b[,2];
```

```

wImag = a[,1]#b[,2] + a[,2]#b[,1];
w = wReal || wImag;
z=ifft(w);
z = z[1:wn,1] / nice; /* take real part and first wn elements */
return (z);
finish;

/* example of convolution of two waveforms */
TimeStep = 0.01;
t = T( do(0,8,TimeStep) );

Signal = j(nrow(t),1,5);
Signal[ loc(t>4) ] = -5;

ImpulseResponse = j(nrow(t),1,0);
ImpulseResponse[ loc(t<=2) ] = 3;

/* The time domain for this convolution is [0,16]
   with the same time step.
   For waveforms, rescale amplitude by the time step. */
y = conv(Signal,ImpulseResponse) * TimeStep;

```

Other applications of the FFT and IFFT functions include windowed spectral estimates and the inverse autocorrelation function.

IMPORTDATASETFROMR Call

CALL IMPORTDATASETFROMR(*SAS-data-set*, *RExpr*);

You can use the IMPORTDATASETFROMR subroutine to transfer data from an R data frame to a SAS data set. It is easier to read the subroutine name when it is written in mixed case: ImportDataSetFromR.

The arguments to the subroutine are as follows:

<i>SAS-data-set</i>	is a literal string or a character matrix that specifies the two-level name of a SAS data set (for example, Work.MyData).
<i>RExpr</i>	is a literal string or a character matrix that specifies the name of an R data frame or, in general, an R expression that can be coerced to an R data frame.

You can call the subroutine provided that the following statements are true:

1. The R statistical software is installed on the SAS workspace server.
2. The SAS system administrator at your site has enabled the RLANG SAS system option. (See “[The RLANG System Option](#)” on page 190.)

The following statements create a data frame in R named RData and copy the data into Work.MyData. The SHOW CONTENTS statement is then used to display attributes of the Work.MyData data, which demonstrates that the data were successfully transferred.


```

proc iml;
submit / R;
z = c('a','b','c','d','e')
RData <- data.frame(x=1:5, y=(1:5)^2, z=z)
endsubmit;

call ImportDataSetFromR("Work.MyData", "RData");

use Work.MyData;
show contents;
close Work.MyData;

```

Figure 23.136 Contents of a SAS Data Set Created from R Data

DATASET : WORK.MYDATA.DATA		
VARIABLE	TYPE	SIZE
-----	----	----
A	num	8
Y	num	8
Z	char	1
Number of Variables : 3		
Number of Observations: 5		

You can transfer data from a SAS data set into an R data frame by using the [EXPORTDATASETTOR](#) call. See Chapter 11, “[Calling Functions in the R Language](#),” for details about transferring data between R and SAS software.

The names of the variables in the SAS data set are derived from the names of the variables in the R data frame. The following rules are used to convert an R variable name to a valid SAS variable name:

1. If the name is longer than 32 characters, it is truncated to 32 characters.
2. A SAS variable name must begin with one of the following characters: ‘A’–‘Z’, ‘a’–‘z’, or the underscore (_). Therefore, if the first character is not a valid beginning character, it is replaced by an underscore (_).
3. A SAS variable name can contain only the following characters: ‘A’–‘Z’, ‘a’–‘z’, ‘0’–‘9’, or the underscore (_). Therefore, if any of the remaining characters is not valid in a SAS variable name, it is replaced by an underscore.
4. If the resulting name duplicates an existing name in the data set, a number is appended to the name to make it unique. If appending the number causes the length of the name to exceed 32 characters, the name is truncated to make room for the number.

IMPORTMATRIXFROMR Call

CALL IMPORTMATRIXFROMR(*IMLMatrix*, *RExpr*);

You can use the IMPORTMATRIXFROMR subroutine to transfer data from an R data frame to a SAS data set. It is easier to read the subroutine name when it is written in mixed case: ImportMatrixFromR.

The arguments to the subroutine are as follows:

IMLMatrix is a SAS/IML matrix to contain the data you want to transfer.
RExpr is a literal string or a character matrix that specifies the name of an R matrix, data frame, or an R expression that can be coerced to an R data frame.

If the *RExpr* argument is a data frame, then the resulting SAS/IML matrix has columns that correspond to variables from the data frame. If the first variable in the data frame is a numeric variable, a numeric matrix is created from all numeric variables in the data frame. If the first variable in the data frame is a character variable, a character matrix is created from all character variables in the data frame.

You can call the subroutine provided that the following statements are true:

1. The R statistical software is installed on the SAS workspace server.
2. The SAS system administrator at your site has enabled the RLANG SAS system option. (See “[The RLANG System Option](#)” on page 190.)

The following statements define an R matrix and copy the data from the matrix to a SAS/IML matrix:

```
proc iml;
submit / R;
m <- matrix( c(1,2,3,4,NA,6), nrow=2, byrow=TRUE)
endsubmit;

call ImportMatrixFromR(a, "m");
print a;
```

To demonstrate that the data were successfully transferred, the PRINT statement is used to print the values of the **a** matrix. The output is shown in [Figure 23.137](#). Note that the R missing value (**NA**) in the R matrix **m** was automatically converted to the SAS missing value in the SAS/IML matrix, **a**.

Figure 23.137 Data from R

a		
1	2	3
4	.	6

You can transfer data from a SAS/IML matrix into an R matrix frame by using the [EXPORTMATRIXTOR](#) call. See Chapter 11, “[Calling Functions in the R Language](#),” for details about transferring data between R and SAS software.

INDEX Statement

INDEX *variables* | **NONE** ;

The INDEX statement creates an index for the named variables in the current input SAS data set. An index is created for each variable listed, provided that the variable does not already have an index. Current retrieval is set to the last variable indexed. Subsequent I/O operations such as [LIST](#), [READ](#), [FIND](#), and [DELETE](#) can use this index to retrieve observations from the data. The indices are automatically updated when a data set is edited with the [APPEND](#), [DELETE](#), or [REPLACE](#) statements. Only one index is in effect at any given time. The [SHOW CONTENTS](#) command indicates which index is in use.

For example, the following statements copy the Sasuser.Class data set and create indexes for the Name and Sex variables. Current retrieval is set to use the Sex variable, as shown in [Figure 23.138](#).

```
data class;
    set sashelp.class;
run;

proc iml;
    use class;
    index name sex;
    list all;
close class;
```

Figure 23.138 Result of Listing Observations of an Indexed Data Set

OBS	Name	Sex	Age	Height	Weight
2	Alice	F	13.0000	56.5000	84.0000
3	Barbara	F	13.0000	65.3000	98.0000
4	Carol	F	14.0000	62.8000	102.5000
7	Jane	F	12.0000	59.8000	84.5000
8	Janet	F	15.0000	62.5000	112.5000
11	Joyce	F	11.0000	51.3000	50.5000
12	Judy	F	14.0000	64.3000	90.0000
13	Louise	F	12.0000	56.3000	77.0000
14	Mary	F	15.0000	66.5000	112.0000
1	Alfred	M	14.0000	69.0000	112.5000
5	Henry	M	14.0000	63.5000	102.5000
6	James	M	12.0000	57.3000	83.0000
9	Jeffrey	M	13.0000	62.5000	84.0000
10	John	M	12.0000	59.0000	99.5000
15	Philip	M	16.0000	72.0000	150.0000
16	Robert	M	12.0000	64.8000	128.0000
17	Ronald	M	15.0000	67.0000	133.0000
18	Thomas	M	11.0000	57.5000	85.0000
19	William	M	15.0000	66.5000	112.0000

The INDEX NONE statement can be used to set retrieval back to physical order.

When a WHERE clause is being processed, the SAS/IML language automatically determines which index

to use, if any. The decision is based on the variables and operators involved in the WHERE clause, and the decision criterion is based on the efficiency of retrieval.

INFILE Statement

INFILE *operand* < *options* > ;

The INFILE statement opens an external file for input or, if the file is already open, makes it the current input file. Subsequent [INPUT statements](#) read from the specified file.

The arguments to the INFILE statement are as follows:

<i>operand</i>	is either a predefined filename or a quoted string that contains in parentheses the filename or character expression that refers to the pathname.
<i>options</i>	are explained in the following list.

The valid values for the *options* argument are as follows:

LENGTH=variable

specifies a variable into which the length of a record is stored.

RECFM=N

specifies that the file be read in as a pure binary file rather than as a file with record separator characters. To do this, you must use the byte operand (<) in the [INPUT statement](#) to get new records rather than use separate input statements or the new line (/) operator.

The following keywords control how a program behaves when an [INPUT statement](#) tries to read past the end of a record. The default behavior is STOPOVER.

FLOWOVER

enables the [INPUT statement](#) to go to the next record to obtain values for the variables.

MISSOEVER

tolerates attempted reading past the end of the record by assigning missing values to variables read past the end of the record.

STOPOVER

treats going past the end of a record as an error condition, which triggers an end-of-file condition.

Several examples of INFILE statements follow:

```
filename in1 "student.dat";      /* specify filename IN1 */
infile in1;                     /* infile pathname      */

infile "student.dat";           /* path by quoted literal */

infile "student.dat" missover;   /* use missover option   */
```

See [Chapter 8](#) for further information.

INPUT Statement

INPUT < variables > < informats > < record-directives > < positionals > ;

The INPUT statement reads records from the current input file, placing the values into matrices. The **INFILE** statement sets up the current input file. See [Chapter 8](#) for details.

The INPUT statement supports the following arguments:

<i>variables</i>	specify the variable or variables you want to read from the current position in the record. Each variable can be followed immediately by an input format specification.
<i>informats</i>	specify an input format. These are of the form <i>w.d</i> or <i>\$w.</i> for standard numeric and character informats, respectively, where <i>w</i> is the width of the field and <i>d</i> is the decimal parameter, if any. You can also use a named SAS format such as BEST <i>w.d</i> . Also, you can use a single \$ or & for list input applications. If the width is unspecified, the informat uses list-input rules to determine the length by searching for a blank (or comma) delimiter. The special format \$RECORD. is used for reading the rest of the record into one variable. For more information about formats, see <i>SAS Language Reference: Dictionary</i> .

Record holding is always implied for RECFM=N binary files, as if the INPUT statement has a trailing @ sign. For more information, see [Chapter 8](#).

Examples of valid INPUT statements follow:

```
input x y;
input @1 name $ @20 sex $ @(20+2) age 3.;

eight=8;
input >9 <eight number2 ib8.;
```

The following example uses binary input:

```
file "out2.dat" recfm=n ;
number=499; at=1;
do i = 1 to 5;
    number=number+1;
    put >at number ib8.; at=at+8;
end;
closefile "out2.dat";

infile "out2.dat" recfm=n;
size=8;      /* 8 bytes */
do pos=1 to 33 by size;
    input >pos number ib8.;
    print number;
end;
```

record-directives are used to advance to a new record. *Record-directives* are the following:

holding @ sign	is used at the end of an INPUT statement to hold the current record so that you can continue to read from the record with later INPUT statements. Otherwise, the next record is used for the next INPUT statement.
/	advances to the next record.
> <i>operand</i>	specifies that the next record to be read start at the indicated byte position in the file (for RECFM= N files only). The <i>operand</i> is a literal number, a variable name, or an expression in parentheses.
< <i>operand</i>	specifies that the indicated number of bytes are read as the next record. The record directive must be specified for binary files (RECFM=N). The <i>operand</i> is a literal number, a variable name, or an expression in parentheses.
<i>positionals</i>	specifies a specific column on the record. The <i>positionals</i> are the following:
@ <i>operand</i>	specifies a column, where <i>operand</i> is a literal number, a variable name, or an expression in parentheses. For example, @30 means to go to column 30. The operand can also be a character operand when pattern searching is needed. For more information, see Chapter 8 .
+ <i>operand</i>	skips the indicated number of columns. The <i>operand</i> is a literal number, a variable name, or an expression in parentheses.

INSERT Function

INSERT(*x*, *y*, *row*<, *column*>);

The INSERT function inserts one matrix inside another.

The arguments to the INSERT function are as follows:

<i>x</i>	is the target matrix. It can be either numeric or character.
<i>y</i>	is the matrix to be inserted into the target. It can be either numeric or character, depending on the type of the target matrix.
<i>row</i>	is the row where the insertion is to be made.
<i>column</i>	is the column where the insertion is to be made.

The INSERT function returns the result of inserting the matrix *y* inside the matrix *x* at the place specified by the *row* and *column* arguments. This is done by splitting *x* either horizontally or vertically before the row or column specified and concatenating *y* between the two pieces. Thus, if *x* has *m* rows and *n* columns, *row* can range from 0 to *m* + 1 and *column* can range from 0 to *n* + 1.

It is not possible to insert in both dimensions simultaneously, so either *row* or *column* must be 0, but not both. The *column* argument is optional and defaults to 0. Also, the matrices must conform in the dimension in which they are joined.

The following statements show two examples of the INSERT function. Figure 23.139 shows that the matrix **c** is the result of inserting matrix **b** prior to the second row of matrix **a**. The matrix **d** is the result of inserting matrix **b** after the second column of matrix **a**.

```
a = {1 2, 3 4};
b = {5 6, 7 8};
c = insert(a, b, 2, 0);
d = insert(a, b, 0, 3);
print c, d;
```

Figure 23.139 Inserted Matrices

				c			
				1		2	
				5		6	
				7		8	
				3		4	
				d			
	1	2		5		6	
	3	4		7		8	

INT Function

INT(*matrix*);

The INT function truncates the decimal portion of the value of the argument. The integer portion of the value of the argument remains. The INT function takes the integer value of each element of the argument matrix, as shown in the following statements:

```
y = 2.8;
b = int(y);
x={12.95 10.999999999999999,
  -30.5 1e-6};
c = int(x);
print b, c;
```

Figure 23.140 Truncated Values

				b			
						2	
				c			
	12			11			
	-30			0			

In [Figure 23.140](#), notice that the value 11 is returned as the second element of **c**. If a value is within 10^{-12} of an integer, the INT function rounds up.

INV Function

INV(*matrix*);

The INV function computes the inverse of a square and nonsingular matrix.

For $\mathbf{G} = \text{INV}(\mathbf{A})$ the inverse has the properties

$$\mathbf{GA} = \mathbf{AG} = \text{identity}$$

To solve a system of linear equations $\mathbf{AX} = \mathbf{B}$ for \mathbf{X} , you can use the expression $\mathbf{x} = \text{inv}(\mathbf{a}) * \mathbf{b}$. However, the [SOLVE function](#) is more accurate and efficient for this task.

The following statements compute a matrix inverse and solve a linear system:

```
A = {0 0 1 0 1,
      1 0 0 1 0,
      0 1 1 0 1,
      1 0 0 0 1,
      0 1 0 1 0};

b = {9, 4, 10, 8, 2};

/* find inverse and solve linear system */
Ainv = inv(A);
x1 = Ainv*b;

/* solve by using a more efficient algorithm */
x2 = solve(A,b);
print x1 x2;
```

Figure 23.141 Solving a Linear System

	x1	x2
	3	3
	1	1
	4	4
	1	1
	5	5

The INV function uses an LU decomposition followed by back substitution to solve for the inverse, as described in Forsythe, Malcom, and Moler (1967).

The INV function (in addition to the [DET](#) and [SOLVE functions](#)) uses the following criterion to decide

whether the input matrix, $\mathbf{A} = [a_{ij}]_{i,j=1,\dots,n}$, is singular:

$$\text{sing} = 100 \times \text{MACHEPS} \times \max_{1 \leq i, j \leq n} |a_{ij}|$$

where MACHEPS is the relative machine precision.

All matrix elements less than or equal to *sing* are considered rounding errors of the largest matrix elements, so they are taken to be zero in subsequent computations. For example, if a diagonal or triangular coefficient matrix has a diagonal value that is less than or equal to *sing*, the matrix is considered singular by the DET, INV, and SOLVE functions.

The criterion is used by some functions to detect a singular matrix and to abort a computation that cannot be performed on a singular matrix. The typical error message is as follows:

ERROR: (execution) Matrix should be non-singular.

If you are getting this error message but believe that your matrix is actually nonsingular, you can try one of the following:

- Center and scale the data.
- Use the [GINV function](#) to compute the generalized inverse.
- Examine the size of the singular values returned by the [SVD call](#). The SVD call can be used to compute a generalized inverse with a user-specified singularity criterion.

If \mathbf{A} is an $n \times n$ matrix, the INV function allocates an $n \times n$ matrix in order to return the inverse. It also temporarily allocates an n^2 array in order to compute the inverse.

INVUPDT Function

INVUPDT(*matrix*, *vector*<, *scalar*>);

The INVUPDT function updates a matrix inverse.

The arguments to the INVUPDT function are as follows:

<i>matrix</i>	is an $n \times n$ nonsingular matrix. In most applications <i>matrix</i> is symmetric positive definite.
<i>vector</i>	is an $n \times 1$ or $1 \times n$ vector.
<i>scalar</i>	is a numeric scalar.

The Sherman-Morrison-Woodbury formula is

$$(\mathbf{A} + \mathbf{UV}')^{-1} = \mathbf{A}^{-1} - \mathbf{A}^{-1}\mathbf{U}(\mathbf{I} + \mathbf{V}'\mathbf{A}^{-1}\mathbf{U})^{-1}\mathbf{V}'\mathbf{A}^{-1}$$

where \mathbf{A} is an $n \times n$ nonsingular matrix and \mathbf{U} and \mathbf{V} are $n \times k$. The formula shows that a rank k update to \mathbf{A} corresponds to a rank k update of \mathbf{A}^{-1} .

The INVUPDT function implements the Sherman-Morrison-Woodbury formula for rank-one updates with $\mathbf{U} = w\mathbf{X}$ and $\mathbf{V} = \mathbf{X}$, where \mathbf{X} is an $n \times 1$ vector and w is a scalar.

If $\mathbf{M} = \mathbf{A}^{-1}$, then you can call the INVUPDT function as follows:

```
R = invupdt (M, X, w);
```

This statement computes the following matrix:

$$\mathbf{R} = \mathbf{M} - w\mathbf{MX}(\mathbf{I} + w\mathbf{X}'\mathbf{MX})^{-1}\mathbf{X}'\mathbf{M}$$

The matrix \mathbf{R} is equivalent to $(\mathbf{A} + w\mathbf{XX}')^{-1}$. If \mathbf{A} is symmetric positive definite, then so is \mathbf{R} .

If w is not specified, then it is given a default value of 1.

A common use of the INVUPDT function is in linear regression. If \mathbf{Z} is a design matrix, $\mathbf{M} = (\mathbf{Z}'\mathbf{Z})^{-1}$ is the associated inverse crossproduct matrix, and \mathbf{v} is a new observation to be used in estimating the parameters of a linear model, then the inverse crossproducts matrix that includes the new observation can be updated from \mathbf{M} by using the following statement:

```
M2 = invupdt (M, v);
```

If w is 1, the function adds an observation to the inverse; if w is -1 , the function removes an observation from the inverse. If weighting is used, w is the weight.

To perform the computation, the INVUPDT function uses about $2n^2$ multiplications and additions, where n is the row dimension of the positive definite argument matrix.

The following program demonstrates adding or removing observations from a linear fit and updating the inverse crossproduct matrix:

```
X = {0, 1, 1, 1, 2, 2, 3, 4, 4};
Y = {1, 1, 2, 6, 2, 3, 3, 3, 4};

/* find linear fit */
Z = j(nrow(X), 1, 1) || X;          /* design matrix */
M = inv(Z`*Z);

b = M*Z`*Y;                        /* LS estimate */
resid = Y - Z*b;                   /* residuals */
print "Original Fit", b resid;

/* residual for observation (1,6) seems too large.
   Take obs number 4 out of data set and refit. */
v = z[4,];
M = invupdt (M, v, -1);             /* update inverse crossprod */

keepObs = (1:3) || (5:nrow(X));
Z = Z[keepObs, ];
Y = Y[keepObs, ];
b = M*Z`*Y;                        /* new LS estimate */
print "After deleting observation 4", b;

/* Add a new obs (x,y) = (0,2) and refit. */
obs = {0 2};
v = 1 || obs[1];                   /* new row in design matrix */
```

```

M = invupdt(M, v);

Z = Z // v;
Y = Y // obs[2];
b = M*Z`*Y;                      /* new LS estimate */
print "After adding observation (0,2)", b;

```

Figure 23.142 Refitting Linear Regression Models

Original Fit	
b	resid
2.0277778	-1.027778
0.375	-1.402778
	-0.402778
3.5972222	
	-0.777778
0.2222222	
	-0.152778
	-0.527778
0.4722222	
After deleting observation 4	
b	
	1
0.6470588	
After adding observation (0,2)	
b	
	1.3
0.5470588	

IPF Call

CALL IPF(*fit*, *status*, *dim*, *table*, *config* < , *initab* > < , *mod* >);

The IPF subroutine performs an iterative proportional fit of a contingency table. This is a standard statistical technique to obtain maximum likelihood estimates for cells under any hierarchical log-linear model. The algorithm is described in Bishop, Fienberg, and Holland (1975).

The arguments to the IPF subroutine are as follows:

fit is a returned matrix. The matrix *fit* contains an array of the estimates of the expected number in each cell under the model specified in *config*. This matrix conforms to *table*, meaning that it has the same dimensions and order of variables.

<i>status</i>	is a returned matrix. The <i>status</i> argument is a row vector of length 3. <i>status</i> [1] is 0 if there is convergence to the desired accuracy, otherwise it is nonzero. <i>status</i> [2] is the maximum difference between estimates of the last two iterations of the IPF algorithm. <i>status</i> [3] is the number of iterations performed.
<i>dim</i>	is an input matrix. If the problem contains v variables, then <i>dim</i> is $1 \times v$ row vector. The value <i>dim</i> [i] is the number of possible levels for variable i in a contingency table.
<i>table</i>	is an input matrix that specifies an array of the number of observations at each level of each variable. Variables are nested across columns and then across rows.
<i>config</i>	is an input matrix that specifies which marginal totals to fit. Each column of <i>config</i> specifies a distinct marginal in the model under consideration. Because the model is hierarchical, all subsets of specified marginals are included in fitting.
<i>initab</i>	is an input matrix that specifies initial values for the iterative procedure. If you do not specify values, ones are used. For incomplete tables, <i>initab</i> is set to 1 if the cell is included in the design, and 0 if it is not.
<i>mod</i>	is a two-element vector that specifies the stopping criteria. If <i>mod</i> = { <i>MaxDev</i> , <i>MaxIter</i> }, then the procedure iterates either until the maximum difference between estimates of the last two iterations is less than <i>MaxDev</i> or until <i>MaxIter</i> iterations are completed. Default values are <i>MaxDev</i> =0.25 and <i>MaxIter</i> =15.

The matrix *table* must conform in size to the contingency table as specified in *dim*. In particular, if *table* is $n \times m$, the product of the entries in *dim* must equal nm . Furthermore, there must be some integer k such that the product of the first k entries in *dim* equals m . If you specify *initab*, then it must be the same size as *table*.

Adjusting a Table from Marginals

A common use of the IPF subroutine is to adjust the entries of a table in order to fit a new set of marginals while retaining the interaction between cell entries.

Example 1: Adjusting Marital Status by Age Bishop, Fienberg, and Holland (1975) present data from D. Friedlander that shows the distribution of women in England and Wales according to their marital status in 1957. One year later, new official marginal estimates were announced. The problem is to adjust the entries in the 1957 table so as to fit the new marginals while retaining the interaction between cells. This problem can arise when you have internal cells that are known from sampling a population and then get margins based on a complete census.

When you want to adjust an observed table of cell frequencies to a new set of margins, you must set the *initab* parameter to be the table of observed values. The new marginals are specified through the *table* argument. The particular cell values for *table* are not important, since only the marginals are used (the proportionality between cells is determined by *initab*).

There are two easy ways to create a table that contains given margins. Recall that a table of independent variables has an expected cell value $A_{ij} = (\text{sum of row } i)(\text{sum of col } j)/(\text{sum of all cells})$. Thus you could form a table with these cell entries. Another possibility is to use a “greedy algorithm” to assign as many of the marginals as possible to the first cell, then assign as many of the remaining marginals as possible to

the second cell, and so on until all of the marginals have been distributed. Both of these approaches are encapsulated into modules in the following program:

```

/* Return a table such that cell (i,j) has value
   (sum of row i)(sum of col j)/(sum of all cells) */
start GetIndepTableFromMargins( bottom, side );
  if bottom[+] ^= side[+] then do;
    print "Marginal totals are not equal";
    abort;
  end;
  table = side*bottom/side[+];
  return (table);
finish;

/* Use a "greedy" algorithm to create a table whose
   marginal totals match given marginal totals.
   Margin1 is the vector of frequencies totaled down
   each column. Margin1 means that
   Variable 1 has NOT been summed over.
   Margin2 is the vector of frequencies totaled across
   each row. Margin2 means that Variable 2
   has NOT been summed over.
   After calling, use SHAPE to change the shape of
   the returned argument. */
start GetGreedyTableFromMargins( Margin1, Margin2 );
  /* copy arguments so they are not corrupted */
  m1 = colvec(Margin1); /* colvec is in IMLMLIB */
  m2 = colvec(Margin2);
  if m1[+] ^= m2[+] then do;
    print "Marginal totals are not equal";
    abort;
  end;
  dim1 = nrow(m1);
  dim2 = nrow(m2);
  table = j(1,dim1*dim2,0);
  /* give as much to cell (1,1) as possible,
     then as much as remains to cell (1,2), etc,
     until all the margins have been distributed */
  idx = 1;
  do i2 = 1 to dim2;
    do i1 = 1 to dim1;
      t = min(m1[i1],m2[i2]);
      table[idx] = t;
      idx = idx + 1;
      m1[i1] = m1[i1]-t;
      m2[i2] = m2[i2]-t;
    end;
  end;
  return (table);
finish;

Mod = {0.01 15}; /* tighten stopping criterion */

Columns = {" Single" " Married" "Widow/Divorced"};

```

```

Rows      = {"15 - 19" "20 - 24" "25 - 29" "30 - 34"
             "35 - 39" "40 - 44" "45 - 49" "50 Or Over"};

/* Marital status has 3 levels. Age has 8 levels */
Dim = {3 8};

/* Use known distribution for start-up values */
IniTab = { 1306  83    0 ,
           619  765    3 ,
           263 1194    9 ,
           173 1372   28 ,
           171 1393   51 ,
           159 1372   81 ,
           208 1350  108 ,
           1116 4100 2329 };

/* New marginal totals for age by marital status */
NewMarital = { 3988 11702 2634 };
NewAge = {1412,1402,1450,1541,1681,1532,1662,7644};

/* Create any table with these marginals */
Table = GetGreedyTableFromMargins(NewMarital, NewAge);
Table = shape(Table, nrow(IniTab), ncol(IniTab));

/* Consider all main effects */
Config = {1 2};

call ipf(Fit, Status, Dim, Table, Config, IniTab, Mod);

if Status[1] = 0 then
  print "Known Distribution (1957)",
    IniTab [colname=Columns rowname=Rows format=8.0],,
    "Adjusted Estimates of Distribution (1958)",
    Fit [colname=Columns rowname=Rows format=8.2];
else
  print "IPF did not converge in "
    (Status[3]) " iterations";

```

The results of this program are shown in [Figure 23.143](#). The same results are obtained if the *table* parameter is formed by using the “independent algorithm.”

Figure 23.143 Iterative Proportional Fitting

Known Distribution (1957)			
IniTab			
	Single	Married	Widow/Divorced
15 - 19	1306	83	0
20 - 24	619	765	3
25 - 29	263	1194	9
30 - 34	173	1372	28
35 - 39	171	1393	51
40 - 44	159	1372	81
45 - 49	208	1350	108
50 Or Over	1116	4100	2329
Adjusted Estimates of Distribution (1958)			
Fit			
	Single	Married	Widow/Divorced
15 - 19	1325.27	86.73	0.00
20 - 24	615.56	783.39	3.05
25 - 29	253.94	1187.18	8.88
30 - 34	165.13	1348.55	27.32
35 - 39	173.41	1454.71	52.87
40 - 44	147.21	1308.12	76.67
45 - 49	202.33	1352.28	107.40
50 Or Over	1105.16	4181.04	2357.81

Example 2: Adjusting Votes by Region A similar technique can be used to standardize data from raw counts into percentages. For example, consider data from a 1836 vote in the U.S. House of Representatives on a resolution that the House should adopt a policy of tabling all petitions for the abolition of slavery. Attitudes toward abolition were different among slaveholding states that would later secede from the Union (“the South”), slaveholding states that refused to secede (“the Border States”), and nonslaveholding states (“the North”).

The raw votes for the resolution are defined in the following statements. The data are hard to interpret because the margins are not homogeneous.

```
/*      Yea Abstain Nay */
IniTab = { 61   12   60, /* North */
           17    6    1, /* Border */
           39   22    7 }; /* South */
```

Standardizing the data by specifying homogeneous margins reveals interactions and symmetry that were not apparent in the raw data. Suppose the margins are specified as follows:

```
NewVotes = {100 100 100};
NewSection = {100,100,100};
```

In this case, the program for marital status by age can be easily rewritten to adjust the votes into a standardized form. The resulting output is shown in [Figure 23.144](#):

Figure 23.144 Standardizing Counts into Percentages

	Fit		
	Yea	Abstain	Nay
North	20.1	10.2	69.7
Border	47.4	42.8	9.8
South	32.5	47.0	20.5

Generating a Table with Given Marginals The “greedy algorithm” presented in the Marital-Status-By-Age example can be extended in a natural way to the case where you have n one-way marginals and want to form an n -dimensional table. For example, a three-dimensional “greedy algorithm” would allocate the vector *table* as `table=j(dim1*dim2*dim3,1,0)`; and have three nested loops as indicated in the following statements. Afterwards, the *table* parameter can be reshaped by using the [SHAPE](#) function.

```
do i3 = 1 to dim3;
  do i2 = 1 to dim2;
    do i1 = 1 to dim1;
      t = min(m1[i1],m2[i2],m3[i3]);
      table[idx] = t;
      idx = idx + 1;
      m1[i1] = m1[i1]-t;
      m2[i2] = m2[i2]-t;
      m3[i3] = m3[i3]-t;
    end;
  end;
end;
```

The idea of the “greedy algorithm” can be extended to marginals that are not one-way. For example, the following three-dimensional table is similar to one that appears in Christensen (1997) based on data from M. Rosenberg. The table presents data on a person’s self-esteem for people classified according to their religion and their father’s educational level.

Religion	Self-Esteem	Father’s Educational Level				
		Not HS Grad	HS Grad	Some Coll	Coll Grad	Post Coll
Catholic	High	575	388	100	77	51
	Low	267	153	40	37	19
Jewish	High	117	102	67	87	62
	Low	48	35	18	12	13
Protestant	High	359	233	109	197	90
	Low	159	173	47	82	32

Since the father’s education level is nested across columns, it is Variable 1 with levels that correspond to not finishing high school, graduating from high school, attending college, graduating from college, and

attending graduate courses. The variable that varies the quickest across rows is Self-Esteem, so Self-Esteem is Variable 2 with values “High” and “Low.” The Religion variable is Variable 3 with values “Catholic,” “Jewish,” and “Protestant.”

The following program encodes this table by using the [MARG](#) call to compute a two-way marginal table by summing over the third variable, and a one-way marginal by summing over the first two variables. Then a new table (**NewTable**) is created by applying the greedy algorithm to the two marginals. Finally, the marginals of **NewTable** are computed and compared with those of **table**.

```
dim={5 2 3};

table={
/* Father's Education:
      NotHSGrad HSGrad Col ColGrad PostCol
      Self-
      Relig Esteem */
/* Cath- Hi */ 575   388 100   77   51,
/* olic  Lo */ 267   153  40   37   19,

/* Jew-  Hi */ 117   102  67   87   62,
/* ish   Lo */  48    35  18   12   13,

/* Prot- Hi */ 359   233 109   197  90,
/* estant Lo */ 159   173  47   82   32
      };

config = { 1 3,
           2 0 };
call marg(locmar, marginal, dim, table, config);
print locmar, marginal, table;

/* Examine marginals: The name indicates the
   variable(s) that are NOT summed over.
   The locmar variable tells where to index
   into the marginal variable. */
Var12_Marg = marginal[1:(locmar[2]-1)];
Var12_Marg = shape(Var12_Marg,dim[2],dim[1]);
Var3_Marg = marginal[locMar[2]:ncol(marginal)];

NewTable = j(nrow(table),ncol(table),0);
/* give as much to cell (1,1,1) as possible,
   then as much as remains to cell (1,1,2), etc,
   until all the margins have been distributed. */
idx = 1;
do i3 = 1 to dim[3];      /* over Var3 */
  do i2 = 1 to dim[2];    /* over Var2 */
    do i1 = 1 to dim[1];  /* over Var1 */
      /* Note Var12_Marg has Var1 varying across
         the columns */
      t = min(Var12_Marg[i2,i1],Var3_Marg[i3]);
      NewTable[idx] = t;
      idx = idx + 1;
      Var12_Marg[i2,i1] = Var12_Marg[i2,i1]-t;
    end;
  end;
end;
```

```

        Var3_Marg[i3] = Var3_Marg[i3]-t;
    end;
end;
end;

call marg(locmar, NewMarginal, dim, table, config);
maxDiff = abs(marginal-NewMarginal)[<>];
if maxDiff=0 then
    print "Marginals are unchanged";
print NewTable;

```

Figure 23.145 Table with Given Marginals

locmar							
		1	11				
marginal							
	COL1	COL2	COL3	COL4	COL5	COL6	COL7
ROW1	1051	723	276	361	203	474	361
marginal							
	COL8	COL9	COL10	COL11	COL12	COL13	
ROW1	105	131	64	1707	561	1481	
table							
	575	388	100	77	51		
	267	153	40	37	19		
	117	102	67	87	62		
	48	35	18	12	13		
	359	233	109	197	90		
	159	173	47	82	32		
Marginals are unchanged							
NewTable							
	1051	656	0	0	0		
	0	0	0	0	0		
	0	67	276	218	0		
	0	0	0	0	0		
	0	0	0	143	203		
	474	361	105	131	64		

Fitting a Log-Linear Model to a Table

A second common usage of the IPF algorithm is to hypothesize that the table of observations can be fitted by a model with known effects and to ask whether the observed values indicate that the model hypothesis can be accepted or should be rejected. In this usage, you normally do not specify the *initab* argument to the IPF subroutine (but see the comment on structural zeros in the section “[Additional Details](#)” on page 741).

Example 3: Food Illness Korff, Taback, and Beard (1952) reported statistics related to the outbreak of food poisoning at a company picnic. A total of 304 people at the picnic were surveyed to determine who had eaten either of two suspect foods: potato salad and crabmeat. The predictor variables are whether the individual ate potato salad (Variable 1: “Yes” or “No”) and whether the person ate crabmeat (Variable 2: “Yes” or “No”). The response variable is whether the person was ill (Variable 3: “Ill” or “Not Ill”). The order of the variables is determined by the *dim* and *table* arguments to the IPF subroutine. The variables are nested across columns, then across rows.

Crabmeat: Potato salad:	Y E S		N O	
	Yes	No	Yes	No
Ill	120	4	22	0
Not Ill	80	31	24	23

The following program defines the variables and observations, and then fits three separate models. How well each model fits the data is determined by computing a Pearson chi-square statistic $\chi^2 = \sum (O - E)^2 / E$, where the sum is over all cells, O stands for the observed cell count, and E stands for the fitted estimate. Other statistics, such as the likelihood-ratio chi-square statistic $G^2 = -2 \sum O \log(E/O)$, could also be used.

The program first fits a model that excludes the three-way interaction. The model fits well, so you can conclude that an association between illness and potato salad does not depend on whether an individual ate crabmeat. The next model excludes the interaction between potato salad and illness. This model is rejected with a large chi-square value, so the data support an association between potato salad and illness. The last model excludes the interaction between the crabmeat and the illness. This model fits moderately well.

```

/* Compute a chi-square score for a table of observed
   values, given a table of expected values. Compare
   this score to a chi-square value with given degrees
   of freedom at 95% confidence level. */
start ChiSqTest( obs, model, degFreedom );
  diff = (obs - model)##2 / model;
  chiSq = diff[+];
  chiSqCutoff = cinv(0.95, degFreedom);
  print chiSq chiSqCutoff;
  if chiSq > chiSqCutoff then
    print "Reject hypothesis";
  else
    print "No evidence to reject hypothesis";
finish;

dim={2 2 2};

/* Crab meat:   Y E S           N O
   Potato:      Yes  No        Yes No  */
table={        120    4        22  0,  /* Ill */
         80    31        24  23 }; /* Not Ill */

crabmeat = "          C R A B      N O C R A B";
potato   = {"YesPot" "NoPot" "YesPot" "NoPot"};
illness  = {"Ill", "Not Ill"};

```

```

hypothesis = "Hypothesis: no three-factor interaction";
config={1 1 2,
        2 3 3};
call ipf(fit,status,dim,table,config);

print hypothesis, "Fitted Model:",
      fit[label=crabmeat colname=potato
          rowname=illness format=6.2];
run ChiSqTest(table, fit, 1); /* 1 deg of freedom */

/* Test for interaction between Var 3 (Illness) and
   Var 1 (Potato Salad) */
hypothesis = "Hypothesis: no Illness-Potato Interaction";
config={1 2,
        2 3};
call ipf(fit,status,dim,table,config);

print hypothesis, "Fitted Model:",
      fit[label=crabmeat colname=potato
          rowname=illness format=6.2];
run ChiSqTest(table, fit, 2); /* 2 deg of freedom */

/* Test for interaction between Var 3 (Illness) and
   Var 2 (Crab meat) */
hypothesis = "Hypothesis: no Illness-Crab Interaction";
config={1 1,
        2 3};
call ipf(fit,status,dim,table,config);

print hypothesis, "Fitted Model:",
      fit[label=crabmeat colname=potato
          rowname=illness format=6.2];
run ChiSqTest(table, fit, 2); /* 2 deg of freedom */

```

Figure 23.146 Fitting Log-Linear Models

hypothesis				
Hypothesis: no three-factor interaction				
Fitted Model:				
	C R A B		N O	C R A B
	YesPot	NoPot	YesPot	NoPot
Ill	121.08	2.92	20.92	1.08
Not Ill	78.92	32.08	25.07	21.93
chiSq chiSqCutoff				
	1.7021335		3.8414588	
No evidence to reject hypothesis				

Figure 23.146 *continued*

hypothesis				
Hypothesis: no Illness-Potato Interaction				
Fitted Model:				
	C R A B		N O	C R A B
	YesPot	NoPot	YesPot	NoPot
Ill	105.53	18.47	14.67	7.33
Not Ill	94.47	16.53	31.33	15.67
chiSq chiSqCutoff				
	44.344643		5.9914645	
Reject hypothesis				
hypothesis				
Hypothesis: no Illness-Crab Interaction				
Fitted Model:				
	C R A B		N O	C R A B
	YesPot	NoPot	YesPot	NoPot
Ill	115.45	2.41	26.55	1.59
Not Ill	84.55	32.59	19.45	21.41
chiSq chiSqCutoff				
	5.0945132		5.9914645	
No evidence to reject hypothesis				

Additional Details

Structural versus Random Zeros In the Marital-Status-By-Age example, the *initab* argument contained a zero for the “15–19 and Widowed/Divorced” category. Because the *initab* parameter determines the proportionality between cells, the fitted model retains a zero in that category. By contrast, in the Food-Illness example, the *table* parameter contained a zero for number of illnesses observed among those who did not eat either crabmeat or potato salad. This is a sampling (*random*) zero. Some models preserve that zero; others do not. If your table has a *structural zero* (for example, the number of ovarian cancers observed among male patients), then you can use the *initab* parameter to preserve that zero. see Bishop, Fienberg, and Holland (1975) or the documentation for the CATMOD procedure in the *SAS/STAT User's Guide* for more information about structural zeros and incomplete tables.

The config Parameter The columns of this matrix specify which interaction effects should be included in the model. The following table gives the model and the configuration parameter for common

interactions for an $I \times J \times K$ table in three dimensions. The so-called *noncomprehensive* models that do not include all variables (for example, *config* = {1}) are not listed in the table, but can be used. You can also specify combinations of main and interaction effects. For example, *config* = {1 3, 2 0} specifies all main effects and the 1-2 interaction. Bishop, Fienberg, and Holland (1975) and Christensen (1997) explain how to compute the degrees of freedom associated with any model. For models with structural zeros, computing the degrees of freedom is complicated.

Model	config	Degrees of Freedom
No three-factor	{1 1 2, {2 3 3}	$(I - 1)(J - 1)(K - 1)$
One two-factor absent	{1 2, {3 3}	$(I - 1)(J - 1)K$
	{1 2, 2 3}	$(I - 1)J(K - 1)$
	{1 1, {2 3}	$I(J - 1)(K - 1)$
Two two-factor absent	{2, 3}	$(I - 1)(JK - 1)$
	{1, 3}	$(J - 1)(IK - 1)$
	{1, 2}	$(K - 1)(IJ - 1)$
No two-factor	{1 2 3}	$IJK - (I + J + K) + 2$
Saturated	{1,2,3}	IJK

The Shape of the table Parameter Since variables are nested across columns and then across rows, any shape that conforms to the *dim* parameter is equivalent.

For example, the section “[Generating a Table with Given Marginals](#)” on page 736 presents data on a person’s self-esteem for people classified according to their religion and their father’s educational level. To save space, the educational levels are subsequently denoted by labels that indicate the typical number of years spent in school: “<12,” “12,” “<16,” “16,” and “>16.”

The table would be encoded as follows:

```
dim={5 2 3};

table={
/* Father's Education:
      <12    12    <16    16    >16
    Self-
    Relig Esteem
/* Cath-  Hi */ 575    388    100    77    51,
/* olic   Lo */ 267    153    40     37    19,

/* Jew-   Hi */ 117    102    67     87    62,
/* ish    Lo */ 48     35     18     12    13,

/* Prot-  Hi */ 359    233    109    197    90,
/* estant Lo */ 159    173    47     82    32
};
```

The same information for the same variables in the same order could also be encoded into an $n \times m$ table in two other ways. Recall that the product of entries in *dim* is nm and that m must equal the product of the first k entries of *dim* for some k . For this example, the product of the entries in *dim* is

30, and so the table must be 6×5 , 3×10 , or 1×30 . The 3×10 table is encoded as concatenating rows 1–2, 3–4, and 5–6 to produce the following:

```
table={
/* Esteem: H I G H           L O W           */
/*    <12  ...  >16    <12  ...  >16           */

      575  ...   51   267  ...   19, /* Catholic */
      117  ...   62    48  ...   13, /* Jewish   */
      359  ...   90   159  ...   32 /* Protestant*/
};
```

The 1×30 table is encoded by concatenating all rows, as follows:

```
table={
/*      CATHOLIC           ...      PROTESTANT
      High           Low           High           Low
<12  ...  >16 <12  ...  >16  ...  <12  ...  >16 <12  ...  >16
*/
575 ...  51 267 ...  19  ...  359 ...  90 159 ...  32
};
```

ITSOLVER Call

CALL ITSOLVER(*x*, *error*, *iter*, *method*, *A*, *b* <, *precon*> <, *tol*> <, *maxiter*> <, *start*> <, *history*>);

The ITSOLVER subroutine solves a sparse linear system by using iterative methods.

The ITSOLVER call returns the following values:

x is the solution to $Ax=b$.
error is the final relative error of the solution.
iter is the number of iterations executed.

The input arguments to the ITSOLVER call are as follows:

method is the type of iterative method to use. The following values are valid:

"CG"	specifies a conjugate gradient algorithm. The matrix <i>A</i> must be symmetric and positive definite.
"CGS"	specifies a conjugate gradient squared algorithm, for general <i>A</i> .
"MINRES"	specifies a minimum residual algorithm, when <i>A</i> is symmetric indefinite.
"BICG"	specifies a biconjugate gradient algorithm, for general <i>A</i> .

A is the sparse coefficient matrix in the equation $Ax=b$. You can use [SPARSE function](#) to convert a matrix from dense to sparse storage.

<i>b</i>	is a column vector, the right side of the equation $Ax=b$.								
<i>precon</i>	is the name of a preconditioning technique to use. The following values are valid: <table> <tr> <td>"NONE"</td><td>specifies no preconditioning. This is the default behavior if the argument is not specified.</td></tr> <tr> <td>"IC"</td><td>specifies an incomplete Cholesky factorization. Specify this value when you specify "CG" or "MINRES" for the <i>method</i> argument.</td></tr> <tr> <td>"DIAG"</td><td>specifies a diagonal Jacobi preconditioner. Specify this value when you specify "CG" or "MINRES" for the <i>method</i> argument.</td></tr> <tr> <td>"MILU"</td><td>specifies a modified incomplete LU factorization. Specify this value when you specify "BICG" for the <i>method</i> argument.</td></tr> </table>	"NONE"	specifies no preconditioning. This is the default behavior if the argument is not specified.	"IC"	specifies an incomplete Cholesky factorization. Specify this value when you specify "CG" or "MINRES" for the <i>method</i> argument.	"DIAG"	specifies a diagonal Jacobi preconditioner. Specify this value when you specify "CG" or "MINRES" for the <i>method</i> argument.	"MILU"	specifies a modified incomplete LU factorization. Specify this value when you specify "BICG" for the <i>method</i> argument.
"NONE"	specifies no preconditioning. This is the default behavior if the argument is not specified.								
"IC"	specifies an incomplete Cholesky factorization. Specify this value when you specify "CG" or "MINRES" for the <i>method</i> argument.								
"DIAG"	specifies a diagonal Jacobi preconditioner. Specify this value when you specify "CG" or "MINRES" for the <i>method</i> argument.								
"MILU"	specifies a modified incomplete LU factorization. Specify this value when you specify "BICG" for the <i>method</i> argument.								
<i>tol</i>	is the relative error tolerance.								
<i>maxiter</i>	is the iteration limit.								
<i>start</i>	is a starting point column vector.								
<i>history</i>	is a matrix to store the relative error at each iteration.								

The ITSOLVER call solves a sparse linear system by iterative methods, which involve updating a trial solution over successive iterations to minimize the error. The ITSOLVER call uses the technique specified in the *method* parameter to update the solution.

The input matrix *A* represents the coefficient matrix in sparse format; it is an $n \times 3$ matrix, where n is the number of nonzero elements. The first column contains the nonzero values, and the second and third columns contain the row and column locations for the nonzero elements, respectively. For the algorithms that assume symmetric *A*, only the lower triangular elements should be specified. The algorithm continues iterating to improve the solution until either the relative error tolerance specified in *tol* is satisfied or the maximum number of iterations specified in *maxiter* is reached. The relative error is defined as

$$\text{error} = \|Ax - b\|_2 / (\|b\|_2 + \epsilon)$$

where the $\|\cdot\|_2$ operator is the Euclidean norm and ϵ is a machine-dependent epsilon value to prevent any division by zero. If *tol* or *maxiter* is not specified in the call, then a default value of 10^{-7} is used for *tol* and 100,000 for *maxiter*.

The convergence of an iterative algorithm can often be enhanced by preconditioning the input coefficient matrix. The preconditioning option is specified with the *precon* parameter.

A starting trial solution can be specified with the *start* parameter; otherwise the ITSOLVER call generates a zero starting point. You can supply a matrix to store the relative error at each iteration with the *history* parameter. The *history* matrix should be dimensioned with enough elements to store the maximum number of iterations you expect.

You should always check the returned *error* and *iter* parameters to verify that the desired relative error tolerance is reached. If the tolerance is not reached, the program might continue the solution process with another ITSOLVER call, with *start* set to the latest result. You might also try a different *precon* option to enhance convergence.

For example, the following linear system has a coefficient matrix that contains several zeros:

$$\begin{bmatrix} 3 & 2 & 0 & 0 \\ 1.1 & 4 & 1 & 3.2 \\ 0 & 1 & -10 & 0 \\ 0 & 3.2 & 0 & 3 \end{bmatrix} x = \begin{bmatrix} 1 \\ 1 \\ 1 \\ 1 \end{bmatrix}$$

You can represent the matrix in sparse form and use the biconjugate gradient algorithm to solve the linear system, as shown in the following statements:

```
/* value      row column */
A = { 3      1      1,
      2      1      2,
      1.1    2      1,
      4      2      2,
      1      3      2,
      3.2    4      2,
     -10     3      3,
      3      4      4};

/* right hand side */
b = {1, 1, 1, 1};
maxiter = 10;
hist = j(maxiter,1,.);
start = {1,1,1,1};
tol = 1e-10;
call itsolver(x, error, iter, "bicg", A, b, "milu", tol,
maxiter, start, hist);
print x;
print iter error;
print hist;
```

Figure 23.147 Solution of a Linear System

x	
0.2040816	
0.1938776	
-0.080612	
0.1265306	
iter	error
3	5.011E-16

Figure 23.147 *continued*

```

                                hist
                                0.0254375
                                0.0080432
                                5.011E-16
                                    .
                                    .
                                    .
                                    .
                                    .
                                    .

```

The following linear system also has a coefficient matrix with several zeros:

$$\begin{bmatrix} 3 & 1.1 & 0 & 0 \\ 1.1 & 4 & 1 & 3.2 \\ 0 & 1 & 10 & 0 \\ 0 & 3.2 & 0 & 3 \end{bmatrix} x = \begin{bmatrix} 1 \\ 1 \\ 1 \\ 1 \end{bmatrix}$$

The following statements represent the matrix in sparse form and use the conjugate gradient algorithm solve the symmetric positive definite system:

```

/* value      row column */
A = { 3        1        1,
      1.1      2        1,
      4        2        2,
      1        3        2,
      3.2      4        2,
      10       3        3,
      3        4        4};

/* right hand side */
b = {1, 1, 1, 1};
call itsolver(x, error, iter, "CG", A, b);
print x, iter, error;

```

Figure 23.148 Solution to Sparse System

```

                                x
                                2.68
                                -6.4
                                0.74
                                7.16

                                iter
                                4

```

Figure 23.148 *continued*

error
2.847E-15

J Function

J(*nrow* <, *ncol* > <, *value* >);

The J function creates a matrix with *nrow* rows and *ncol* columns with all elements equal to *value*.

The arguments to the J function are as follows:

nrow is a numeric matrix or literal that contains the number of rows.
ncol is a numeric matrix or literal that contains the number of columns.
value is a numeric or character matrix or literal for filling the rows and columns of the matrix.

If *ncol* is not specified, it defaults to *nrow*. If *value* is not specified, it defaults to 1. The [REPEAT](#) and [SHAPE](#) functions can also perform this operation, and they are more general.

Examples of the J function are as follows:

```
b = j(3, 4);
c = j(5, 2, "xyz");
print b, c;
```

Figure 23.149 Constant Matrices

	b			
	1	1	1	1
	1	1	1	1
	1	1	1	1
	c			
	xyz	xyz		
	xyz	xyz		
	xyz	xyz		
	xyz	xyz		
	xyz	xyz		

JROOT Function

JROOT(*order*, *n*);

The JROOT function computes the first nonzero roots of a Bessel function of the first kind and the derivative of the Bessel function at each root. The function returns an $n \times 2$ matrix with the computed roots in the first column and the derivatives in the second column. You can evaluate the Bessel function itself by calling the JBESSEL function.

The arguments to the JROOT function are as follows:

- order* is a scalar that denotes the order of the Bessel function, with *order* > -1. The order of a Bessel function is often indicated with the Greek subscript ν , so that J_ν indicates the Bessel function of order ν .
- n* is a positive integer that denotes the number of roots.

The JROOT function returns a matrix in which the first column contains the first n roots of the Bessel function; these roots are the solutions to the equation

$$J_\nu(x_i) = 0, i = 1, \dots, n$$

The second column of this matrix contains the derivatives $J'_\nu(x_i)$ of the Bessel function at each of the roots x_i . The expression $J_\nu(x)$ is a solution to the differential equation

$$x^2 \frac{d^2 J_\nu}{dx^2} + x \frac{dJ_\nu}{dx} + (x^2 - \nu^2) J_\nu = 0$$

One of the expressions for such a function is given by the series

$$J_\nu(x) = \left(\frac{1}{2}x\right)^\nu \sum_{k=0}^{\infty} \frac{(-1)^k x^{2k}}{k! \Gamma(\nu + k + 1)}$$

where $\Gamma(\cdot)$ is the gamma function. See Abramowitz and Stegun (1972) for more details concerning the Bessel and gamma functions.

The root-finding algorithm is a Newton method coupled with a reasonable initial guess. For large values of n or ν , the algorithm could fail due to machine limitations. In this case, JROOT returns a matrix with zero rows and zero columns. The values that cause the algorithm to fail are machine-dependent.

The following statements compute the first few roots for the Bessel function of the first kind:

```
x = jroot(1, 4);
print x;
```

Figure 23.150 Roots of a Bessel Function

x	
3.831706	-0.402759
7.0155867	0.3001158
10.173468	-0.249705
13.323692	0.2183594

To obtain only the roots, you can use the following statement, which extracts the first column of the returned matrix:

```
r = x[,1];
```

KALCVF Call

CALL KALCVF(*pred*, *vpred*, *filt*, *vfilt*, *data*, *lead*, *a*, *f*, *b*, *h*, *var* <, *z0* > <, *vz0* >);

The KALCVF subroutine computes the one-step prediction $z_{t+1|t}$ and the filtered estimate $z_{t|t}$, in addition to their covariance matrices. The call uses forward recursions, and you can also use it to obtain k -step estimates.

The input arguments to the KALCVF subroutine are as follows:

<i>data</i>	is a $T \times N_y$ matrix that contains data $(y_1, \dots, y_T)'$.
<i>lead</i>	is the number of steps to forecast after the end of the data.
<i>a</i>	is an $N_z \times 1$ vector for a time-invariant input vector in the transition equation, or a $(T + \text{lead})N_z \times 1$ vector that contains input vectors in the transition equation.
<i>f</i>	is an $N_z \times N_z$ matrix for a time-invariant transition matrix in the transition equation, or a $(T + \text{lead})N_z \times N_z$ matrix that contains transition matrices in the transition equation.
<i>b</i>	is an $N_y \times 1$ vector for a time-invariant input vector in the measurement equation, or a $(T + \text{lead})N_y \times 1$ vector that contains input vectors in the measurement equation.
<i>h</i>	is an $N_y \times N_z$ matrix for a time-invariant measurement matrix in the measurement equation, or a $(T + \text{lead})N_y \times N_z$ matrix that contains measurement matrices in the measurement equation.
<i>var</i>	is an $(N_z + N_y) \times (N_z + N_y)$ matrix for a time-invariant variance matrix for the error in the transition equation and the error in the measurement equation, or a $(T + \text{lead})(N_z + N_y) \times (N_z + N_y)$ matrix that contains variance matrices for the error in the transition equation and the error in the measurement equation—that is, $(\eta'_t, \epsilon'_t)'$.
<i>z0</i>	is an optional $1 \times N_z$ initial state vector $z'_{1 0}$.
<i>vz0</i>	is an optional $N_z \times N_z$ covariance matrix of an initial state vector $P_{1 0}$.

The KALCVF call returns the following values:

<i>pred</i>	is a $(T + \text{lead}) \times N_z$ matrix that contains one-step predicted state vectors $(z_{1 0}, \dots, z_{T+1 T}, z_{T+2 T}, \dots, z_{T+\text{lead} T})'$.
<i>vpred</i>	is a $(T + \text{lead})N_z \times N_z$ matrix that contains mean square errors of predicted state vectors $(P_{1 0}, \dots, P_{T+1 T}, P_{T+2 T}, \dots, P_{T+\text{lead} T})'$.
<i>filt</i>	is a $T \times N_z$ matrix that contains filtered state vectors $(z_{1 1}, \dots, z_{T T})'$.
<i>vfilt</i>	is a $TN_z \times N_z$ matrix that contains mean square errors of filtered state vectors $(P_{1 1}, \dots, P_{T T})'$.

The KALCVF call computes the conditional expectation of the state vector z_t given the observations, assuming that the mean and the variance of the initial state vector are known. The filtered value is the conditional

expectation of the state vector z_t given the observations up to time t . For k -step forecasting where $k > 0$, the conditional expectation at time $t+k$ is computed given observations up to t . For notation, V_t and R_t are variances of η_t and ϵ_t , respectively, and G_t is a covariance of η_t and ϵ_t , and A^- stands for the generalized inverse of A . The filtered value and its covariance matrix are denoted $z_{t|t}$ and $P_{t|t}$, respectively. For $k > 0$, $z_{t+k|t}$ and $P_{t+k|t}$ stand for the k -step forecast of z_{t+k} and its mean square error. The Kalman filtering algorithm for one-step prediction and filtering is given as follows:

$$\begin{aligned}
 \hat{\epsilon}_t &= y_t - b_t - H_t z_{t|t-1} \\
 D_t &= H_t P_{t|t-1} H_t' + R_t \\
 z_{t|t} &= z_{t|t-1} + P_{t|t-1} H_t' D_t^- \hat{\epsilon}_t \\
 P_{t|t} &= P_{t|t-1} - P_{t|t-1} H_t' D_t^- H_t P_{t|t-1} \\
 K_t &= (F_t P_{t|t-1} H_t' + G_t) D_t^- \\
 z_{t+1|t} &= a_t + F_t z_{t|t-1} + K_t \hat{\epsilon}_t \\
 P_{t+1|t} &= F_t P_{t|t-1} F_t' + V_t - K_t D_t K_t'
 \end{aligned}$$

And for k -step forecasting for $k > 1$,

$$\begin{aligned}
 z_{t+k|t} &= a_{t+k-1} + F_{t+k-1} z_{t+k-1|t} \\
 P_{t+k|t} &= F_{t+k-1} P_{t+k-1|t} F_{t+k-1}' + V_{t+k-1}
 \end{aligned}$$

When you use the alternative transition equation

$$z_t = a_t + F_t z_{t-1} + \eta_t$$

the forward recursion algorithm is written

$$\begin{aligned}
 \hat{\epsilon}_t &= y_t - b_t - H_t z_{t|t-1} \\
 D_t &= H_t P_{t|t-1} H_t' + H_t G_t + G_t' H_t' + R_t \\
 z_{t|t} &= z_{t|t-1} + (P_{t|t-1} H_t' + G_t) D_t^- \hat{\epsilon}_t \\
 P_{t|t} &= P_{t|t-1} - (P_{t|t-1} H_t' + G_t) D_t^- (H_t P_{t|t-1} + G_t') \\
 K_t &= (F_{t+1} P_{t|t-1} H_t' + G_t) D_t^- \\
 z_{t+1|t} &= a_{t+1} + F_{t+1} z_{t|t-1} + K_t \hat{\epsilon}_t \\
 P_{t+1|t} &= F_{t+1} P_{t|t-1} F_{t+1}' + V_{t+1} - K_t D_t K_t'
 \end{aligned}$$

And for k -step forecasting ($k > 1$),

$$\begin{aligned}
 z_{t+k|t} &= a_{t+k} + F_{t+k} z_{t+k-1|t} \\
 P_{t+k|t} &= F_{t+k} P_{t+k-1|t} F_{t+k}' + V_{t+k}
 \end{aligned}$$

You can use the KALCVF call when you specify the alternative transition equation and $G_t = \mathbf{0}$.

The initial state vector and its covariance matrix of the time-invariant Kalman filters are computed under the stationarity condition

$$z_{1|0} = (I - F)^{-1}a$$

$$P_{1|0} = (I - F \otimes F)^{-1}\text{vec}(V)$$

where F and V are the time-invariant transition matrix and the covariance matrix of transition equation noise, and $\text{vec}(V)$ is an $N_z^2 \times 1$ column vector that is constructed by the stacking N_z columns of matrix V . Note that all eigenvalues of the matrix F are inside the unit circle when the SSM is stationary. When the preceding formula cannot be applied, the initial state vector estimate $z_{1|0}$ is set to a_1 and its covariance matrix $P_{1|0}$ is given by $10^6 I$. Optionally, you can specify initial values.

The KALCVF call accepts missing values in observations. If there is a missing observation, the filtered state vector for the missing observation is given by the one-step forecast.

The following program gives an example of the KALCVF call:

```
q = 2;
p = 2;
n = 10;
lead = 3;
total = n + lead;

seed = 25735;
x = round(10*normal(j(n, p, seed)))/10;
f = round(10*normal(j(q*total, q, seed)))/10;
a = round(10*normal(j(total*q, 1, seed)))/10;
h = round(10*normal(j(p*total, q, seed)))/10;
b = round(10*normal(j(p*total, 1, seed)))/10;

do i = 1 to total;
    temp = round(10*normal(j(p+q, p+q, seed)))/10;
    var = var/(temp*temp`);
end;

call kalcvf(pred, vpred, filt, vfilt, x, lead, a, f, b, h, var);

/* default initial state and covariance */
call kalcvs(sm, vsm, x, a, f, b, h, var, pred, vpred);
print sm[format=9.4] vsm[format=9.4];
```

Figure 23.151 Smoothed Estimate and Covariance

sm		vsm	
-1.5236	-0.1000	1.5813	-0.4779
0.3058	-0.1131	-0.4779	0.3963
-0.2593	0.2496	2.4629	0.2426
-0.5533	0.0332	0.2426	0.0944
-0.5813	0.1251	0.2023	-0.0228
-0.3017	0.7480	-0.0228	0.5799
1.1333	-0.2144	0.8615	-0.7653
1.5193	-0.6237	-0.7653	1.2334
-0.6641	-0.7770	1.0836	0.8706
0.5994	2.3333	0.8706	1.5252
		0.3677	0.2510
		0.2510	0.2051
		0.3243	-0.4093
		-0.4093	1.2287
		0.1736	-0.0712
		-0.0712	0.9048
		1.3153	0.8748
		0.8748	1.6575
		8.6650	0.1841
		0.1841	4.4770

KALCVS Call

CALL KALCVS(*sm*, *vsm*, *data*, *a*, *f*, *b*, *h*, *var*, *pred*, *vpred* < , *un* > < , *vun* >);

The KALCVS subroutine uses backward recursions to compute the smoothed estimate $z_{t|T}$ and its covariance matrix, $P_{t|T}$, where T is the number of observations in the complete data set.

The input arguments to the KALCVS subroutine are as follows.

<i>data</i>	is a $T \times N_y$ matrix that contains data $(y_1, \dots, y_T)'$.
<i>a</i>	is an $N_z \times 1$ vector for a time-invariant input vector in the transition equation, or a $TN_z \times 1$ vector that contains input vectors in the transition equation.
<i>f</i>	is an $N_z \times N_z$ matrix for a time-invariant transition matrix in the transition equation, or a $TN_z \times N_z$ matrix that contains T transition matrices.
<i>b</i>	is an $N_y \times 1$ vector for a time-invariant input vector in the measurement equation, or a $TN_y \times 1$ vector that contains input vectors in the measurement equation.
<i>h</i>	is an $N_y \times N_z$ matrix for a time-invariant measurement matrix in the measurement equation, or a $TN_y \times N_z$ matrix that contains T time-variant H_t matrices in the measurement equation.
<i>var</i>	is an $(N_z + N_y) \times (N_z + N_y)$ covariance matrix for the errors in the transition and the measurement equations, or a $T(N_z + N_y) \times (N_z + N_y)$ matrix that contains covariance matrices in the transition equation and measurement equation noises—that is, $(\eta'_t, \epsilon'_t)'$.
<i>pred</i>	is a $T \times N_z$ matrix that contains one-step forecasts $(z_{1 0}, \dots, z_{T T-1})'$.

- vpred* is a $TN_z \times N_z$ matrix that contains mean square error matrices of predicted state vectors $(P_{1|0}, \dots, P_{T|T-1})'$.
- un* is an optional $1 \times N_z$ vector that contains u_T . The returned value is u_0 .
- vun* is an optional $N_z \times N_z$ matrix that contains U_T . The returned value is U_0 .

The KALCVS call returns the following values:

- sm* is a $T \times N_z$ matrix that contains smoothed state vectors $(z_{1|T}, \dots, z_{T|T})'$.
- vsm* is a $TN_z \times N_z$ matrix that contains covariance matrices of smoothed state vectors $(P_{1|T}, \dots, P_{T|T})'$.

When the Kalman filtering is performed in the [KALCVF call](#), the KALCVS call computes smoothed state vectors and their covariance matrices. The fixed-interval smoothing state vector at time t is obtained by the conditional expectation given all observations.

The smoothing algorithm uses one-step forecasts and their covariance matrices, which are given in the [KALCVF call](#). For notation, $z_{t|T}$ is the smoothed value of the state vector z_t , and the mean square error matrix is denoted $P_{t|T}$. For smoothing,

$$\begin{aligned}
 \hat{\epsilon}_t &= y_t - b_t - H_t z_{t|t-1} \\
 D_t &= H_t P_{t|t-1} H_t' + R_t \\
 K_t &= (F_t P_{t|t-1} H_t' + G_t) D_t^- \\
 L_t &= F_t - K_t H_t \\
 u_{t-1} &= H_t' D_t^- \hat{\epsilon}_t + L_t' u_t \\
 U_{t-1} &= H_t' D_t^- H_t + L_t' U_t L_t \\
 z_{t|T} &= z_{t|t-1} + P_{t|t-1} u_{t-1} \\
 P_{t|T} &= P_{t|t-1} - P_{t|t-1} U_{t-1} P_{t|t-1}
 \end{aligned}$$

where $t = T, T-1, \dots, 1$. The initial values are $u_T = \mathbf{0}$ and $U_T = \mathbf{0}$.

When the SSM is specified by using the alternative transition equation

$$z_t = a_t + F_t z_{t-1} + \eta_t$$

the fixed-interval smoothing is performed by using the following backward recursions:

$$\begin{aligned}
 \hat{\epsilon}_t &= y_t - b_t - H_t z_{t|t-1} \\
 D_t &= H_t P_{t|t-1} H_t' + R_t \\
 K_t &= F_{t+1} P_{t|t-1} H_t' D_t^- \\
 L_t &= F_{t+1} - K_t H_t \\
 u_{t-1} &= H_t' D_t^- \hat{\epsilon}_t + L_t' u_t \\
 U_{t-1} &= H_t' D_t^- H_t + L_t' U_t L_t \\
 z_{t|T} &= z_{t|t-1} + P_{t|t-1} u_{t-1} \\
 P_{t|T} &= P_{t|t-1} - P_{t|t-1} U_{t-1} P_{t|t-1}
 \end{aligned}$$

where it is assumed that $G_t = \mathbf{0}$.

You can use the KALCVS call regardless of the specification of the transition equation when $G_t = \mathbf{0}$. Harvey (1989) gives the following fixed-interval smoothing formula, which produces the same smoothed value:

$$\begin{aligned}
 z_{t|T} &= z_{t|t} + P_t^* (z_{t+1|T} - z_{t+1|t}) \\
 P_{t|T} &= P_{t|t} + P_t^* (P_{t+1|T} - P_{t+1|t}) P_t^{*'}
 \end{aligned}$$

where

$$P_t^* = P_{t|t} F_t' P_{t+1|t}^-$$

under the shifted transition equation, but

$$P_t^* = P_{t|t} F_{t+1}' P_{t+1|t}^-$$

under the alternative transition equation.

The KALCVS call is accompanied by the [KALCVF](#) call, as shown in the following statements. Note that you do not need to specify UN and VUN.

```
call kalcvf(pred, vpred, filt, vfilt, y, 0, a, f, b, h, var);
call kalcvs(sm, vsm, y, a, f, b, h, var, pred, vpred);
```

You can also compute the smoothed estimate and its covariance matrix on an observation-by-observation basis. When the SSM is time invariant, the following example performs smoothing. In this situation, you should initialize UN and VUN as matrices of value 0, as shown in the following statements:

```
call kalcvf(pred, vpred, filt, vfilt, y, 0, a, f, b, h, var);
n = nrow(y);
nz = ncol(f);
un = j(1, nz, 0);
vun = j(nz, nz, 0);

do i = 1 to n;
```

```

y_i = y[n-i+1,];
pred_i = pred[n-i+1,];
vpred_i = vpred[(n-i)*nz+1:(n-i+1)*nz,];
call kalcvs(sm_i, vsm_i, y_i, a, f, b, h, var,
            pred_i, vpred_i, un, vun);
sm = sm_i // sm;
vsm = vsm_i // vsm;
end;

```

The **KALCVF** call has an example program that includes the **KALCVS** call.

KALDFF Call

CALL KALDFF(*pred, vpred, initial, s2, data, lead, int, coef, var, intd, coefd* <, *n0* > <, *at* > <, *mt* > <, *qt* >);

The **KALDFF** subroutine computes the one-step forecast of state vectors in an SSM by using the diffuse Kalman filter. The call estimates the conditional expectation of z_t , and also estimates the initial random vector, δ , and its covariance matrix.

The input arguments to the **KALDFF** subroutine are as follows:

<i>data</i>	is a $T \times N_y$ matrix that contains data $(y_1, \dots, y_T)'$.
<i>lead</i>	is the number of steps to forecast after the end of the data set.
<i>int</i>	is an $(N_z + N_y) \times N_\beta$ matrix for a time-invariant fixed matrix, or a $(T + \text{lead})(N_z + N_y) \times N_\beta$ matrix that contains fixed matrices for the time-variant model in the transition equation and the measurement equation—that is, $(W'_t, X'_t)'$.
<i>coef</i>	is an $(N_z + N_y) \times N_z$ matrix for a time-invariant coefficient, or a $(T + \text{lead})(N_z + N_y) \times N_z$ matrix that contains coefficients at each time in the transition equation and the measurement equation—that is, $(F'_t, H'_t)'$.
<i>var</i>	is an $(N_z + N_y) \times (N_z + N_y)$ matrix for a time-invariant variance matrix for the error in the transition equation and the error in the measurement equation, or a $(T + \text{lead})(N_z + N_y) \times (N_z + N_y)$ matrix that contains covariance matrices for the error in the transition equation and the error in the measurement equation—that is, $(\eta'_t, \epsilon'_t)'$.
<i>intd</i>	is an $(N_z + N_\beta) \times 1$ vector that contains the intercept term in the equation for the initial state vector z_0 and the mean effect β —that is, $(a', b')'$.
<i>coefd</i>	is an $(N_z + N_\beta) \times N_\delta$ matrix that contains coefficients for the initial state δ in the equation for the initial state vector z_0 and the mean effect β —that is, $(A', B')'$.
<i>n0</i>	is an optional scalar including an initial denominator. If $n0 > 0$, the denominator for $\hat{\sigma}_t^2$ is $n0$ plus the number n_t of elements of $(y_1, \dots, y_t)'$. If $n0 \leq 0$ or $n0$ is not specified, the denominator for $\hat{\sigma}_t^2$ is n_t . With $n0 \geq 0$, the initial values, A_1 , M_1 , and Q_1 , are assumed to be known and, hence, <i>at</i> , <i>mt</i> , and <i>qt</i> are used for input that contains the initial values. If the value of $n0$ is negative or $n0$ is not specified, the initial values for <i>at</i> , <i>mt</i> , and <i>qt</i> are computed. The value of $n0$ is updated as $\max(n0, 0) + n_t$ after the KALDFF call.

<i>at</i>	is an optional $kN_z \times (N_\delta + 1)$ matrix. If $n0 \geq 0$, <i>at</i> contains $(A'_1, \dots, A'_k)'$. However, only the first matrix A_1 is used as input. When you specify the KALDFF call, <i>at</i> returns $(A'_{T-k+\text{lead}+1}, \dots, A'_{T+\text{lead}})'$. If $n0$ is negative or the matrix A_1 contains missing values, A_1 is automatically computed.
<i>mt</i>	is an optional $kN_z \times N_z$ matrix. If $n0 \geq 0$, <i>mt</i> contains $(M_1, \dots, M_k)'$. However, only the first matrix M_1 is used as input. If $n0$ is negative or the matrix M_1 contains missing values, <i>mt</i> is used for output, and it contains $(M_{T-k+\text{lead}+1}, \dots, M_{T+\text{lead}})'$. Note that the matrix M_1 can be used as an input matrix if either of the off-diagonal elements is not missing. The missing element $M_1(i, j)$ is replaced by the nonmissing element $M_1(j, i)$.
<i>qt</i>	is an optional $k(N_\delta + 1) \times (N_\delta + 1)$ matrix. If $n0 \geq 0$, <i>qt</i> contains $(Q_1, \dots, Q_k)'$. However, only the first matrix Q_1 is used as input. If $n0$ is negative or the matrix Q_1 contains missing values, <i>qt</i> is used for output and contains $(Q_{T-k+\text{lead}+1}, \dots, Q_{T+\text{lead}})'$. The matrix Q_1 can also be used as an input matrix if either of the off-diagonal elements is not missing since the missing element $Q_1(i, j)$ is replaced by the nonmissing element $Q_1(j, i)$.

The KALDFF call returns the following values:

<i>pred</i>	is a $(T + \text{lead}) \times N_z$ matrix that contains estimated predicted state vectors $(\hat{z}_{1 0}, \dots, \hat{z}_{T+1 T}, \hat{z}_{T+2 T}, \dots, \hat{z}_{T+\text{lead} T})'$.
<i>vpred</i>	is a $(T + \text{lead})N_z \times N_z$ matrix that contains estimated mean square errors of predicted state vectors $(P_{1 0}, \dots, P_{T+1 T}, P_{T+2 T}, \dots, P_{T+\text{lead} T})'$.
<i>initial</i>	is an $N_d \times (N_d + 1)$ matrix that contains an estimate and its variance for initial state δ , that is, $(\hat{\delta}_T, \hat{\Sigma}_{\delta,T})$.
<i>s2</i>	is a scalar that contains the estimated variance $\hat{\sigma}_T^2$.

The KALDFF call computes the one-step forecast of state vectors in an SSM by using the diffuse Kalman filter. The SSM for the diffuse Kalman filter is written

$$\begin{aligned}
 y_t &= X_t \beta + H_t z_t + \epsilon_t \\
 z_{t+1} &= W_t \beta + F_t z_t + \eta_t \\
 z_0 &= a + A \delta \\
 \beta &= b + B \delta
 \end{aligned}$$

where z_t is an $N_z \times 1$ state vector, y_t is an $N_y \times 1$ observed vector, and

$$\begin{aligned}
 \begin{bmatrix} \eta_t \\ \epsilon_t \end{bmatrix} &\sim N \left(\mathbf{0}, \sigma^2 \begin{bmatrix} V_t & G_t \\ G'_t & R_t \end{bmatrix} \right) \\
 \delta &\sim N(\mu, \sigma^2 \Sigma)
 \end{aligned}$$

It is assumed that the noise vector $(\eta'_t, \epsilon'_t)'$ is independent and δ is independent of the vector $(\eta'_t, \epsilon'_t)'$. The matrices, W_t , F_t , X_t , H_t , a , A , b , B , V_t , G_t , and R_t , are assumed to be known. The KALDFF call

estimates the conditional expectation of the state vector z_t given the observations. The KALDFF subroutine also produces the estimates of the initial random vector δ and its covariance matrix. For k -step forecasting where $k > 0$, the estimated conditional expectation at time $t + k$ is computed with observations given up to time t . The estimated k -step forecast and its estimated MSE are denoted $z_{t+k|t}$ and $P_{t+k|t}$ (for $k > 0$). $A_{t+k(\delta)}$ and $E_{t(\delta)}$ are last-column-deleted submatrices of A_{t+k} and E_t , respectively. The algorithm for one-step prediction is given as follows:

$$\begin{aligned}
E_t &= (X_t B, y_t - X_t b) - H_t A_t \\
D_t &= H_t M_t H_t' + R_t \\
Q_{t+1} &= Q_t + E_t' D_t^- E_t \\
&= \begin{bmatrix} S_t & s_t \\ s_t' & q_t \end{bmatrix} \\
\hat{\sigma}_t^2 &= (q_t - s_t' S_t^- s_t) / n_t \\
\hat{\delta}_t &= S_t^- s_t \\
\hat{\Sigma}_{\delta,t} &= \hat{\sigma}_t^2 S_t^- \\
K_t &= (F_t M_t H_t' + G_t) D_t^- \\
A_{t+1} &= W_t(-B, b) + F_t A_t + K_t E_t \\
M_{t+1} &= (F_t - K_t H_t) M_t F_t' + V_t - K_t G_t' \\
z_{t+1|t} &= A_{t+1}(-\hat{\delta}_t', 1)' \\
P_{t+1|t} &= \hat{\sigma}_t^2 M_{t+1} + A_{t+1(\delta)} \hat{\Sigma}_{\delta,t} A_{t+1(\delta)}'
\end{aligned}$$

where n_t is the number of elements of $(y_1, \dots, y_t)'$ plus $\max(n_0, 0)$. Unless initial values are given and $n_0 \geq 0$, initial values are set as follows:

$$\begin{aligned}
A_1 &= W_1(-B, b) + F_1(-A, a) \\
M_1 &= V_1 \\
Q_1 &= \mathbf{0}
\end{aligned}$$

For k -step forecasting where $k > 1$,

$$\begin{aligned}
A_{t+k} &= W_{t+k-1}(-B, b) + F_{t+k-1} A_{t+k-1} \\
M_{t+k} &= F_{t+k-1} M_{t+k-1} F_{t+k-1}' + V_{t+k-1} \\
D_{t+k} &= H_{t+k} M_{t+k} H_{t+k}' + R_{t+k} \\
z_{t+k|t} &= A_{t+k}(-\hat{\delta}_t', 1)' \\
P_{t+k|t} &= \hat{\sigma}_t^2 M_{t+k} + A_{t+k(\delta)} \hat{\Sigma}_{\delta,t} A_{t+k(\delta)}'
\end{aligned}$$

If there is a missing observation, the KALDFF call computes the one-step forecast for the observation that follows the missing observation as the two-step forecast from the previous observation.

An example that uses the KALDFF call is in the documentation for the [KALDFS call](#).

KALDFS Call

CALL KALDFS(*sm, vsm, data, int, coef, var, bvec, bmat, initial, at, mt, s2 <, un, vun >*);

The KALDFS subroutine computes the smoothed state vector and its mean square error matrix from the one-step forecast and mean square error matrix computed by [KALDFF](#).

The input arguments to the KALDFS subroutine are as follows:

<i>data</i>	is a $T \times N_y$ matrix that contains data $(y_1, \dots, y_T)'$.
<i>int</i>	is an $(N_z + N_y) \times N_\beta$ vector for a time-invariant intercept, or a $(T + \text{lead})(N_z + N_y) \times N_\beta$ vector that contains fixed matrices for the time-variant model in the transition equation and the measurement equation—that is, $(W'_t, X'_t)'$.
<i>coef</i>	is an $(N_z + N_y) \times N_z$ matrix for a time-invariant coefficient, or a $(T + \text{lead})(N_z + N_y) \times N_z$ matrix that contains coefficients at each time in the transition equation and the measurement equation—that is, $(F'_t, H'_t)'$.
<i>var</i>	is an $(N_z + N_y) \times (N_z + N_y)$ matrix for a time-invariant variance matrix for transition equation noise and the measurement equation noise, or a $(T + \text{lead})(N_z + N_y) \times (N_z + N_y)$ matrix that contains covariance matrices for the transition equation and measurement equation errors—that is, $(\eta'_t, \epsilon'_t)'$.
<i>bvec</i>	is an $N_\beta \times 1$ constant vector for the intercept for the mean effect β .
<i>bmat</i>	is an $N_\beta \times N_\delta$ matrix for the coefficient for the mean effect β .
<i>initial</i>	is an $N_\delta \times (N_\delta + 1)$ matrix that contains an initial random vector estimate and its covariance matrix—that is, $(\hat{\delta}_T, \hat{\Sigma}_{\delta,T})$.
<i>at</i>	is a $TN_z \times (N_\delta + 1)$ matrix that contains $(A'_1, \dots, A'_T)'$.
<i>mt</i>	is a $(TN_z) \times N_z$ matrix that contains $(M_1, \dots, M_T)'$.
<i>s2</i>	is the estimated variance in the end of the data set, $\hat{\sigma}_T^2$.
<i>un</i>	is an optional $N_z \times (N_\delta + 1)$ matrix that contains u_T . The returned value is u_0 .
<i>vun</i>	is an optional $N_z \times N_z$ matrix that contains U_T . The returned value is U_0 .

The KALDFS call returns the following values:

<i>sm</i>	is a $T \times N_z$ matrix that contains smoothed state vectors $(z_{1 T}, \dots, z_{T T})'$.
<i>vsm</i>	is a $TN_z \times N_z$ matrix that contains mean square error matrices of smoothed state vectors $(P_{1 T}, \dots, P_{T T})'$.

Given the one-step forecast and mean square error matrix in the [KALDFF call](#), the KALDFS call computes a smoothed state vector and its mean square error matrix. Then the KALDFS subroutine produces an estimate of the smoothed state vector at time t —that is, the conditional expectation of the state vector z_t given all

observations. Using the notations and results from the [KALDFF](#) section, the backward recursion algorithm for smoothing is denoted for $t = T, T - 1, \dots, 1$,

$$\begin{aligned}
 E_t &= (X_t B, y_t - X_t b) - H_t A_t \\
 D_t &= H_t M_t H_t' + R_t \\
 L_t &= F_t - (F_t M_t H_t' + G_t) D_t^{-1} H_t \\
 u_{t-1} &= H_t' D_t^{-1} E_t + L_t' u_t \\
 U_{t-1} &= H_t' D_t^{-1} H_t + L_t' U_t L_t \\
 z_{t|T} &= (A_t + M_t u_{t-1}) (-\hat{\delta}_T', 1)' \\
 C_t &= A_t + M_t u_{t-1} \\
 P_{t|T} &= \hat{\sigma}_T^2 (M_t - M_t R_{t-1} M_t) + C_{t(\delta)} \hat{\Sigma}_{\delta, T} C_{t(\delta)}'
 \end{aligned}$$

where the initial values are $u_T = b0$ and $U_T = \mathbf{0}$, and $C_{t(\delta)}$ is the last-column-deleted submatrix of C_t . See De Jong, P. (1991) for details about smoothing in the diffuse Kalman filter.

The KALDFS call is accompanied by the [KALDFF](#) call as shown in the following statements:

```

ny = ncol(y);
nz = ncol(coef);
nb = ncol(int);
nd = ncol(coefd);
at = j(nz, nd+1, .);
mt = j(nz, nz, .);
qt = j(nd+1, nd+1, .);
n0 = -1;
call kaldff(pred, vpred, initial, s2, y, 0, int, coef, var, intd,
            coefd, n0, at, mt, qt);
bvec = intd[nz+1:nz+nb,];
bmat = coefd[nz+1:nz+nb,];
call kaldfs(sm, vsm, x, int, coef, var, bvec, bmat,
            initial, at, mt, s2);

```

You can also compute the smoothed estimate and its covariance matrix observation by observation. When the SSM is time invariant, the following statements perform smoothing. You should initialize UN and VUN as matrices in which all elements are zero.

```

n = nrow(y);
ny = ncol(y);
nz = ncol(coef);
nb = ncol(int);
nd = ncol(coefd);
at = j(nz, nd+1, .);
mt = j(nz, nz, .);
qt = j(nd+1, nd+1, .);
n0 = -1;
call kaldff(pred, vpred, initial, s2, y, 0, int, coef, var, intd,
            coefd, n0, at, mt, qt);
bvec = intd[nz+1:nz+nb,];

```

```

bmat = coefd[nz+1:nz+nb,];
un  = j(nz, nd+1, 0);
vun = j(nz, nz, 0);
do i = 1 to n;
    call kaldfs(sm_i, vsm_i, y[n-i+1], int, coef, var, bvec, bmat,
               initial, at, mt, s2, un, vun);
    sm  = sm_i // sm;
    vsm = vsm_i // vsm;
end;

```

LAG Function

LAG(x <, $lags$ >);

The LAG function computes one or more lagged (shifted) values for time series data. The arguments are as follows:

x specifies an $n \times 1$ numerical matrix of time series data.

$lags$ specifies integer lags. The $lags$ argument can be an integer matrix with d elements. If so, the LAG function returns an $n \times d$ matrix where the i th column represents the i th lag applied to the time series.

The values of the $lags$ argument are usually positive integers. A positive lag shifts the time series data backwards in time. A lag of 0 represents the original time series. A negative value for the $lags$ argument shifts the time series data forward in time; this is sometimes called a *lead effect*.

For example, the following statements compute several lags:

```

x = {1,3,4,7,9};
lag = lag(x, {0 1 3});
print lag;

```

Figure 23.152 Lagged Data

	lag		
	1	.	.
3	1	.	.
4	3	.	.
7	4	1	.
9	7	3	.

LAV Call

CALL LAV(rc , xr , a , b <, $x0$ > <, opt >);

The LAV subroutine performs linear least absolute value regression by solving the L_1 norm minimization problem.

The LAV subroutine returns the following values:

rc is a scalar return code that indicates the reason for optimization termination.

<i>rc</i>	Termination
0	Successful
1	Successful, but approximate covariance matrix and standard errors cannot be computed
−1 or −3	Unsuccessful: error in the input arguments
−2	Unsuccessful: matrix A is rank-deficient ($\text{rank}(A) < n$)
−4	Unsuccessful: maximum iteration limit exceeded
−5	Unsuccessful: no solution found for ill-conditioned problem

xr specifies a vector or matrix with n columns. If the optimization process is not successfully completed, *xr* is a row vector with n missing values. If termination is successful and the *opt*[3] option is not set, *xr* is the vector with the optimal estimate, x^* . If termination is successful and the *opt*[3] option is specified, *xr* is an $(n + 2) \times n$ matrix that contains the optimal estimate, x^* , in the first row, the asymptotic standard errors in the second row, and the $n \times n$ covariance matrix of parameter estimates in the remaining rows.

The input arguments to the LAV subroutine are as follows:

a specifies an $m \times n$ matrix A with $m \geq n$ and full column rank, $\text{rank}(A) = n$. If you want to include an intercept in the model, you must include a column of ones in the matrix A .

b specifies the $m \times 1$ vector b .

x0 specifies an optional $n \times 1$ vector that specifies the starting point of the optimization.

opt is an optional vector used to specify options. If an element of the *opt* vector is missing, the default value is used.

- *opt*[1] specifies the maximum number *maxi* of outer iterations (this corresponds to the number of changes of the Huber parameter γ). The default is $\text{maxi} = \min(100, 10n)$. (The number of inner iterations is restricted by an internal threshold. If the number of inner iterations exceeds this threshold, a new outer iteration is started with an increased value of γ .)
- *opt*[2] specifies the amount of printed output. Higher values request additional output and include the output of lower values.

<i>opt[2]</i>	Termination
0	No output is printed.
1	Error and warning messages are printed.
2	The iteration history is printed (this is the default).
3	The n least squares (L_2 norm) estimates are printed if no starting point is specified, the L_1 norm estimates are always printed, and if <i>opt[3]</i> is set, the estimates are printed together with the asymptotic standard errors.
4	The $n \times n$ approximate covariance matrix of parameter estimates is printed if <i>opt[3]</i> is set.
5	The residual and predicted values for all m rows (equations) of A are printed.

- *opt[3]* specifies which estimate of the variance of the median of nonzero residuals be used as a factor for the approximate covariance matrix of parameter estimates and for the approximate standard errors (ASE). If *opt[3]* = 0, the McKean-Schrader (1987) estimate is used, and if *opt[3]* > 0, the Cox-Hinkley (1974) estimate, with $v = \text{opt}[3]$, is used. The default behavior is that the covariance matrix is not computed.
- *opt[4]* specifies whether a computationally expensive test for necessary and sufficient optimality of the solution x is executed. The default behavior (*opt[4]* = 0) is that the convergence test is not performed.

Missing values are not permitted in the a or b argument. The $x0$ argument is ignored if it contains any missing values. Missing values in the *opt* argument cause the default value to be used.

The LAV subroutine is designed for solving the unconstrained linear L_1 norm minimization problem,

$$\min_x L_1(x) \text{ where } L_1(x) = \|Ax - b\|_1 = \sum_{i=1}^m \left| \sum_{j=1}^n a_{ij}x_j - b_i \right|$$

for m equations with n (unknown) parameters $x = (x_1, \dots, x_n)$. This is equivalent to estimating the unknown parameter vector, x , by least absolute value regression in the model

$$b = Ax + \epsilon$$

where b is the vector of n observations, A is the design matrix, and ϵ is a random error term.

An algorithm by Madsen and Nielsen (1993) is used, which can be faster for large values of m and n than the Barrodale and Roberts (1974) algorithm. The current version of the algorithm assumes that A has full column rank. Also, constraints cannot be imposed on the parameters in this version.

The L_1 norm minimization problem is more difficult to solve than the least squares (L_2 norm) minimization problem because the objective function of the L_1 norm problem is not continuously differentiable (the first derivative has jumps). A function that is continuous but not continuously differentiable is called *nonsmooth*. By using PROC NLP and the nonlinear optimization subroutines, you can obtain the estimates in linear and nonlinear L_1 norm estimation (even subject to linear or nonlinear constraints) as long as the number of parameters, n , is small. Using the nonlinear optimization subroutines, there are two ways to solve the nonlinear L_p norm, $p \geq 1$, problem:

- For small values of n , you can implement the Nelder-Mead simplex algorithm with the [NLPNMS subroutine](#) to solve the minimization problem in its original specification. The Nelder-Mead simplex algorithm does not assume a smooth objective function, does not take advantage of any derivatives, and therefore does not require continuous differentiability of the objective function. See the section “[NLPNMS Call](#)” on page 837 for details.
- Gonin and Money (1989) describe how an original L_p norm estimation problem can be modified to an equivalent optimization problem with nonlinear constraints which has a simple differentiable objective function. You can invoke the [NLPQN subroutine](#), which implements a quasi-Newton algorithm, to solve the nonlinearly constrained L_p norm optimization problem. See the section “[NLPQN Call](#)” on page 847 for details about the [NLPQN subroutine](#).

Both approaches are successful only for a small number of parameters and good initial estimates. If you cannot supply good initial estimates, the optimal results of the corresponding nonlinear least squares (L_2 norm) estimation can provide fairly good initial estimates.

Gonin and Money (1989) show that the nonlinear L_1 norm estimation problem

$$\min_x \sum_{i=1}^m |f_i(x)|$$

can be reformulated as a linear optimization problem with nonlinear constraints in the following ways.

- as a linear optimization problem with $2m$ nonlinear inequality constraints in $m + n$ variables u_i and x_j ,

$$\min_x \sum_{i=1}^m u_i \text{ subject to } \left. \begin{array}{lcl} f_i(x) - u_i & \leq & 0 \\ f_i(x) + u_i & \geq & 0 \\ u_i & \geq & 0 \end{array} \right\} \quad i = 1, \dots, m$$

- as a linear optimization problem with $2m$ nonlinear equality constraints in $2m + n$ variables y_i , z_i , and x_j ,

$$\min_x \sum_{i=1}^m (y_i + z_i) \text{ subject to } \left. \begin{array}{lcl} f_i(x) + y_i - z_i & = & 0 \\ y_i & \geq & 0 \\ z_i & \geq & 0 \end{array} \right\} \quad i = 1, \dots, m$$

For linear functions $f_i(x) = \sum_{j=1}^n (a_{ij}x_j - b_i)$, $i = 1, \dots, m$, you obtain linearly constrained linear optimization problems, for which the number of variables and constraints is on the order of the number of observations, m . The advantage that the algorithm by Madsen and Nielsen (1993) has over the Barrodale and Roberts (1974) algorithm is that its computational cost increases only linearly with m , and it can be faster for large values of m .

In addition to computing an optimal solution x^* that minimizes $L_1(x)$, you can also compute approximate standard errors and the approximate covariance matrix of x^* . The standard errors can be used to compute confidence limits.

The following example is the same one used for illustrating the LAV subroutine by Lee and Gentle (1986). A and b are as follows:

$$A = \begin{bmatrix} 1 & 0 \\ 1 & 1 \\ 1 & -1 \\ 1 & -1 \\ 1 & 2 \\ 1 & 2 \end{bmatrix} \quad b = \begin{bmatrix} 1 \\ 2 \\ 1 \\ -1 \\ 2 \\ 4 \end{bmatrix}$$

The following statements specify the matrix A , the vector b , and the options vector opt . The options vector specifies that all output is printed ($opt[2]=5$), that the asymptotic standard errors and covariance matrix are computed based on the McKean-Schrader (1987) estimate λ of the variance of the median ($opt[3]=0$), and that the convergence test be performed ($opt[4]=1$).

```
a = { 0, 1, -1, -1, 2, 2 };
m = nrow(a);
a = j(m, 1, 1.) || a;
b = { 1, 2, 1, -1, 2, 4 };

opt= { .5 0 1 };
call lav(rc, xr, a, b, , opt);
```

The first part of the output is shown in Figure 23.153. This output displays the least squares solution, which is used as the starting point. The estimates of the largest and smallest nonzero eigenvalues of $A'A$ give only an idea of the magnitude of these values, and they can be very crude approximations.

Figure 23.153 Least Squares Solution

LS Solution		
Est	1	1

The second part of the printed output shows the iteration history. It is shown in Figure 23.154.

Figure 23.154 Iteration History

LAV (L1) Estimation						
Start with LS Solution						
Start Iter: gamma=1 ActEqn=6						
Iter	N Huber	Act Eqn	Rank	Gamma	L1 (x)	F (Gamma)
1	1	2	2	0.9000	4.000000	2.200000
1	1	2	2	0.0000	4.000000	2.200000

The third part of the output is shown in Figure 23.155. This output displays the L_1 norm solution (first row) together with asymptotic standard errors (second row) and the asymptotic covariance matrix of parameter estimates. The ASEs are the square roots of the diagonal elements of this covariance matrix.

Figure 23.155 Parameter and Covariance Estimates

L1 Solution with ASE			
Est	1		1
ASE	0.4482711811	0.3310702082	
Cov Matrix: McKean-Schrader			
	0.2009470518	-0.054803741	
	-0.054803741	0.1096074828	

The last part of the printed output shows the predicted values and residuals, as in Lee and Gentle (1986). It is shown in Figure 23.156.

Figure 23.156 Predicted and Residual Values

Predicted Values and Residuals			
N	Observed	Predicted	Residual
1	1.0000	1.0000	0
2	2.0000	2.0000	0
3	1.0000	0.0000	1.000000
4	-1.0000	0.0000	-1.000000
5	2.0000	3.0000	-1.000000
6	4.0000	3.0000	1.000000

LCP Call

CALL LCP(*rc, w, z, m, q* < , *epsilon* >);

The LCP subroutine solves the linear complementarity problem:

$$\begin{aligned} \mathbf{w} &= \mathbf{M}\mathbf{z} + \mathbf{q} \\ \mathbf{w}'\mathbf{z} &= 0 \\ \mathbf{w}, \mathbf{z} &\geq 0 \end{aligned}$$

That is, given a matrix \mathbf{M} and a vector \mathbf{q} , the LCP subroutine computes orthogonal, nonnegative vectors \mathbf{w} and \mathbf{z} which satisfy the previous equations.

The input arguments to the LCP subroutine are as follows:

- m* is an $m \times m$ matrix.
- q* is an $m \times 1$ matrix.
- epsilon* is a scalar that defines virtual zero. The default value of *epsilon* is $1\text{E}-8$.

The LCP subroutine returns the following matrices:

rc returns one of the following scalar return codes:

<i>rc</i>	Termination
0	A solution is found.
1	No solution is possible.
5	The solution is numerically unstable.
6	The subroutine could not obtain enough memory.

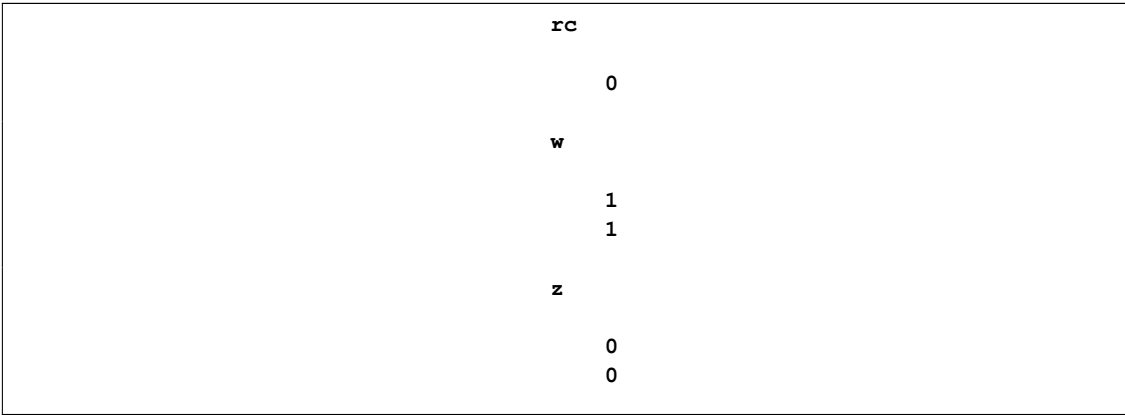
w returns an *m*-element column vector

z returns an *m*-element column vector

The following statements give a simple example:

```
q = {1, 1};  
m = {1 0,  
      0 1};  
call lcp(rc, w, z, m, q);  
print rc, w, z;
```

Figure 23.157 Solution to a Linear Complementarity Problem



The next example shows the relationship between quadratic programming and the linear complementarity problem. Consider the linearly constrained quadratic program:

$$\begin{array}{ll} \min \mathbf{c}'\mathbf{x} & + \frac{1}{2}\mathbf{x}'\mathbf{H}\mathbf{x} \\ \text{st. } \mathbf{G}\mathbf{x} & \geq \mathbf{b} \quad (\text{QP}) \\ \mathbf{x} & \geq 0 \end{array}$$

If **H** is positive semidefinite, then a solution to the Kuhn-Tucker conditions solves QP. The Kuhn-Tucker

conditions for QP are

$$\begin{aligned}\mathbf{c} + \mathbf{H}\mathbf{x} &= \mu + \mathbf{G}'\lambda \\ \lambda'(\mathbf{G}\mathbf{x} - \mathbf{b}) &= 0 \\ \mu'\mathbf{x} &= 0 \\ \mathbf{G}\mathbf{x} &\geq \mathbf{b} \\ x, \mu, \lambda &\geq 0\end{aligned}$$

In the linear complementarity problem, let

$$\begin{aligned}\mathbf{M} &= \begin{bmatrix} H & -G' \\ G & 0 \end{bmatrix} \\ \mathbf{w}' &= (\mu' \mathbf{s}') \\ \mathbf{z}' &= (\mathbf{x}' \lambda') \\ \mathbf{q}' &= (\mathbf{c}' - \mathbf{b})\end{aligned}$$

Then the Kuhn-Tucker conditions are expressed as finding \mathbf{w} and \mathbf{z} that satisfy

$$\begin{aligned}\mathbf{w} &= \mathbf{M}\mathbf{z} + \mathbf{q} \\ \mathbf{w}'\mathbf{z} &= 0 \\ \mathbf{w}, \mathbf{z} &\geq 0\end{aligned}$$

From the solution \mathbf{w} and \mathbf{z} to this linear complementarity problem, the solution to QP is obtained; namely, \mathbf{x} is the primal structural variable, $\mathbf{s} = \mathbf{G}\mathbf{x} - \mathbf{b}$ the surpluses, and μ and λ are the dual variables. Consider a quadratic program with the following data:

$$\begin{aligned}\mathbf{C}' &= (1245) \quad \mathbf{B}' = (11) \\ \mathbf{H} &= \begin{bmatrix} 100 & 10 & 1 & 0 \\ 10 & 100 & 10 & 1 \\ 1 & 10 & 100 & 10 \\ 0 & 1 & 10 & 100 \end{bmatrix} \\ \mathbf{G} &= \begin{bmatrix} 1 & 2 & 3 & 4 \\ 10 & 20 & 30 & 40 \end{bmatrix}\end{aligned}$$

This problem is solved by using the LCP subroutine as follows:

```
/*---- Data for the Quadratic Program ----*/
c = {1, 2, 3, 4};
h = {100 10 1 0, 10 100 10 1, 1 10 100 10, 0 1 10 100};
g = {1 2 3 4, 10 20 30 40};
b = {1, 1};
```

```

/*----- Express the Kuhn-Tucker Conditions as an LCP -----*/
m = h || -g`;
m = m // (g || j(nrow(g),nrow(g),0));
q = c // -b;

/*----- Solve for a Kuhn-Tucker Point -----*/
call lcp(rc, w, z, m, q);

/*----- Extract the Solution to the Quadratic Program -----*/
x = z[1:nrow(h)];
print rc x;

```

Figure 23.158 Solution to a Quadratic Programming Problem

	rc	x
	0	0.0307522
		0.0619692
		0.0929721
		0.1415983

LENGTH Function

LENGTH(*matrix*);

The LENGTH function takes a character matrix as an argument and produces a numeric matrix as a result. The result matrix has the same dimensions as the argument and contains the lengths of the corresponding string elements in *matrix*. The length of a string is equal to the position of the rightmost nonblank character in the string. If a string is entirely blank, its length value is set to 1. An example of the LENGTH function follows:

```

c = {"Hello" "My name is Jenny"};
b = length(c);
print b;

```

Figure 23.159 Length of Elements of a Character Matrix

	b
	5 16

See also the description of the [NLENG](#) function.

LINK Statement

```
LINK(label);

    statements ;

label:statements ;

RETURN ;
```

The LINK statement provides a way of calling a group of statements as if they were defined as a subroutine. When the LINK statement is executed, the program jumps immediately to the statement with the given *label* and begins executing statements from that point as it does for the [GOTO statement](#). However, when the program executes a [RETURN statement](#), the program returns to the statement that immediately follows the LINK statement, which is different behavior than the GOTO statement.

The LINK statement can be used only inside modules and DO groups. LINK statements can be nested within other LINK statements to any level. A [RETURN statement](#) without a LINK statement is executed the same as the [STOP statement](#).

Instead of using a LINK statement, you can define a module and call the module by using a [RUN statement](#).

An example that uses the LINK statement follows:

```
start a;
    x=1;
    y=2;
    link sum1; /* go to label; execute until return stmt */
    print z;
    stop;
    sum1:
        z=x+y;
    return;
finish a;

run a;
```

Figure 23.160 Result of Linking to a Group of Statements

	z
	3

LIST Statement

```
LIST <range> <VAR operand> <WHERE(expression)> ;
```

The LIST statement displays observations of a data set.

The arguments to the LIST statement are as follows:

<i>range</i>	specifies a range of observations.
<i>operand</i>	specifies a set of variables.
<i>expression</i>	is an expression that selects certain observations.

The LIST statement prints selected observations of a data set. If all data values for variables in the VAR clause fit on a single line, values are displayed in columns headed by the variable names. Each record occupies a separate line. If the data values do not fit on a single line, values from each record are grouped into paragraphs. Each element in the paragraph has the form *name=value*.

Options for Specifying the Observations

You can use any of the following keywords for *range*:

ALL	specifies all observations.
CURRENT	specifies the current observation (this is the default for the LIST statement).
NEXT < <i>number</i> >	specifies the next observation or the next <i>number</i> of observations.
AFTER	specifies all observations after the current one.
POINT <i>value</i>	specifies observations specified by number, where <i>value</i> can be one of the following:

Value	Example
A single record number	point 5
A literal that contains several record numbers	point {2 5 10}
The name of a matrix that contains record numbers	point p
An expression in parentheses	point (p+1)

If the current data set has an index in use (see the [INDEX statement](#)), the POINT option is invalid.

Options for Specifying the Variables

You can specify a set of variables to use with the VAR clause. The *operand* can be specified as one of the following:

- a literal that contains variable names
- the name of a matrix that contains variable names
- an expression in parentheses that yields variable names
- one of the keywords described in the following list:

ALL for all variables

CHAR for all character variables
NUM for all numeric variables

The following examples show each possible way you can use the VAR clause:

```
var {x1 x5 x9};           /* a literal matrix of names      */
var x;                    /* a matrix that contains the names */
var ("x1":"x9");         /* an expression                  */
var _all_;                /* a keyword                      */
```

Options for Filtering the Observations

The WHERE clause conditionally selects observations, within the *range* specification, according to conditions given in the clause. The general form of the WHERE clause is

WHERE (*variable comparison-op operand*) ;

The arguments to the WHERE clause are as follows:

variable is a variable in the SAS data set.

comparison-op is any one of the following comparison operators:

<	less than
<=	less than or equal to
=	equal to
>	greater than
>=	greater than or equal to
^=	not equal to
?	contains a given string
^?	does not contain a given string
=:	begins with a given string
=*	sounds like or is spelled like a given string

operand is a literal value, a matrix name, or an expression in parentheses.

WHERE comparison arguments can be matrices. For the following operators, the WHERE clause succeeds if *all* the elements in the matrix satisfy the condition:

^= ^? < <= > >=

For the following operators, the WHERE clause succeeds if *any* of the elements in the matrix satisfy the condition:

= ? =: =*

Logical expressions can be specified within the WHERE clause by using the AND (&) and OR (!) operators. The general form is as follows:

clause & *clause* (for an AND clause)

clause | *clause* (for an OR clause)

where *clause* can be a comparison, a parenthesized clause, or a logical expression clause that is evaluated by using operator precedence.

NOTE: The expression on the left-hand side refers to values of the data set variables and the expression on the right-hand side refers to matrix values.

The following examples demonstrate the use of the LIST statement. The output is not shown.

```
data class;
    set sashelp.class;
run;

proc iml;
use class;

list all;                                /* lists whole data set */
list;                                    /* lists current observation */
list var{name age};                     /* lists NAME and AGE in current obs */
list all where(age<=13); /* lists all obs where condition holds */
list next;                               /* lists next observation */
list point 18;                           /* lists observation 18 */
list point (10:15);                      /* lists observations 10 through 15 */

close class;
```

LMS Call

CALL LMS(*sc*, *coef*, *wgt*, *opt*, *y* < , *x* > < , *sorb* >);

The LMS subroutine performs least median of squares (LMS) robust regression (sometimes called *resistant* regression) by minimizing the *h*th-ordered squared residual. The subroutine is able to detect outliers and perform a least squares regression on the remaining observations.

The algorithm used in the LMS subroutine is based on the PROGRESS program of Rousseeuw and Hubert (1996), which is an updated version of Rousseeuw and Leroy (1987). In the special case of regression through the origin with a single regressor, Barreto and Maharry (2006) show that the PROGRESS algorithm does not, in general, find the slope that yields the least median of squares. Starting with SAS/IML 9.2, the LMS subroutine uses the algorithm of Barreto and Maharry (2006) to obtain the correct LMS slope in the case of regression through the origin with a single regressor. In this case, input arguments that are specific to the PROGRESS algorithm are ignored and output specific to the PROGRESS algorithm is suppressed.

The value of *h* can be specified, but in most applications the default value works well and the results seem to be quite stable toward different choices of *h*.

In the following discussion, *N* is the number of observations and *n* is the number of regressors. The input arguments to the LMS subroutine are as follows:

opt refers to an options vector with the following components (missing values are treated as default values). The options vector can be a null vector.

opt[1] specifies whether an intercept is used in the model (*opt*[1]=0) or not (*opt*[1]≠ 0). If *opt*[1]=0, then a column of ones is added as the last column to the input matrix **X**; that is, you do not need to add this column of ones yourself. The default is *opt*[1]=0.

opt[2] specifies the amount of printed output. Higher values request additional output and include the output of lower values.

- 0 prints no output except error messages.
- 1 prints all output except (1) arrays of $O(N)$, such as weights, residuals, and diagnostics; (2) the history of the optimization process; and (3) subsets that result in singular linear systems.
- 2 additionally prints arrays of $O(N)$, such as weights, residuals, and diagnostics; also prints the case numbers of the observations in the best subset and some basic history of the optimization process.
- 3 additionally prints subsets that result in singular linear systems.

The default is *opt*[2]=0.

opt[3] specifies whether only LMS is computed or whether, additionally, least squares (LS) and weighted least squares (WLS) regression are computed.

- 0 computes only LMS.
- 1 computes, in addition to LMS, weighted least squares regression on the observations with *small* LMS residuals (where *small* is defined by *opt*[8]).
- 2 computes, in addition to LMS, unweighted least squares regression.
- 3 adds both unweighted and weighted least squares regression to LMS regression.

The default is *opt*[3]=0.

opt[4] specifies the quantile h to be minimized. This is used in the objective function. The default is *opt*[4]= $h = \left\lceil \frac{N+n+1}{2} \right\rceil$, which corresponds to the highest possible breakdown value. This is also the default of the PROGRESS program. The value of h should be in the range $\frac{N}{2} + 1 \leq h \leq \frac{3N}{4} + \frac{n+1}{4}$.

opt[5] specifies the number N_{Rep} of generated subsets. Each subset consists of n observations (k_1, \dots, k_n) , where $1 \leq k_i \leq N$. The total number of subsets that contain n observations out of N observations is

$$N_{\text{tot}} = \binom{N}{n} = \frac{\prod_{j=1}^n (N - j + 1)}{\prod_{j=1}^n j}$$

where n is the number of parameters including the intercept.

Due to computer time restrictions, not all subset combinations of n observations out of N can be inspected for larger values of N and n . Specifying a value of $N_{\text{Rep}} < N_{\text{tot}}$ enables you to save computer time at the expense of computing a suboptimal solution.

If *opt*[5] is zero or missing, the default number of subsets is taken from the following table.

n	1	2	3	4	5	6	7	8	9	10
N_{lower}	500	50	22	17	15	14	0	0	0	0
N_{upper}	10^6	1414	182	71	43	32	27	24	23	22
N_{Rep}	500	1000	1500	2000	2500	3000	3000	3000	3000	3000

n	11	12	13	14	15
N_{lower}	0	0	0	0	0
N_{upper}	22	22	22	23	23
N_{Rep}	3000	3000	3000	3000	3000

If the number of cases (observations) N is smaller than N_{lower} , then all possible subsets are used; otherwise, N_{Rep} subsets are chosen randomly. This means that an exhaustive search is performed for $\text{opt}[5]=-1$. If N is larger than N_{upper} , a note is printed in the log file that indicates how many subsets exist.

$\text{opt}[6]$ is not used.

$\text{opt}[7]$ specifies whether the last argument *sorb* contains a given parameter vector **b** or a given subset for which the objective function should be evaluated.

0 *sorb* contains a given subset index.

1 *sorb* contains a given parameter vector **b**.

The default is $\text{opt}[7]=0$.

$\text{opt}[8]$ is relevant only for LS and WLS regression ($\text{opt}[3] > 0$). It specifies whether the covariance matrix of parameter estimates and approximate standard errors (ASEs) are computed and printed.

0 does not compute covariance matrix and ASEs.

1 computes covariance matrix and ASEs but prints neither of them.

2 computes the covariance matrix and ASEs but prints only the ASEs.

3 computes and prints both the covariance matrix and the ASEs.

The default is $\text{opt}[8]=0$.

y refers to an N response vector.

x refers to an $N \times n$ matrix **X** of regressors. If $\text{opt}[1]$ is zero or missing, an intercept $\mathbf{x}_{n+1} \equiv 1$ is added by default as the last column of **X**. If the matrix **X** is not specified, *y* is analyzed as a univariate data set.

sorb refers to an n vector that contains either of the following:

- n observation numbers of a subset for which the objective function should be evaluated; this subset can be the start for a pairwise exchange algorithm if $\text{opt}[7]$ is specified.
- n given parameters **b** = (b_1, \dots, b_n) (including the intercept, if necessary) for which the objective function should be evaluated.

Missing values are not permitted in *x* or *y*. Missing values in *opt* cause the default value to be used.

The LMS subroutine returns the following values:

sc is a column vector that contains the following scalar information, where rows 1–9 correspond to LMS regression and rows 11–14 correspond to either LS or WLS:

- sc*[1] the quantile h used in the objective function
- sc*[2] number of subsets generated
- sc*[3] number of subsets with singular linear systems
- sc*[4] number of nonzero weights w_i
- sc*[5] lowest value of the objective function F_{LMS} attained
- sc*[6] preliminary LMS scale estimate S_P
- sc*[7] final LMS scale estimate S_F
- sc*[8] robust R square (*coefficient of determination*)
- sc*[9] asymptotic consistency factor

If *opt*[3] > 0, then the following are also set:

- sc*[11] LS or WLS objective function (sum of squared residuals)
- sc*[12] LS or WLS scale estimate
- sc*[13] R square value for LS or WLS
- sc*[14] F value for LS or WLS

For *opt*[3]=1 or *opt*[3]=3, these rows correspond to WLS estimates; for *opt*[3]=2, these rows correspond to LS estimates.

coef is a matrix with n columns that contains the following results in its rows:

- coef*[1,] LMS parameter estimates
- coef*[2,] indices of observations in the best subset

If *opt*[3] > 0, then the following are also set:

- coef*[3,] LS or WLS parameter estimates
- coef*[4,] approximate standard errors of LS or WLS estimates
- coef*[5,] t values
- coef*[6,] p -values
- coef*[7,] lower boundary of Wald confidence intervals
- coef*[8,] upper boundary of Wald confidence intervals

For *opt*[3]=1 or *opt*[3]=3, these rows correspond to WLS estimates; for *opt*[3]=2, these rows correspond to LS estimates.

wgt is a matrix with N columns that contains the following results in its rows:

- wgt*[1,] weights (1 for small residuals; 0 for large residuals)
- wgt*[2,] residuals $r_i = y_i - \mathbf{x}_i \mathbf{b}$
- wgt*[3,] resistant diagnostic u_i (the resistant diagnostic cannot be computed for a perfect fit when the objective function is zero or nearly zero)

Example

Consider results for Brownlee (1965) stackloss data. The three explanatory variables correspond to measurements for a plant that oxidizes ammonia to nitric acid on 21 consecutive days.

- x_1 air flow to the plant
- x_2 cooling water inlet temperature
- x_3 acid concentration

The response variable y_i gives the permillage of ammonia lost (stackloss). The data are also given by Rousseeuw and Leroy (1987) and Osborne (1985). Rousseeuw and Leroy (1987) cite a large number of papers where this data set was analyzed and state that most researchers “concluded that observations 1, 3, 4, and 21 were outliers,” and that some people also reported observation 2 as an outlier.

For $N = 21$ and $n = 4$ (three explanatory variables including intercept), you obtain a total of 5,985 different subsets of 4 observations out of 21. If you decide not to specify `opt[5]`, the LMS subroutine chooses $N_{rep} = 2,000$ random sample subsets. Since there is a large number of subsets with singular linear systems, which you do not want to print, choose `opt[2]=2` for reduced printed output.

```

/* X1  X2  X3   Y  Stackloss data */
aa = { 1  80  27  89  42,
       1  80  27  88  37,
       1  75  25  90  37,
       1  62  24  87  28,
       1  62  22  87  18,
       1  62  23  87  18,
       1  62  24  93  19,
       1  62  24  93  20,
       1  58  23  87  15,
       1  58  18  80  14,
       1  58  18  89  14,
       1  58  17  88  13,
       1  58  18  82  11,
       1  58  19  93  12,
       1  50  18  89   8,
       1  50  18  86   7,
       1  50  19  72   8,
       1  50  19  79   8,
       1  50  20  80   9,
       1  56  20  82  15,
       1  70  20  91  15 };

a = aa[, 2:4]; b = aa[, 5];
opt = j(8, 1, .);
opt[2]= 2;    /* ipri */
opt[3]= 3;    /* ilsq */
opt[8]= 3;    /* icov */

call lms(sc, coef, wgt, opt, b, a);

```


The first portion of the output displays descriptive statistics, as shown in [Figure 23.161](#):

Figure 23.161 Descriptive Statistics

LMS: The 13th ordered squared residual will be minimized.		
Median and Mean		
	Median	Mean
VAR1	58	60.428571429
VAR2	20	21.095238095
VAR3	87	86.285714286
Intercep	1	1
Response	15	17.523809524
There are 5985 subsets of 4 cases out of 21 cases.		
The algorithm will draw 2000 random subsets of 4 cases.		
Random Subsampling for LMS		
Minimum Criterion= 0.1264668282		
Least Median of Squares (LMS) Method		
Minimizing 13th Ordered Squared Residual.		
Highest Possible Breakdown Value = 42.86 %		
Random Selection of 2103 Subsets		
Among 2103 subsets 103 is/are singular.		
LMS Objective Function = 0.75		
Dispersion and Standard Deviation		
	Dispersion	StdDev
VAR1	5.930408874	9.1682682584
VAR2	2.965204437	3.160771455
VAR3	4.4478066555	5.3585712381
Intercep	0	0
Response	5.930408874	10.171622524

The next portion of the output shows the least squares estimates and the covariance of the estimates. Information about the residuals are also displayed, but are not shown in [Figure 23.162](#).

Figure 23.162 Least Squares Estimates

Dispersion and Standard Deviation						
		Dispersion		StdDev		
VAR1		5.930408874		9.1682682584		
VAR2		2.965204437		3.160771455		
VAR3		4.4478066555		5.3585712381		
Intercep		0		0		
Response		5.930408874		10.171622524		
Unweighted Least-Squares Estimation						
LS Parameter Estimates						
Variable	Estimate	Approx Std Err	t Value	Pr > t	Lower WCI	Upper WCI
VAR1	0.7156402	0.13485819	5.31	<.0001	0.45132301	0.97995739
VAR2	1.29528612	0.36802427	3.52	0.0026	0.57397182	2.01660043
VAR3	-0.1521225	0.15629404	-0.97	0.3440	-0.4584532	0.15420818
Intercep	-39.919674	11.8959969	-3.36	0.0038	-63.2354	-16.603949
Preliminary LMS Scale = 1.0478510755						
Robust R Squared = 0.96484375						
Final LMS Scale = 1.2076147288						
Distribution of Residuals						
Median(U)= 4.5864208797						
Weighted Least-Squares Estimation						
Weighted Sum of Squares = 20.400800254						
Degrees of Freedom = 13						
RLS Scale Estimate = 1.2527139846						
Weighted R-squared = 0.9750062263						

Figure 23.162 *continued*

```

Sum of Squares = 178.8299616
Degrees of Freedom = 17
LS Scale Estimate = 3.2433639182

Cov Matrix of Parameter Estimates

VAR1          VAR2          VAR3          Intercep
VAR1      0.0181867302      -0.036510675      -0.007143521      0.2875871057
VAR2      -0.036510675      0.1354418598      0.0000104768      -0.651794369
VAR3      -0.007143521      0.0000104768      0.024427828      -1.676320797
Intercep   0.2875871057      -0.651794369      -1.676320797      141.51474107

F(3,13) Statistic = 169.04317954
Probability = 1.158521E-10
There are 17 points with nonzero weight.
Average Weight = 0.8095238095

Distribution of Residuals

The run has been executed successfully.

R-squared = 0.9135769045
F(3,17) Statistic = 59.9022259
Probability = 3.0163272E-9

```

The LMS subroutine prints results for the 2,000 random subsets. [Figure 23.163](#) shows the iteration history, the best subset of observations that are used to form estimates, and the estimated parameters. The subroutine also displays residual information (not shown).

Figure 23.163 Least Median Squares Estimates

MinRes	1st Qu.	Median
-7.237712859	-1.814569436	-0.455092955
Mean	3rd Qu.	MaxRes
3.383537E-16	1.8867828182	5.6977741706

Figure 23.163 *continued*

There are 5985 subsets of 4 cases out of 21 cases.			
The algorithm will draw 2000 random subsets of 4 cases.			
Random Subsampling for LMS			
Subset	Singular	Best Criterion	Percent
500	23	0.163262	25
1000	55	0.140519	50
1500	79	0.140519	75
2000	103	0.126467	100
Minimum Criterion= 0.1264668282			
Least Median of Squares (LMS) Method			
Minimizing 13th Ordered Squared Residual.			
Highest Possible Breakdown Value = 42.86 %			
Random Selection of 2103 Subsets			
Among 2103 subsets 103 is/are singular.			
Observations of Best Subset			
15	11	19	10
Estimated Coefficients			
VAR1	VAR2	VAR3	Intercep
0.75	0.5	0	-39.25

Observations 1, 3, 4, and 21 have scaled residuals larger than 2.0 (table not shown) and are considered outliers. The corresponding WLS estimates are shown in [Figure 23.164](#):

Figure 23.164 Weighted Least Squares Estimates

Estimated Coefficients			
VAR1	VAR2	VAR3	Intercep
0.75	0.5	0	-39.25

Figure 23.164 *continued*

LMS Objective Function = 0.75				
Preliminary LMS Scale = 1.0478510755				
Robust R Squared = 0.96484375				
Final LMS Scale = 1.2076147288				
LMS Residuals				
N	Observed	Estimated	Residual	Res / S
1	42.000000	34.250000	7.750000	6.417610
2	37.000000	34.250000	2.750000	2.277216
3	37.000000	29.500000	7.500000	6.210590
4	28.000000	19.250000	8.750000	7.245688
5	18.000000	18.250000	-0.250000	-0.207020
6	18.000000	18.750000	-0.750000	-0.621059
7	19.000000	19.250000	-0.250000	-0.207020
8	20.000000	19.250000	0.750000	0.621059
9	15.000000	15.750000	-0.750000	-0.621059
10	14.000000	13.250000	0.750000	0.621059
11	14.000000	13.250000	0.750000	0.621059
12	13.000000	12.750000	0.250000	0.207020
13	11.000000	13.250000	-2.250000	-1.863177
14	12.000000	13.750000	-1.750000	-1.449138
15	8.000000	7.250000	0.750000	0.621059
16	7.000000	7.250000	-0.250000	-0.207020
17	8.000000	7.750000	0.250000	0.207020
18	8.000000	7.750000	0.250000	0.207020
19	9.000000	8.250000	0.750000	0.621059
20	15.000000	12.750000	2.250000	1.863177
21	15.000000	23.250000	-8.250000	-6.831649
Distribution of Residuals				
MinRes		1st Qu.	Median	
-8.25		-0.5	0.25	
Mean		3rd Qu.	MaxRes	
0.9047619048		0.75	8.75	

Figure 23.164 *continued*

Resistant Diagnostic						
N	U	Resistant Diagnostic				
1	10.448052	2.278040				
2	7.931751	1.729399				
3	10.000000	2.180349				
4	11.666667	2.543741				
5	2.729730	0.595176				
6	3.486486	0.760176				
7	4.729730	1.031246				
8	4.243243	0.925175				
9	3.648649	0.795533				
10	3.759835	0.819775				
11	4.605767	1.004218				
12	4.925169	1.073859				
13	3.888889	0.847914				
14	4.586421	1.000000				
15	5.297030	1.154938				
16	4.009901	0.874299				
17	6.679576	1.456381				
18	4.305340	0.938715				
19	4.019976	0.876495				
20	3.000000	0.654105				
21	11.000000	2.398384				
Median(U)= 4.5864208797						
Weighted Least-Squares Estimation						
RLS Parameter Estimates Based on LMS						
Variable	Estimate	Approx Std Err	t Value	Pr > t	Lower WCI	Upper WCI
VAR1	0.79768556	0.06743906	11.83	<.0001	0.66550742	0.9298637
VAR2	0.57734046	0.16596894	3.48	0.0041	0.25204731	0.9026336
VAR3	-0.0670602	0.06160314	-1.09	0.2961	-0.1878001	0.05367975
Intercep	-37.652459	4.73205086	-7.96	<.0001	-46.927108	-28.37781

Figure 23.164 *continued*

Weighted Sum of Squares = 20.400800254				
Degrees of Freedom = 13				
RLS Scale Estimate = 1.2527139846				
Cov Matrix of Parameter Estimates				
	VAR1	VAR2	VAR3	Intercep
VAR1	0.0045480273	-0.007921409	-0.001198689	0.0015681747
VAR2	-0.007921409	0.0275456893	-0.00046339	-0.065017508
VAR3	-0.001198689	-0.00046339	0.0037949466	-0.246102248
Intercep	0.0015681747	-0.065017508	-0.246102248	22.392305355
Weighted R-squared = 0.9750062263				
F(3,13) Statistic = 169.04317954				
Probability = 1.158521E-10				
There are 17 points with nonzero weight.				
Average Weight = 0.8095238095				

LOAD Statement

LOAD <MODULE=(*module-list*)> <*matrix-list*> ;

The LOAD statement loads modules and matrix values from the current library storage into the current workspace.

The arguments to the LOAD statement are as follows:

module-list is a list of modules.

matrix-list is a list of matrices.

For example, to load three modules A, B, and C and one matrix X, use the following statement:

```
load module=(A B C) X;
```

The special operand `_ALL_` can be used to load all matrices or all modules. For example, if you want to load all matrices, use the following statement:

```
load _all_;
```

If you want to load all modules, use the following statement:

```
load module=_all_;
```

To load all matrices and modules stored in the library storage, you can enter the LOAD command without any arguments, as follows:

```
load;
```

The storage library can be specified by using a **RESET STORAGE** command. The default library is `Work.Imlstor`. For more information, see [Chapter 17](#) and the descriptions of the **STORE**, **REMOVE**, **RESET**, and **SHOW** statements.

LOC Function

LOC(*matrix*);

The LOC function finds nonzero elements of a matrix. It creates a $1 \times n$ row vector, where n is the number of nonzero elements in the argument matrix. Missing values are treated as zeros. The values in the resulting row vector are the locations of the nonzero elements in the argument (in row-major order).

For example, consider the following statements:

```
a = {1 0 2 3 0};
b = loc(a);
print b;
```

Because the first, third, and fourth elements of **A** are nonzero, these statements result in the row vector shown in [Figure 23.165](#):

Figure 23.165 Location of Nonzero Elements

b			
1	3	4	

If every element of the argument vector is 0, the result is empty; that is, **B** has zero rows and zero columns.

The LOC function is useful for subscripting parts of a matrix that satisfy some condition. For example, the following statements create a matrix **Y** that contains the rows of **X** that have a positive element in the diagonal of **X**:

```
x = {1  1  0,
     0 -2  2,
     0  0  3};
y = x[loc(vecdiag(x)>0), ];
print y;
```

Figure 23.166 Rows with Positive Diagonal Elements

y		
1	1	0
0	0	3

LOG Function

LOG(*matrix*);

The LOG function is the scalar function that takes the natural logarithm of each element of the argument matrix. An example of a valid statement follows:

```
c = {1 2 3};
b = log(c);
print b;
```

Figure 23.167 Natural Logarithms

b		
0	0.6931472	1.0986123

LP Call

CALL LP(*rc, x, dual, a, b* <, *cntl* > <, *u* > <, *l* > <, *basis* >);

The LP subroutine solves the linear programming problem.

The input arguments to the LP subroutine are as follows:

- a* is an $m \times n$ vector that specifies the technological coefficients, where m is less than or equal to n .
- b* is an $m \times 1$ vector that specifies the right-side vector.
- cntl* is an optional row vector with one to five elements. If *cntl*=(*indx, nprimal, ndual, epsilon, infinity*), then
 - indx* is the subscript of nonzero objective coefficient.
 - nprimal* is the maximum number of primal iterations.
 - ndual* is the maximum number of dual iterations.
 - epsilon* is the value of virtual zero.
 - infinity* is the value of virtual infinity.

The default values are as follows: *indx* equals n , *nprimal* equals 999,999, *ndual* equals 999,999, *epsilon* equals $1.0\text{E}-8$, and *infinity* is machine-dependent. If you specify *ndual* or *nprimal* or both, then on return they contain the number of iterations actually performed.

- u* is an optional array of dimension n that specifies upper bounds on the decision variables. If you do not specify *u*, the upper bounds are assumed to be *infinity*.
- l* is an optional array of dimension n that specifies lower bounds on the decision variables. If *l* is not given, then the lower bounds are assumed to be 0 for all the decision variables. This includes the decision variable associated with the objective value, which is specified by the value of *indx*.

- basis* is an optional array of dimension n that specifies the current basis. This is given by identifying which columns are explicitly in the basis and which columns are at their upper bound, as given in u . The absolute value of the elements in this vector is a permutation of the column indices. The columns specified in the first m elements of *basis* are considered the explicit basis. The absolute value of the last $n - m$ elements of *basis* are the indices of the nonbasic variables. Any of the last $n - m$ elements of *basis* that are negative indicate that the corresponding nonbasic variable is at its upper bound. On return from the LP subroutine, the *basis* vector contains the final basis encountered. If you do not specify *basis*, then the subroutine assumes that an initial basis is in the last m columns of \mathbf{A} and that no nonbasic variables are at their upper bound.
- rc* returns one of the following scalar return codes:

<i>rc</i>	Termination
0	The solution is optimal.
1	The solution is primal infeasible and dual feasible.
2	The solution is dual infeasible and primal feasible.
3	The solution is neither primal nor dual feasible.
4	A singular basis was encountered.
5	The solution is numerically unstable.
6	The subroutine could not obtain enough memory.
7	The number of iterations was exceeded.

- x returns the current primal solution in a column vector of length n .
- dual* returns the current dual solution in a row vector of length m .

The LP subroutine solves the linear program:

$$\begin{aligned} &\max(0, \dots, 0, 1, 0, \dots, 0)\mathbf{x} \\ &\text{st. } \mathbf{Ax} = \mathbf{b} \\ &\quad l \leq \mathbf{x} \leq \mathbf{u} \end{aligned}$$

The subroutine first inverts the initial basis. If the *basis* vector is given, then the initial basis is the $m \times m$ submatrix identified by the first m elements in *basis*; otherwise, the initial basis is defined by the last m columns of \mathbf{A} . If the initial basis is singular, the subroutine returns with RC=4. If the basis is nonsingular, then the current dual and primal solutions are evaluated. If neither is feasible, then the subroutine returns with RC=3. If the primal solution is feasible, then the primal algorithm iterates until either a dual feasible solution is encountered or the number of NPRIMAL iterations is exceeded. If the dual solution is feasible, then the dual algorithm iterates until either a primal feasible solution is encountered or the number of NDUAL iterations is exceeded. When a basis is identified that is both primal and dual feasible, then the subroutine returns with RC=0.

Care must be taken when solving a sequence of linear programs that use the NPRIMAL or NDUAL control parameters. Because the LP subroutine resets the NPRIMAL and NDUAL parameters to reflect the number of iterations executed, subsequent invocations of the LP subroutine will have the number of iterations limited to the number used by the last LP subroutine executed. In these cases you should consider resetting these parameters prior to each LP call.

Consider the following example to maximize X_1 subject to the constraints $X_1 + X_2 \leq 10$, and $X_1 \geq 0$, and $X_2 \geq 0$. The problem is solved by using the following statements:

```

/* the problem data */
obj = {1 0};
coef = {1 1};
b = {0, 10};

/* embed the objective function in the coefficient matrix */
a = obj // coef;
a = a || {-1, 0};

/* solve the problem */
call lp(rc, x, dual, a, b);
print rc, x, dual;

```

Figure 23.168 Solution to a Constrained Linear Problem

rc	
	0
x	
	10
	0
	10
dual	
-1	1

LTS Call

CALL LTS(*sc*, *coef*, *wgt*, *opt*, *y* <, *x* > <, *sorb* >);

The LTS subroutine performs least trimmed squares (LTS) robust regression by minimizing the sum of the h smallest squared residuals. The subroutine also detects outliers and perform a least squares regression on the remaining observations. The LTS subroutine implements the FAST-LTS algorithm described by Rousseeuw and Van Driessen (1998).

The value of h can be specified, but for many applications the default value works well and the results seem to be quite stable toward different choices of h .

In the following discussion, N is the number of observations and n is the number of regressors. The input arguments to the LTS subroutine are as follows:

opt refers to an options vector with the following components (missing values are treated as default values). The options vector can be a null vector.

opt[1] specifies whether an intercept is used in the model (*opt*[1]=0) or not (*opt*[1]≠ 0). If *opt*[1]=0, then a column of ones is added as the last column to the input matrix **X**; that is,

you do not need to add this column of ones yourself. The default is $opt[1]=0$.

$opt[2]$ specifies the amount of printed output. Higher values request additional output and include the output of lower values.

- 0 prints no output except error messages.
- 1 prints all output except (1) arrays of $O(N)$, such as weights, residuals, and diagnostics; (2) the history of the optimization process; and (3) subsets that result in singular linear systems.
- 2 additionally prints arrays of $O(N)$, such as weights, residuals, and diagnostics; it also prints the case numbers of the observations in the best subset and some basic history of the optimization process.
- 3 additionally prints subsets that result in singular linear systems.

The default is $opt[2]=0$.

$opt[3]$ specifies whether only LTS is computed or whether, additionally, least squares (LS) and weighted least squares (WLS) regression are computed:

- 0 computes only LTS.
- 1 computes, in addition to LTS, weighted least squares regression on the observations with *small* LTS residuals (where *small* is defined by $opt[8]$).
- 2 computes, in addition to LTS, unweighted least squares regression.
- 3 adds both unweighted and weighted least squares regression to LTS regression.

The default is $opt[3]=0$.

$opt[4]$ specifies the quantile h to be minimized. This is used in the objective function. The default is $opt[4]=h=\left\lceil \frac{N+n+1}{2} \right\rceil$, which corresponds to the highest possible breakdown value. This is also the default of the PROGRESS program. The value of h should be in the range $\frac{N}{2} + 1 \leq h \leq \frac{3N}{4} + \frac{n+1}{4}$.

$opt[5]$ specifies the number N_{Rep} of generated subsets. Each subset consists of n observations (k_1, \dots, k_n) , where $1 \leq k_i \leq N$. The total number of subsets that contain n observations out of N observations is

$$N_{\text{tot}} = \binom{N}{n} = \frac{\prod_{j=1}^n (N - j + 1)}{\prod_{j=1}^n j}$$

where n is the number of parameters including the intercept.

Due to computer time restrictions, not all subset combinations of n observations out of N can be inspected for larger values of N and n . Specifying a value of $N_{\text{Rep}} < N_{\text{tot}}$ enables you to save computer time at the expense of computing a suboptimal solution.

When $opt[5]$ is zero or missing:

- If $N > 600$, the default FAST-LTS algorithm constructs up to five disjoint random subsets with sizes as equal as possible, but not to exceed 300. Inside each subset, the algorithm chooses $500/5 = 100$ subset combinations of n observations.

The number of subsets is taken from the following table:

n	1	2	3	4	5	6	7	8	9	10
N_{lower}	500	50	22	17	15	14	0	0	0	0
N_{upper}	10^6	1414	182	71	43	32	27	24	23	22
N_{Rep}	500	1000	1500	2000	2500	3000	3000	3000	3000	3000

n	11	12	13	14	15
N_{lower}	0	0	0	0	0
N_{upper}	22	22	22	23	23
N_{Rep}	3000	3000	3000	3000	3000

- If the number of cases (observations) N is smaller than N_{lower} , then all possible subsets are used; otherwise, fixed 500 subsets for FAST-LTS or N_{Rep} subsets for algorithm before SAS/IML 8.1 are chosen randomly. This means that an exhaustive search is performed for $\text{opt}[5]=-1$. If N is larger than N_{upper} , a note is printed in the log file that indicates how many subsets exist.

$\text{opt}[6]$ is not used.

$\text{opt}[7]$ specifies whether the last argument *sorb* contains a given parameter vector **b** or a given subset for which the objective function should be evaluated.

0 *sorb* contains a given subset index.

1 *sorb* contains a given parameter vector **b**.

The default is $\text{opt}[7]=0$.

$\text{opt}[8]$ is relevant only for LS and WLS regression ($\text{opt}[3] > 0$). It specifies whether the covariance matrix of parameter estimates and approximate standard errors (ASEs) are computed and printed.

0 does not compute covariance matrix and ASEs.

1 computes covariance matrix and ASEs but prints neither of them.

2 computes the covariance matrix and ASEs but prints only the ASEs.

3 computes and prints both the covariance matrix and the ASEs.

The default is $\text{opt}[8]=0$.

$\text{opt}[9]$ is relevant only for LTS. If $\text{opt}[9]=0$, the algorithm FAST-LTS of Rousseeuw and Van Driessen (1998) is used. If $\text{opt}[9] = 1$, the algorithm of Rousseeuw and Leroy (1987) is used. The default is $\text{opt}[9]=0$.

y a response vector with N observations.

x an $N \times n$ matrix **X** of regressors. If $\text{opt}[1]$ is zero or missing, an intercept $\mathbf{x}_{n+1} \equiv 1$ is added by default as the last column of **X**. If the matrix **X** is not specified, *y* is analyzed as a univariate data set.

sorb refers to an n vector that contains either of the following:

- n observation numbers of a subset for which the objective function should be evaluated; this subset can be the start for a pairwise exchange algorithm if $\text{opt}[7]$ is specified.
- n given parameters **b** = (b_1, \dots, b_n) (including the intercept, if necessary) for which the objective function should be evaluated.

Missing values are not permitted in x or y . Missing values in *opt* cause the default value to be used.

The LTS subroutine returns the following values:

sc is a column vector that contains the following scalar information, where rows 1–9 correspond to LTS regression and rows 11–14 correspond to either LS or WLS:

- sc*[1] the quantile h used in the objective function
- sc*[2] number of subsets generated
- sc*[3] number of subsets with singular linear systems
- sc*[4] number of nonzero weights w_i
- sc*[5] lowest value of the objective function F_{LTS} attained
- sc*[6] preliminary LTS scale estimate S_P
- sc*[7] final LTS scale estimate S_F
- sc*[8] robust R square (*coefficient of determination*)
- sc*[9] asymptotic consistency factor

If *opt*[3] > 0, then the following are also set:

- sc*[11] LS or WLS objective function (sum of squared residuals)
- sc*[12] LS or WLS scale estimate
- sc*[13] R square value for LS or WLS
- sc*[14] F value for LS or WLS

For *opt*[3]=1 or *opt*[3]=3, these rows correspond to WLS estimates; for *opt*[3]=2, these rows correspond to LS estimates.

coef is a matrix with n columns that contains the following results in its rows:

- coef*[1,] LTS parameter estimates
- coef*[2,] indices of observations in the best subset

If *opt*[3] > 0, then the following are also set:

- coef*[3,] LS or WLS parameter estimates
- coef*[4,] approximate standard errors of LS or WLS estimates
- coef*[5,] t values
- coef*[6,] p -values
- coef*[7,] lower boundary of Wald confidence intervals
- coef*[8,] upper boundary of Wald confidence intervals

For *opt*[3]=1 or *opt*[3]=3, these rows correspond to WLS estimates; for *opt*[3]=2, these rows correspond to LS estimates.

wgt is a matrix with N columns that contains the following results in its rows:

`wgt[1,]` weights (1 for small residuals; 0 for large residuals)
`wgt[2,]` residuals $r_i = y_i - \mathbf{x}_i \mathbf{b}$
`wgt[3,]` resistant diagnostic u_i (the resistant diagnostic cannot be computed for a perfect fit when the objective function is zero or nearly zero)

Example

Consider Brownlee (1965) stackloss data used in the example for the LMS subroutine.

For $N = 21$ and $n = 4$ (three explanatory variables including intercept), you obtain a total of 5,985 different subsets of 4 observations out of 21. If you decide not to specify `opt[5]`, the FAST-LTS algorithm chooses 500 random sample subsets, as in the following statements:

```

/* X1  X2  X3   Y  Stackloss data */
aa = { 1  80  27  89  42,
        1  80  27  88  37,
        1  75  25  90  37,
        1  62  24  87  28,
        1  62  22  87  18,
        1  62  23  87  18,
        1  62  24  93  19,
        1  62  24  93  20,
        1  58  23  87  15,
        1  58  18  80  14,
        1  58  18  89  14,
        1  58  17  88  13,
        1  58  18  82  11,
        1  58  19  93  12,
        1  50  18  89   8,
        1  50  18  86   7,
        1  50  19  72   8,
        1  50  19  79   8,
        1  50  20  80   9,
        1  56  20  82  15,
        1  70  20  91  15 };

a = aa[, 2:4]; b = aa[, 5];
opt = j(8, 1, .);
opt[2]= 1;      /* ipri */
opt[3]= 3;      /* ilsq */
opt[8]= 3;      /* icov */

call lts(sc, coef, wgt, opt, b, a);

```

Figure 23.169 Least Trimmed Squares

LTS: The sum of the 13 smallest squared residuals will be minimized.		
Median and Mean		
	Median	Mean
VAR1	58	60.428571429
VAR2	20	21.095238095
VAR3	87	86.285714286
Intercep	1	1
Response	15	17.523809524
Least Trimmed Squares (LTS) Method		
Minimizing Sum of 13 Smallest Squared Residuals.		
Highest Possible Breakdown Value = 42.86 %		
Random Selection of 517 Subsets		
Among 517 subsets 17 is/are singular.		
The best half of the entire data set obtained after full iteration consists of the cases:		
LTS Objective Function = 0.474940583		
Preliminary LTS Scale = 0.9888435617		
Robust R Squared = 0.9745520119		
Final LTS Scale = 1.0360272594		
Dispersion and Standard Deviation		
	Dispersion	StdDev
VAR1	5.930408874	9.1682682584
VAR2	2.965204437	3.160771455
VAR3	4.4478066555	5.3585712381
Intercep	0	0
Response	5.930408874	10.171622524

Figure 23.169 *continued*

Unweighted Least-Squares Estimation						
LS Parameter Estimates						
Variable	Estimate	Approx Std Err	t Value	Pr > t	Lower WCI	Upper WCI
VAR1	0.7156402	0.13485819	5.31	<.0001	0.45132301	0.97995739
VAR2	1.29528612	0.36802427	3.52	0.0026	0.57397182	2.01660043
VAR3	-0.1521225	0.15629404	-0.97	0.3440	-0.4584532	0.15420818
Intercep	-39.919674	11.8959969	-3.36	0.0038	-63.2354	-16.603949
Weighted Least-Squares Estimation						
Weighted Sum of Squares = 10.273044977						
Degrees of Freedom = 11						
RLS Scale Estimate = 0.9663918355						
Weighted R-squared = 0.9622869127						
F(3,11) Statistic = 93.558645037						
Probability = 4.1136826E-8						
There are 15 points with nonzero weight.						
Average Weight = 0.7142857143						
The run has been executed successfully.						
Sum of Squares = 178.8299616						
Degrees of Freedom = 17						
LS Scale Estimate = 3.2433639182						
Cov Matrix of Parameter Estimates						
	VAR1	VAR2	VAR3	Intercep		
VAR1	0.0181867302	-0.036510675	-0.007143521	0.2875871057		
VAR2	-0.036510675	0.1354418598	0.0000104768	-0.651794369		
VAR3	-0.007143521	0.0000104768	0.024427828	-1.676320797		
Intercep	0.2875871057	-0.651794369	-1.676320797	141.51474107		

Figure 23.169 continued

R-squared = 0.9135769045
 F(3,17) Statistic = 59.9022259
 Probability = 3.0163272E-9

Least Trimmed Squares (LTS) Method

Least Trimmed Squares (LTS) Method
 Minimizing Sum of 13 Smallest Squared Residuals.
 Highest Possible Breakdown Value = 42.86 %
 Random Selection of 517 Subsets
 Among 517 subsets 17 is/are singular.

The best half of the entire data set obtained after full iteration consists of the cases:

5	6	7	8	9	10	11	12	15	16	17	18	19
---	---	---	---	---	----	----	----	----	----	----	----	----

Estimated Coefficients

VAR1	VAR2	VAR3	Intercep
0.7409210642	0.3915267228	0.0111345398	-37.32332647

LTS Objective Function = 0.474940583

Preliminary LTS Scale = 0.9888435617

Robust R Squared = 0.9745520119

Final LTS Scale = 1.0360272594

Weighted Least-Squares Estimation

RLS Parameter Estimates Based on LTS

Variable	Estimate	Approx Std Err	t Value	Pr > t	Lower WCI	Upper WCI
VAR1	0.75694055	0.07860766	9.63	<.0001	0.60287236	0.91100874
VAR2	0.45353029	0.13605033	3.33	0.0067	0.18687654	0.72018405
VAR3	-0.05211	0.05463722	-0.95	0.3607	-0.159197	0.054977
Intercep	-34.05751	3.82881873	-8.90	<.0001	-41.561857	-26.553163

Figure 23.169 *continued*

```

Weighted Sum of Squares = 10.273044977
Degrees of Freedom = 11
RLS Scale Estimate = 0.9663918355

Cov Matrix of Parameter Estimates

VAR1          VAR2          VAR3          Intercep
VAR1    0.0061791648    -0.005776855    -0.002300587    -0.034290068
VAR2    -0.005776855    0.0185096933    0.0002582502    -0.069740883
VAR3    -0.002300587    0.0002582502    0.0029852254    -0.131487406
Intercep -0.034290068    -0.069740883    -0.131487406    14.659852903

Weighted R-squared = 0.9622869127
F(3,11) Statistic = 93.558645037
Probability = 4.1136826E-8
There are 15 points with nonzero weight.
Average Weight = 0.7142857143

The run has been executed successfully.

```

The preceding program produces the following output associated with the LTS analysis. In this analysis, observations, 1, 2, 3, 4, 13, and 21 have scaled residuals larger than 2.5 (table not shown) and are considered outliers.

See the documentation for the [LMS subroutine](#) for additional details.

LUPDT Call

CALL LUPDT(*lup*, *bup*, *sup*, *L*, *z* <, *b* > <, *y* > <, *ssq* >);

The LUPDT subroutine provides updating and downdating for rank deficient linear least squares solutions, complete orthogonal factorization, and Moore-Penrose inverses.

The LUPDT subroutine returns the following values:

<i>lup</i>	is an $n \times n$ lower triangular matrix L that is updated or downdated by using the q rows in Z .
<i>bup</i>	is an $n \times p$ matrix B of right-hand sides that is updated or downdated by using the q rows in Y . If b is not specified, <i>bup</i> is not accessible.
<i>sup</i>	is a p vector of square roots of residual sum of squares that is updated or downdated by using the q rows in Y . If <i>ssq</i> is not specified, <i>sup</i> is not accessible.

The input arguments to the LUPDT subroutine are as follows:

L	specifies an $n \times n$ lower triangular matrix \mathbf{L} to be updated or downdated by q row vectors z stored in the $q \times n$ matrix Z . Only the lower triangle of L is used; the upper triangle can contain any information.
z	is a $q \times n$ matrix Z used rowwise to update or downdate the matrix L .
b	specifies an optional $n \times p$ matrix \mathbf{B} of right-hand sides that have to be updated or downdated simultaneously with L . If b is specified, the argument y must be specified.
y	specifies an optional $q \times p$ matrix Y used rowwise to update or downdate the right-hand-side matrix b .
ssq	specifies an optional $p \times 1$ vector that, if b is specified, specifies the square root of the error sum of squares that should be updated or downdated simultaneously with L and b .

The relevant formula for the LUPDT call is $\tilde{\mathbf{L}}\tilde{\mathbf{L}}' = \mathbf{L}\mathbf{L}' + \mathbf{Z}\mathbf{Z}'$. See the [example](#) in the documentation for the RZLIND call.

MAD Function

MAD(x <, *method* >);

The MAD function computes the univariate (scaled) median absolute deviation of each column of the input matrix.

The arguments to the MAD function are as follows:

x	is an $n \times p$ input data matrix.
<i>method</i>	is an optional string argument with the following values: <ul style="list-style-type: none"> “MAD” for computing the median absolute deviation (MAD); this is the default. “NMAD” for computing the normalized version of MAD “SN” for computing S_n “QN” for computing Q_n

For simplicity, the following descriptions assume that the input argument x is a column vector. The notation x_i means the i th element of the column vector x .

The MAD function can be used for computing one of the following three robust scale estimates:

- median absolute deviation (MAD) or normalized form of MAD,

$$\text{MAD}_n = b * \text{med}_i^n |x_i - \text{med}_j^n x_j|$$

where $b = 1$ is the unscaled default and $b = 1.4826$ is used for the scaled version (consistency with the Gaussian distribution).

- S_n , which is a more efficient alternative to MAD,

$$S_n = c_n * \text{med}_i \text{med}_{j \neq i} |x_i - x_j|$$

where the outer median is a low median (order statistic of rank $\lfloor \frac{n+1}{2} \rfloor$) and the inner median is a high median (order statistic of rank $\lfloor \frac{n}{2} + 1 \rfloor$), and where c_n is a scalar that depends on sample size n .

- Q_n is another efficient alternative to MAD. It is based on the k th-order statistic of the $\binom{n}{2}$ inter-point distances,

$$Q_n = d_n * \{|x_i - x_j|; i < j\}_{(k)} \quad \text{with} \quad k \approx \binom{n}{2} / 4$$

where d_n is a scalar similar to but different from c_n . See Rousseeuw and Croux (1993) for more details.

The scalars c_n and d_n are defined as follows:

$$c_n = 1.1926 * \begin{cases} 0.743 & \text{for } n=2 \\ 1.851 & \text{for } n=3 \\ 0.954 & \text{for } n=4 \\ 1.351 & \text{for } n=5 \\ 0.993 & \text{for } n=6 \\ 1.198 & \text{for } n=7 \\ 1.005 & \text{for } n=8 \\ 1.131 & \text{for } n=9 \\ n/(n-0.9) & \text{for other odd } n \\ 1.0 & \text{otherwise} \end{cases} \quad d_n = 2.2219 * \begin{cases} 0.399 & \text{for } n=2 \\ 0.994 & \text{for } n=3 \\ 0.512 & \text{for } n=4 \\ 0.844 & \text{for } n=5 \\ 0.611 & \text{for } n=6 \\ 0.857 & \text{for } n=7 \\ 0.669 & \text{for } n=8 \\ 0.872 & \text{for } n=9 \\ n/(n+1.4) & \text{for other odd } n \\ n/(n+3.8) & \text{otherwise} \end{cases}$$

Example

The following example uses the univariate data set of Barnett and Lewis (1978). The data set is used in Chapter 12 to illustrate the univariate LMS and LTS estimates.

```
b = {3, 4, 7, 8, 10, 949, 951};
```

```
rmad1 = mad(b);
rmad2 = mad(b, "mad");
rmad3 = mad(b, "nmad");
rmad4 = mad(b, "sn");
rmad5 = mad(b, "qn");
print "Default MAD=" rmad1,
      "Common MAD =" rmad2,
      "MAD*1.4826 =" rmad3,
      "Robust S_n =" rmad4,
      "Robust Q_n =" rmad5;
```

Figure 23.170 Median Absolute Deviations

	rmad1
Default MAD=	4
	rmad2
Common MAD =	4
	rmad3
MAD*1.4826 =	5.9304089
	rmad4
Robust S_n =	7.143674
	rmad5
Robust Q_n =	5.7125049

MARG Call

CALL MARG(*locmar*, *marginal*, *dim*, *table*, *config*);

The MARG subroutine evaluates marginal totals in a multiway contingency table.

The input arguments to the MARG subroutine are as follows:

<i>locmar</i>	is a returned matrix that contains a vector of indices to each new set of marginal totals under the model specified by <i>config</i> . A marginal total is exhibited for each level of the specified marginal. These indices help locate particular totals.
<i>marginal</i>	is a return vector of marginal totals.
<i>dim</i>	is an input matrix. If the problem contains v variables, then <i>dim</i> is $1 \times v$ row vector. The value <i>dim</i> [i] is the number of possible levels for variable i in a contingency table.
<i>table</i>	is an input matrix. The <i>table</i> argument specifies an array of the number of observations at each level of each variable. Variables are nested across columns and then across rows.
<i>config</i>	is an input matrix. The <i>config</i> argument specifies which marginal totals to evaluate. Each column of <i>config</i> specifies a distinct marginal in the model under consideration.

The matrix *table* must conform in size to the contingency table specified in *dim*. In particular, if *table* is $n \times m$, the product of the entries in the *dim* vector must equal nm . In addition, there must be some integer k such that the product of the first k entries in *dim* equals m . See the description of the IPF function for more information about specifying *table*.

For example, consider the three-dimensional table discussed in the [IPF](#) call, based on data that appear in Christensen (1997). The table presents data on a person's self-esteem for people classified according to their religion and their father's educational level.

Religion	Self-Esteem	Father's Educational Level				
		Not HS Grad	HS Grad	Some Coll	Coll Grad	Post Coll
Catholic	High	575	388	100	77	51
	Low	267	153	40	37	19
Jewish	High	117	102	67	87	62
	Low	48	35	18	12	13
Protestant	High	359	233	109	197	90
	Low	159	173	47	82	32

As explained in the [IPF](#) documentation, the father's education level is Variable 1, self-esteem is Variable 2, and religion is Variable 3.

The following program encodes this table, uses the MARG call to compute a two-way marginal table by summing over the third variable and a one-way marginal by summing over the first two variables.

```
dim={5 2 3};

table={
/* Father's Education:
      NotHSGrad HSGrad Col ColGrad PostCol
      Self-
      Relig Esteem
/* Cath- Hi */ 575   388  100    77   51,
/* olic  Lo */ 267   153   40    37   19,

/* Jew-  Hi */ 117   102   67    87   62,
/* ish   Lo */  48    35   18    12   13,

/* Prot- Hi */ 359   233  109   197   90,
/* estant Lo */ 159   173   47    82   32
      };

config = { 1 3,
          2 0 };
call marg(locmar, marginal, dim, table, config);
print locmar, marginal;
```

Figure 23.171 Marginal Totals in a Three-Way Table

locmar	
1	11

Figure 23.171 *continued*

			marginal				
	COL1	COL2	COL3	COL4	COL5	COL6	COL7
ROW1	1051	723	276	361	203	474	361
			marginal				
	COL8	COL9	COL10	COL11	COL12	COL13	
ROW1	105	131	64	1707	561	1481	

The first marginal total is contained in locations 1 through 10 of the **marginal** vector, which is shown in [Figure 23.171](#). It represents the results of summing **table** over the religion variable. The first entry of **marginal** is the number of subjects with high self-esteem whose fathers did not graduate from high school ($1051 = 575 + 117 + 359$). The second entry is the number of subjects with high self-esteem whose fathers were high school graduates ($723 = 388 + 102 + 233$). The tenth entry is the number of subjects with low self-esteem whose fathers had some post-collegiate education ($64 = 19 + 13 + 32$).

The second marginal is contained in locations 11 through 13 of the **marginal** vector. It represents the results of summing **table** over the education and self-esteem variables. The eleventh entry of the **marginal** vector is the number of Catholics in the study. The thirteenth entry is the number of Protestants.

You can also extract the marginal totals into separate vectors, as shown in the following statements:

```
/* Examine marginals: The name indicates the
   variable(s) that are NOT summed over.
   The locmar variable tells where to index
   into the marginal variable. */
Var12_Marg = marginal[1:(locmar[2]-1)];
Var12_Marg = shape(Var12_Marg, dim[2], dim[1]);
Var3_Marg = marginal[locMar[2]:ncol(marginal)];
print Var12_Marg, Var3_Marg;
```

Figure 23.172 Marginal Totals

Var12_Marg					
1051	723	276	361	203	
474	361	105	131	64	
Var3_Marg					
		1707			
		561			
		1481			

MATTRIB Statement

```
MATTRIB name    <ROWNAME=row-name>    <COLNAME=column-name>    <LABEL=label>
                <FORMAT=format> ;
```

The MATTRIB subroutine associates printing attributes with matrices.

The input arguments to the MATTRIB subroutine are as follows:

name is a character matrix or quoted literal that contains the name of a matrix.

row-name is a character matrix or quoted literal that specifies row names.

column-name is a character matrix or quoted literal that specifies column names.

label is a character matrix or quoted literal that associates a label with the matrix. The *label* argument has a maximum length of 256 characters.

format is a valid SAS format.

The MATTRIB statement associates printing attributes with matrices. Each matrix can be associated with a ROWNAME= matrix and a COLNAME= matrix, which are used whenever the matrix is printed to label the rows and columns, respectively. The statement is written as the keyword MATTRIB followed by a list of one or more names and attribute associations. It is not necessary to specify all attributes. The attribute associations are applied to the previous *name*. Thus, the following statement associates a row name RA and a column name CA to **a**, and a column name CB to **b**:

```
a = {1 2 3, 4 5 6};
ra = {"Row 1", "Row 2"};
ca = 'C1': 'C3';
b = 1:4;
cb = {"A" "B" "C" "D"};
mattrib a rowname=ra colname=ca b colname=cb;
print a, b;
```

Figure 23.173 Matrix Attributes

a				
	C1	C2	C3	
Row 1	1	2	3	
Row 2	4	5	6	

b				
A	B	C	D	
1	2	3	4	

You cannot group names. The following statement does not associate anything with **a**. In fact, it clears any attributes that were previously associated with **a**.

```
mattrib a b colname=cb;
```

```
print a, b;
```

Figure 23.174 Modified Matrix Attributes

a				
	c1	c2	c3	
Row 1	1	2	3	
Row 2	4	5	6	

b				
A	B	C	D	
1	2	3	4	

The values of the associated matrices are not looked up until they are needed. Thus, they need not have values at the time the MATTRIB statement is specified. They can be specified later when the object matrix is printed. The attributes continue to bind with the matrix until reassigned with another MATTRIB statement. To eliminate an attribute, specify EMPTY as the name (for example, ROWNAME=EMPTY). Use the [SHOW NAMES statement](#) to view current matrix attributes.

The following example uses all options in the MATTRIB statement:

```
rows = "xr1":"xr3";
cols = "c11":"c14";
x = {1 1 1 1,
     2 2 2 2,
     3 3 3 3};
mattrib x rowname=rows
        colname=cols
        label={"My Matrix, x"}
        format=5.2;
print x;
```

Figure 23.175 Matrix Attributes

My Matrix, x				
	c11	c12	c13	c14
xr1	1.00	1.00	1.00	1.00
xr2	2.00	2.00	2.00	2.00
xr3	3.00	3.00	3.00	3.00

MAX Function

```
MAX(matrix1 <, matrix2, ..., matrix15> );
```

The MAX function returns the maximum value of a matrix or set of matrices. The matrices can be numeric or character.

For numeric arguments, the MAX function returns a single numeric value that is the largest element among all arguments. For character arguments, the MAX function returns the character string that is largest in the ASCII order. For character arguments, the size of the result is the maximum number of characters among the arguments.

There can be as many as 15 argument matrices. The function checks for missing numeric values and does not include them in the result. If all arguments are missing, then the machine's most negative representable number is the result.

If you want to find the elementwise maximums of the corresponding elements of two matrices, use the maximum operator ($\langle \rangle$).

An example that uses the MAX function follows:

```
c = {1 -123 13 56 128 -81 12};
b = max(c);
print b;
```

Figure 23.176 Maximum Value of a Matrix

	b
	128

MAXQFORM Call

CALL MAXQFORM(*rc*, *maxq*, *V*, *b* <, *best*>);

The MAXQFORM subroutine computes the subsets of a matrix system that maximize the quadratic form.

If V and b are an $n \times n$ matrix and an $n \times 1$ vector, respectively, then the MAXQFORM function computes the subsets of components s such that $b'[s]V^{-1}[s, s]b[s]$ is maximized.

The MAXQFORM subroutine returns the following values:

rc is one of the following scalar return codes:

- | | |
|---|--|
| 0 | normal return |
| 1 | error: the number of elements of b is too large to process |
| 2 | error: V is not positive semidefinite |

maxq is an $m \times (n + 2)$ matrix, where m is the total number of subsets computed and n is the number of elements of b . The value of m depends on the value of *best* and is equal to $2^n - 1$ if *best* is not specified. Each row of *maxq* contains information for a selected subset of V and b . The first element of the row is the number of components in the subset. The second element is the value of the quadratic form. The following elements of the row are either 0 or 1, to indicate whether the corresponding components of V and b are included in the subset.

The input arguments to the MAXQFORM subroutine are as follows:

- V* specifies an $n \times n$ positive semidefinite matrix. Often this is generated as a crossproduct matrix, $X'X$, where X is a $k \times n$ matrix.
- b* specifies an $n \times 1$ vector. Often this arises as $X'y$, where X is a $k \times n$ matrix, and y is a $k \times 1$ vector.
- best* specifies an optional scalar. If *best* is specified with the value p , then the p subsets with the largest value for the quadratic form are returned for each subset size.

The leaps and bounds algorithm by Furnival and Wilson (1974) computes the maximum value of quadratic forms for subsets of components. Many statistics computed as a quadratic form can then be used as the criterion for the method of subset selection. These include the regression sum of squares, Wald statistics, and score statistics.

Consider the following fitness data, which consists of observations with values for age measured in years, weight measured in kilograms, time to run 1.5 miles measured in minutes, heart rate while resting, heart rate while running, maximum heart rate recorded while running, and oxygen intake rate while running measured in milliliters per kilogram of body weight per minute.

```
fit = {
  44  89.47  11.37  62  178  182  44.609,
  40  75.07  10.07  62  185  185  45.313,
  44  85.84   8.65  45  156  168  54.297,
  42  68.15   8.17  40  166  172  59.571,
  38  89.02   9.22  55  178  180  49.874,
  47  77.45  11.63  58  176  176  44.811,
  40  75.98  11.95  70  176  180  45.681,
  43  81.19  10.85  64  162  170  49.091,
  44  81.42  13.08  63  174  176  39.442,
  38  81.87   8.63  48  170  186  60.055,
  44  73.03  10.13  45  168  168  50.541,
  45  87.66  14.03  56  186  192  37.388,
  45  66.45  11.12  51  176  176  44.754,
  47  79.15  10.60  47  162  164  47.273,
  54  83.12  10.33  50  166  170  51.855,
  49  81.42   8.95  44  180  185  49.156,
  51  69.63  10.95  57  168  172  40.836,
  51  77.91  10.00  48  162  168  46.672,
  48  91.63  10.25  48  162  164  46.774,
  49  73.37  10.08  67  168  168  50.388,
  57  73.37  12.63  58  174  176  39.407,
  54  79.38  11.17  62  156  165  46.080,
  52  76.32   9.63  48  164  166  45.441,
  50  70.87   8.92  48  146  155  54.625,
  51  67.25  11.08  48  172  172  45.118,
  54  91.63  12.88  44  168  172  39.203,
  51  73.71  10.47  59  186  188  45.790,
  57  59.08   9.93  49  148  155  50.545,
  49  76.32   9.40  56  186  188  48.673,
  48  61.24  11.50  52  170  176  47.920,
  52  82.78  10.50  53  170  172  47.467 };
```

Use the following statement to center the data:

```
fitc = fit - fit[:,];
```

Now compute the crossproduct matrices, as follows:

```
x = fitc[, 1:6];
y = fitc[, 7];
xpx = x`*x;
xpy = x`*y;
```

The following statements compute the best three regression sums of squares for each size of regressor set:

```
call maxqform(rc, maxq, xpx, xpy, 3);
print maxq;
```

Figure 23.177 Best Three Regression Sums of Squares

maxq							
1	632.9001	0	0	1	0	0	0
1	135.78285	0	0	0	1	0	0
1	134.84474	0	0	0	0	1	0
2	650.66573	1	0	1	0	0	0
2	648.26218	0	0	1	0	1	0
2	634.46746	0	0	1	0	0	1
3	690.55086	1	0	1	0	1	0
3	689.60921	0	0	1	0	1	1
3	665.55064	1	0	1	0	0	1
4	712.45153	1	0	1	0	1	1
4	695.14669	1	1	1	0	1	0
4	694.5988	0	1	1	0	1	1
5	721.97309	1	1	1	0	1	1
5	712.63302	1	0	1	1	1	1
5	696.05218	1	1	1	1	1	0
6	722.54361	1	1	1	1	1	1

MCD Call

CALL MCD(*sc, coef, dist, opt, x*);

The MCD subroutine computes the minimum covariance determinant estimator. The MCD call is the robust estimation of multivariate location and scatter, defined by minimizing the determinant of the covariance matrix computed from h points. The algorithm for the MCD subroutine is based on the FAST-MCD algorithm given by Rousseeuw and Van Driessen (1999).

These robust locations and covariance matrices can be used to detect multivariate outliers and leverage points. For this purpose, the MCD subroutine provides a table of robust distances.

In the following discussion, N is the number of observations and n is the number of regressors. The input arguments to the MCD subroutine are as follows:

opt refers to an options vector with the following components (missing values are treated as default values):

opt[1] specifies the amount of printed output. Higher option values request additional output and include the output of lower values.

- 0 prints no output except error messages.
- 1 prints most of the output.
- 2 additionally prints case numbers of the observations in the best subset and some basic history of the optimization process.
- 3 additionally prints how many subsets result in singular linear systems.

The default is *opt*[1]=0.

opt[2] specifies whether the classical, initial, and final robust covariance matrices are printed. The default is *opt*[2]=0. The final robust covariance matrix is always returned in *coef*.

opt[3] specifies whether the classical, initial, and final robust correlation matrices are printed or returned. The default is *opt*[3]=0.

- 0 does not return or print.
- 1 prints the robust correlation matrix.
- 2 returns the final robust correlation matrix in *coef*.
- 3 prints and returns the final robust correlation matrix.

opt[4] specifies the quantile h used in the objective function. The default is *opt*[4]= $h = \lceil \frac{N+n+1}{2} \rceil$. If the value of h is specified outside the range $\frac{N}{2} + 1 \leq h \leq \frac{3N}{4} + \frac{n+1}{4}$, it is reset to the closest boundary of this region.

opt[5] specifies the number N_{Rep} of subset generations. This option is the same as described for the **LMS** and **LTS subroutines**. Due to computer time restrictions, not all subset combinations can be inspected for larger values of N and n .

When *opt*[5] is zero or missing:

- If $N > 600$, up to five disjoint random subsets are constructed with sizes as equal as possible, but not to exceed 300. Inside each subset, $N_{\text{Rep}} = 500/5 = 100$ subset combinations of n observations are chosen.
- If $N \leq 600$, the number of subsets is taken from the following table.

n	1	2	3	4	5	6	7 or more
N_{lower}	500	50	22	17	15	14	0

- If the number of observations N is smaller than N_{lower} , as given in the table, then all possible subsets are used; otherwise, $N_{\text{Rep}} = 500$ subsets are chosen randomly. This means that an exhaustive search is performed for *opt*[5]=−1.

x refers to an $N \times n$ matrix **X** of regressors.

Missing values are not permitted in x . Missing values in *opt* cause default values to be used for each option.

The MCD subroutine returns the following values:

sc is a column vector that contains the following scalar information:

- sc*[1] the quantile h used in the objective function
- sc*[2] number of subsets generated
- sc*[3] number of subsets with singular linear systems
- sc*[4] number of nonzero weights w_i
- sc*[5] lowest value of the objective function F_{MCD} attained (smallest determinant)
- sc*[6] Mahalanobis-like distance used in the computation of the lowest value of the objective function F_{MCD}
- sc*[7] the cutoff value used for the outlier decision

coef is a matrix with n columns that contains the following results in its rows:

- coef*[1,] location of ellipsoid center
- coef*[2,] eigenvalues of final robust scatter matrix
- coef*[3:2+ n ,] the final robust scatter matrix for *opt*[2]=1 or *opt*[2]=3
- coef*[2+ n +1:2+2 n ,] the final robust correlation matrix for *opt*[3]=1 or *opt*[3]=3

dist is a matrix with N columns that contains the following results in its rows:

- dist*[1,] Mahalanobis distances
- dist*[2,] robust distances based on the final estimates
- dist*[3,] weights (1 for small robust distances; 0 for large robust distances)

Example

Consider the Brownlee (1965) stackloss data used in the example for the MVE subroutine.

For $N = 21$ and $n = 4$ (three explanatory variables including intercept), you obtain a total of 5,985 different subsets of 4 observations out of 21. If you decide not to specify *opt* [5], the MCD algorithm chooses 500 random sample subsets, as in the following statements:

```
/* X1  X2  X3   Y  Stackloss data */
aa = { 1  80  27  89  42,
        1  80  27  88  37,
        1  75  25  90  37,
        1  62  24  87  28,
        1  62  22  87  18,
        1  62  23  87  18,
        1  62  24  93  19,
        1  62  24  93  20,
        1  58  23  87  15,
        1  58  18  80  14,
        1  58  18  89  14,
```

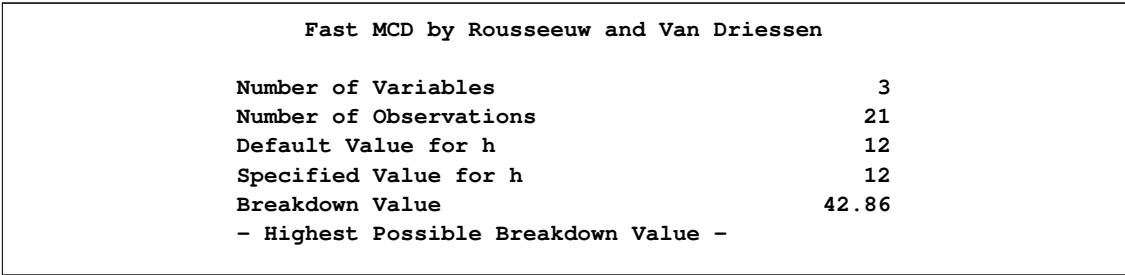
```
1  58  17  88  13,
1  58  18  82  11,
1  58  19  93  12,
1  50  18  89   8,
1  50  18  86   7,
1  50  19  72   8,
1  50  19  79   8,
1  50  20  80   9,
1  56  20  82  15,
1  70  20  91  15 };
```

```
a = aa[,2:4];
opt = j(8, 1, .);
opt[1] = 2;           /* ipri */
opt[2] = 1;           /* pcov: print COV */
opt[3] = 1;           /* pcov: print CORR */

call mcd(sc, xmcd, dist, opt, a);
```

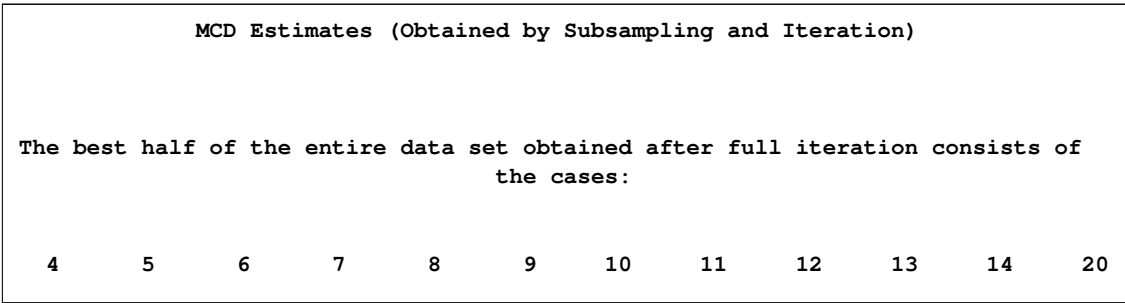
A portion of the output is shown in the following figures. [Figure 23.178](#) shows a summary of the MCD algorithm and the final *h* points selected.

Figure 23.178 Summary of MCD



[Figure 23.179](#) shows the observations that were chosen that are used to form the robust estimates.

Figure 23.179 Selected Observations



[Figure 23.180](#) shows the MCD estimators of the location, scatter matrix, and correlation matrix. The MCD scatter matrix is multiplied by a factor to make it consistent with the data that come from a single Gaussian distribution.

Figure 23.180 MCD Estimators

MCD Location Estimate			
	VAR1	VAR2	VAR3
	59.5	20.833333333	87.333333333
MCD Scatter Matrix Estimate			
	VAR1	VAR2	VAR3
VAR1	5.1818181818	4.8181818182	4.7272727273
VAR2	4.8181818182	7.6060606061	5.0606060606
VAR3	4.7272727273	5.0606060606	19.151515152
Consistent Scatter Matrix			
	VAR1	VAR2	VAR3
VAR1	8.6578437815	8.0502757968	7.8983838007
VAR2	8.0502757968	12.708297013	8.4553211199
VAR3	7.8983838007	8.4553211199	31.998580526

Figure 23.181 shows the classical Mahalanobis distances, the robust distances, and the weights that identify the outlying observations (that is, leverage points when explaining y with these three regressor variables).

Figure 23.181 Robust Distances

Classical Distances and Robust (Rousseeuw) Distances			
Unsquared Mahalanobis Distance and			
Unsquared Rousseeuw Distance of Each Observation			
N	Mahalanobis Distances	Robust Distances	Weight
1	2.253603	12.173282	0
2	2.324745	12.255677	0
3	1.593712	9.263990	0
4	1.271898	1.401368	1.000000
5	0.303357	1.420020	1.000000
6	0.772895	1.291188	1.000000
7	1.852661	1.460370	1.000000
8	1.852661	1.460370	1.000000
9	1.360622	2.120590	1.000000
10	1.745997	1.809708	1.000000
11	1.465702	1.362278	1.000000
12	1.841504	1.667437	1.000000
13	1.482649	1.416724	1.000000
14	1.778785	1.988240	1.000000
15	1.690241	5.874858	0
16	1.291934	5.606157	0
17	2.700016	6.133319	0
18	1.503155	5.760432	0
19	1.593221	6.156248	0
20	0.807054	2.172300	1.000000
21	2.176761	7.622769	0

Robust distances are based on reweighted estimates.

The cutoff value is the square root of the 0.975 quantile of the chi square distribution with 3 degrees of freedom.

Points whose robust distance exceeds 3.0575159206 have received a zero weight in the last column above.

There were 9 such points in the data.
These may include boundary cases.

Only points whose robust distance is substantially larger than the cutoff should be considered outliers.

MEAN Function

MEAN(x <, *method* > <, *param* >);

The MEAN function computes a sample mean of data. The arguments are as follows:

x specifies an $n \times p$ numerical matrix. The MEAN function computes means of the p columns of this matrix.

<i>method</i>	specifies the method used to compute the mean. This argument is optional. The following are valid values:
"arithmetic"	specifies that arithmetic means be computed. This is the default value.
"trimmed"	specifies that trimmed means be computed. The number of observations that are trimmed is determined by the <i>param</i> option.
"winsorized"	specifies that Winsorized means be computed. The number of observations that are Winsorized is determined by the <i>param</i> option.
<i>param</i>	specifies the number of observations trimmed or Winsorized. (This argument is ignored when "arithmetic" is specified for the <i>method</i> argument.) The default value for <i>param</i> is 0.1, which corresponds to trimming or Winsorizing 10% of the observations with the lowest values and 10% of the observations with the largest values.

The *method* argument is not case-sensitive. The first four characters are used to determine the value. For example, "WINS", "Winsor", and "winsorized" specify the same option.

The MEAN function uses the same algorithms as the UNIVARIATE procedure for computing the means, trimmed means, and Winsorized means. For additional details and formulas, see the UNIVARIATE procedure documentation (especially the TRIMMED= and WINSORIZED= options) in the *Base SAS Procedures Guide: Statistical Procedures*.

The *param* argument determines how many observations are trimmed (or Winsorized). The value for this argument can be an integer or a proportion. If the value is an integer k , then k observations are trimmed, provided that k is between 0 and half the number of nonmissing observations. If value is a proportion p in the interval $[0, 0.5)$, then the number of observations trimmed is equal to the smallest integer that is greater than or equal to np , where n is the number of nonmissing observations.

The following example demonstrates basic usage:

```
x = {5, 6, 6, 6, 7, 7, 7, 8, 8, 15};
mean = mean(x);
trim = mean(x, "trimmed", 0.2); /* 20% of obs */
winsor = mean(x, "winsorized", 1); /* one obs */
print mean trim winsor;
```

Figure 23.182 Arithmetic, Trimmed, and Winsorized Means

	mean	trim	winsor
	7.5	6.8333333	6.9

The MEAN function operates on columns of matrices. If x is an $n \times p$ matrix, the function returns a $1 \times p$ row vector. The value of the j th element is the mean for the j th column of the matrix, as the following example demonstrates:

```
x = {5 1 10,
      6 2 3,
      6 8 5,
      6 7 9,
```

```

    7 2 13};
mean = mean(x);
print mean;

```

Figure 23.183 Arithmetic Mean of Columns

mean		
6	4	8

Missing values in a column are excluded from the computation. The default behavior of the MEAN function is identical to the subscript reduction operator that computes the mean. That is, `mean(x)` and `x[:,]` both compute the means of the columns of `x`. See the section “[Subscript Reduction Operators](#)” on page 59 for more information about subscript reduction operators.

MIN Function

```
MIN(matrix1 <, matrix2, ..., matrix15 >);
```

The MIN function returns the minimum value of a matrix or set of matrices. The matrices can be numeric or character.

The MIN function produces a single numeric value (or a character string value) that is the smallest element (lowest character string value) in all arguments. There can be as many as 15 argument matrices. The function checks for missing numeric values and excludes them from the result. If all arguments are missing, then the machine’s largest representable number is the result.

If you want to find the elementwise minimums of the corresponding elements of two matrices, use the element minimum operator (`><`).

For character arguments, the size of the result is the size of the largest of all arguments.

The following statements use the MIN function to compute the minimum value of a vector:

```

c = {1 -123 13 56 128 -81 12};
b = min(c);
print b;

```

Figure 23.184 Minimum Value

b
-123

MOD Function

MOD(*value*, *divisor*);

The MOD function returns the remainder of the division of elements of the first argument by elements of the second argument.

The arguments to the MOD function are as follows:

value is a numeric matrix or literal that contains the dividend.
divisor is a numeric matrix or literal that contains the divisor.

If either operand is a scalar, the MOD function performs the operation for each element of the matrix with the scalar value. If either operand is a row or column vector, then the operation is performed by using that vector on each of the rows or columns of the matrix.

Unlike the MOD function in Base SAS software, the MOD function in SAS/IML software does not perform any numerical “fuzzing” to return an exact zero when the result would otherwise be very small. Thus the results of the SAS/IML MOD function is more similar to the MODZ function in Base SAS software.

An example of a valid statement follows:

```
c = {-7 14 20 -81 23};
b = mod(c, 4);
print b;
```

Figure 23.185 Remainders after Division

b				
-3	2	0	-1	3

MODULEI Call

CALL MODULEI(*control*, *modname*, < *matrix1*, ..., *matrix13* >);

The MODULEI subroutine calls an external routine that does not return a value.

The input arguments to the MODULEI subroutine are as follows:

control is a character matrix that contains a control string.
modname is a character matrix that contains the name of the external routine to be called.
matrix specifies matrix parameters to be passed to the external routine.

The CALL MODULEI routine executes a routine *modname* that resides in an external shared library with the specified arguments.

The `MODULEI` call routine is similar to the `MODULE` call routine that is available in the SAS DATA step. It is also closely related to the `MODULEIN` function, which returns a scalar numeric value, and the `MODULEIC` function, which returns a character value. `CALL MODULEI` builds a parameter list by using the information in the arguments and a routine description and argument attribute table that you define in a separate file. The attribute table is a sequential text file that contains descriptions of the routines that you can invoke with the `CALL MODULEI` routine and `MODULEIN` and `MODULEIC` functions. The purpose of the table is to define how `CALL MODULEI` should interpret its supplied arguments when it builds a parameter list to pass to the external routine. The attribute table should contain a description for each external routine that you intend to call, and descriptions of each argument associated with that routine. This enables you to call external routines that have been compiled in different programming languages that use different calling and matrix representation conventions.

Before you invoke `CALL MODULEI`, you must define the fileref of `SASCBTBL` to point to the external file that contains the attribute table. You can name the file whatever you want when you create it. You can then use matrices as arguments to `CALL MODULEI` and ensure that these arguments are properly converted before being passed to the external routine. The exact syntax for the attribute table is system-dependent, and can be found in the *SAS Companion* for your operating system. Attempting to use `CALL MODULEI` for a module without a correct attribute table entry can cause the SAS System to fail.

MODULEIC Function

MODULEIC(*control*, *modname*, < *matrix1*, ..., *matrix13* >);

The `MODULEIC` subroutine calls an external routine that returns a character value.

The arguments to the `MODULEIC` function are as follows:

<i>control</i>	is a character matrix that contains a control string.
<i>modname</i>	is a character matrix that contains the name of the external routine to be called.
<i>matrix</i>	specifies matrix parameters to be passed to the external routine.

The `MODULEIC` routine executes a routine *modname* that resides in an external shared library with the specified arguments and that returns a character value.

The description of this function is identical to the description of the [MODULEI call](#), except that the `MODULEIC` function returns a character value from the external routine. See the [MODULEI call](#) for a full description of the function and its arguments.

MODULEIN Function

MODULEIN(*control*, *modname*, < *matrix1*, ..., *matrix13* >);

The `MODULEIN` subroutine calls an external routine that returns a numerical value.

The arguments to the MODULEIN function are as follows:

control is a character matrix that contains a control string.
modname is a character matrix that contains the name of the external routine to be called.
matrix specifies matrix parameters to be passed to the external routine.

The MODULEIN routine executes a routine *modname* that resides in an external shared library with the specified arguments and that returns a numeric value.

The description of this function is identical to the description of the [MODULEI call](#), except that the MODULEIN function returns a scalar numeric value from the external routine. See the [MODULEI call](#) for a full description of the function and its arguments.

This example invokes the CHANGI routine from the TRYMOD.DLL module on a Windows platform. Use the following attribute table.

```
routine changi module=trymod returns=long;
arg 1 input num format=ib4. byvalue;
arg 2 update num format=ib4.;
```

The following statements call the CHANGI function:

```
proc iml;
  ones = J(4,5,1);
  i = do(10, 40, 10);
  j = 4:8;
  x1 = i` # ones + j;

  y1=x1;
  x2=x1;
  y2=y1;
  rc=modulein("*i", "changi", 6, x2);
```

MVE Call

CALL MVE(*sc, coef, dist, opt, x <, s >*);

The MVE subroutine computes the robust estimation of multivariate location and scatter, defined by minimizing the volume of an ellipsoid that contains h points.

The MVE subroutine computes the minimum volume ellipsoid estimator. These robust locations and covariance matrices can be used to detect multivariate outliers and leverage points. For this purpose, the MVE subroutine provides a table of robust distances.

In the following discussion, N is the number of observations and n is the number of regressors. The input arguments to the MVE subroutine are as follows:

opt refers to an options vector with the following components (missing values are treated as default values):

opt[1] specifies the amount of printed output. Higher option values request additional output and include the output of lower values.

- 0 prints no output except error messages.
- 1 prints most of the output.
- 2 additionally prints case numbers of the observations in the best subset and some basic history of the optimization process.
- 3 additionally prints how many subsets result in singular linear systems.

The default is *opt[1]*=0.

opt[2] specifies whether the classical, initial, and final robust covariance matrices are printed. The default is *opt[2]*=0. The final robust covariance matrix is always returned in *coef*.

opt[3] specifies whether the classical, initial, and final robust correlation matrices are printed or returned. The default is *opt[3]*=0.

- 0 does not return or print.
- 1 prints the robust correlation matrix.
- 2 returns the final robust correlation matrix in *coef*.
- 3 prints and returns the final robust correlation matrix.

opt[4] specifies the quantile h used in the objective function. The default is *opt[5]*= $h = \left\lceil \frac{N+n+1}{2} \right\rceil$. If the value of h is specified outside the range $\frac{N}{2} + 1 \leq h \leq \frac{3N}{4} + \frac{n+1}{4}$, it is reset to the closest boundary of this region.

opt[5] specifies the number N_{Rep} of subset generations. This option is the same as described previously for the LMS and LTS subroutines. Due to computer time restrictions, not all subset combinations can be inspected for larger values of N and n . If *opt[5]* is zero or missing, the default number of subsets is taken from the following table.

n	1	2	3	4	5	6	7	8	9	10
N_{lower}	500	50	22	17	15	14	0	0	0	0
N_{upper}	10^6	1414	182	71	43	32	27	24	23	22
N_{Rep}	500	1000	1500	2000	2500	3000	3000	3000	3000	3000

n	11	12	13	14	15
N_{lower}	0	0	0	0	0
N_{upper}	22	22	22	23	23
N_{Rep}	3000	3000	3000	3000	3000

If the number of cases (observations) N is smaller than N_{lower} , as given in the table, then all possible subsets are used; otherwise, N_{Rep} subsets are chosen randomly. This means that an exhaustive search is performed for *opt[5]*= -1. If N is larger than N_{upper} , a note is printed in the log file that indicates how many subsets exist.

x refers to an $N \times n$ matrix **X** of regressors. Missing values are not permitted in x .

s refers to an $n + 1$ vector that contains $n + 1$ observation numbers of a subset for which the objective function should be evaluated, where n is the number of parameters. In other words, the MVE algorithm computes the minimum volume of the ellipsoid that contains the observation numbers contained in *s*.

The MVE subroutine returns the following values:

sc is a column vector that contains the following scalar information:

- sc*[1] the quantile h used in the objective function
- sc*[2] number of subsets generated
- sc*[3] number of subsets with singular linear systems
- sc*[4] number of nonzero weights w_i
- sc*[5] lowest value of the objective function F_{MVE} attained (volume of smallest ellipsoid found)
- sc*[6] Mahalanobis-like distance used in the computation of the lowest value of the objective function F_{MVE}
- sc*[7] the cutoff value used for the outlier decision

coef is a matrix with n columns that contains the following results in its rows:

- coef*[1,] location of ellipsoid center
- coef*[2,] eigenvalues of final robust scatter matrix
- coef*[3:2+n,] the final robust scatter matrix for *opt*[2]=1 or *opt*[2]=3
- coef*[2+n+1:2+2n,] the final robust correlation matrix for *opt*[3]=1 or *opt*[3]=3

dist is a matrix with N columns that contains the following results in its rows:

- dist*[1,] Mahalanobis distances
- dist*[2,] robust distances based on the final estimates
- dist*[3,] weights (1 for small robust distances; 0 for large robust distances)

Example

Consider results for Brownlee (1965) stackloss data. The three explanatory variables correspond to measurements for a plant that oxidizes ammonia to nitric acid on 21 consecutive days:

- x_1 air flow to the plant
- x_2 cooling water inlet temperature
- x_3 acid concentration

The response variable y_i gives the permillage of ammonia lost (stackloss). These data are also given by Rousseeuw and Leroy (1987).

```

/* X1  X2  X3  Y      Stackloss data */
aa = { 1  80  27  89  42,
        1  80  27  88  37,
        1  75  25  90  37,
        1  62  24  87  28,
        1  62  22  87  18,
        1  62  23  87  18,
        1  62  24  93  19,
        1  62  24  93  20,
        1  58  23  87  15,
        1  58  18  80  14,
        1  58  18  89  14,
        1  58  17  88  13,
        1  58  18  82  11,
        1  58  19  93  12,
        1  50  18  89   8,
        1  50  18  86   7,
        1  50  19  72   8,
        1  50  19  79   8,
        1  50  20  80   9,
        1  56  20  82  15,
        1  70  20  91  15 };

```

Rousseeuw and Leroy (1987) cite a large number of papers where this data set was analyzed and state that most researchers “concluded that observations 1, 3, 4, and 21 were outliers”; some people also reported observation 2 as an outlier.

By default, subroutine MVE chooses only 2,000 randomly selected subsets in its search. There are in total 5,985 subsets of 4 cases out of 21 cases, as shown in [Figure 23.186](#), which is produced by the following statements:

```

a = aa[, 2:4];
opt = j(8, 1, .);
opt[1] = 2;           /* ipri */
opt[2] = 1;           /* pcov: print COV */
opt[3] = 1;           /* pcov: print CORR */
opt[5] = -1;          /* nrep: use all subsets */

call mve(sc, xmve, dist, opt, a);

```

The first part of the output ([Figure 23.186](#)) shows the classical scatter and correlation matrix, along with the means of each variable.

Figure 23.186 Classical Estimates of Scatter and Location

Classical Covariance Matrix				
	VAR1	VAR2	VAR3	
VAR1	84.057142857	22.657142857	24.571428571	
VAR2	22.657142857	9.9904761905	6.6214285714	
VAR3	24.571428571	6.6214285714	28.714285714	

Figure 23.186 *continued*

Classical Correlation Matrix			
	VAR1	VAR2	VAR3
VAR1	1	0.781852333	0.5001428749
VAR2	0.781852333	1	0.3909395378
VAR3	0.5001428749	0.3909395378	1
Classical Mean			
VAR1	60.428571429		
VAR2	21.095238095		
VAR3	86.285714286		

The second part of the output (Figure 23.187) shows the results of the optimization (complete subset sampling):

Figure 23.187 Subset Sampling and Optimal Subset

Subset	Singular	Best Criterion	Percent
1497	22	253.312431	25
2993	46	224.084073	50
4489	77	165.830053	75
5985	156	165.634363	100
Observations of Best Subset			
7	10	14	20
Initial MVE Location Estimates			
VAR1	58.5		
VAR2	20.25		
VAR3	87		
Initial MVE Scatter Matrix			
	VAR1	VAR2	VAR3
VAR1	34.829014749	28.413143611	62.32560534
VAR2	28.413143611	38.036950318	58.659393261
VAR3	62.32560534	58.659393261	267.63348175

The third part of the output (Figure 23.188) shows the optimization results after local improvement:

Figure 23.188 Robust Estimates of Scatter and Location

Robust MVE Location Estimates			
	VAR1	56.705882353	
	VAR2	20.235294118	
	VAR3	85.529411765	
Robust MVE Scatter Matrix			
	VAR1	VAR2	VAR3
VAR1	23.470588235	7.5735294118	16.102941176
VAR2	7.5735294118	6.3161764706	5.3676470588
VAR3	16.102941176	5.3676470588	32.389705882
Eigenvalues of Robust Scatter Matrix			
	VAR1	46.597431018	
	VAR2	12.155938483	
	VAR3	3.423101087	
Robust Correlation Matrix			
	VAR1	VAR2	VAR3
VAR1	1	0.6220269501	0.5840361335
VAR2	0.6220269501	1	0.375278187
VAR3	0.5840361335	0.375278187	1

The final output (Figure 23.189) presents a table that contains the classical Mahalanobis distances, the robust distances, and the weights that identify the outlying observations (that is leverage points when explaining y with these three regressor variables):

Figure 23.189 Distances and Weights

Classical Distances and Robust (Rousseeuw) Distances Unsquared Mahalanobis Distance and Unsquared Rousseeuw Distance of Each Observation			
N	Mahalanobis Distances	Robust Distances	Weight
1	2.253603	5.528395	0
2	2.324745	5.637357	0
3	1.593712	4.197235	0
4	1.271898	1.588734	1.000000
5	0.303357	1.189335	1.000000
6	0.772895	1.308038	1.000000
7	1.852661	1.715924	1.000000
8	1.852661	1.715924	1.000000
9	1.360622	1.226680	1.000000
10	1.745997	1.936256	1.000000
11	1.465702	1.493509	1.000000
12	1.841504	1.913079	1.000000
13	1.482649	1.659943	1.000000
14	1.778785	1.689210	1.000000
15	1.690241	2.230109	1.000000
16	1.291934	1.767582	1.000000
17	2.700016	2.431021	1.000000
18	1.503155	1.523316	1.000000
19	1.593221	1.710165	1.000000
20	0.807054	0.675124	1.000000
21	2.176761	3.657281	0
	MinRes	1st Qu.	Median
	0.6751244996	1.5084120761	1.7159242054
	Mean	3rd Qu.	MaxRes
	2.2282960174	2.0831826658	5.6373573538

NAME Function

NAME(arguments);

The NAME function returns the names of the arguments in a column vector. The *arguments* parameter specifies the names of existing matrices.

In the following example, **N** is a 3×1 character matrix that contains the character values 'A', 'B', and 'C':

```
Seq = 1:3;
Const = -1;
N = name(Seq, Const);
do i = 1 to nrow(N);
    msg = "Values of Matrix " + N[i];
    x = value(N[i]);
```

```
print x[label=msg];
end;
```

Figure 23.190 Matrix Names

Values of Matrix Seq		
1	2	3
Values of Matrix Const		
		-1

A primary use of the NAME function is in writing macros in which you want to use an argument for both its name and its value.

NCOL Function

```
NCOL(matrix);
```

The NCOL function returns the number of columns in its matrix argument. If the matrix has not been given a value, the NCOL function returns a value of 0.

For example, following statements display the number of columns of the matrix **m**:

```
m = {1 2 3, 4 5 6, 3 2 1, 4 3 2, 5 4 3};
p = ncol(m);
print p;
```

Figure 23.191 Number of Columns in a Matrix

p
3

NLENG Function

```
NLENG(matrix);
```

The NLENG function returns a single numeric value that is the size in bytes of each element in *matrix*. All matrix elements have the same size. For English text, this size is also the number of characters that can be stored in a matrix element.

If the matrix does not have a value, then the NLENG function returns a value of 0. This function is different from the **LENGTH** function, which returns the size of each element of a character matrix, omitting the trailing blanks.

The following statements demonstrate the NLENG function:

```
m = {"ab " "ijklm ",
      "x"  " "      };
len = nlen(m);
print len;
```

Figure 23.192 Number of Bytes in Each Matrix Element

len
7

Nonlinear Optimization and Related Subroutines

The following list shows the syntax for nonlinear optimization subroutines. Subsequent sections describe each subroutine in detail.

- conjugate gradient optimization method:
CALL NLP CG(*rc*, *xr*, "fun", *x0* < , *opt* < , *bic* < , *tc* < , *par* < , "ptit" < , "grd" >);
- double-dogleg optimization method:
CALL NLP DD(*rc*, *xr*, "fun", *x0* < , *opt* < , *bic* < , *tc* < , *par* < , "ptit" < , "grd" >);
- Nelder-Mead simplex optimization method:
CALL NLP NMS(*rc*, *xr*, "fun", *x0* < , *opt* < , *bic* < , *tc* < , *par* < , "ptit" < , "nlc" >);
- Newton-Raphson optimization method:
CALL NLP NRA(*rc*, *xr*, "fun", *x0* < , *opt* < , *bic* < , *tc* < , *par* < , "ptit" > , < , "grd" > < , "hes" >);
- Newton-Raphson ridge optimization method:
CALL NLP NRR(*rc*, *xr*, "fun", *x0* < , *opt* < , *bic* < , *tc* < , *par* < , "ptit" > < , "grd" > < , "hes" >);
- (dual) quasi-Newton optimization method:
CALL NLP QN(*rc*, *xr*, "fun", *x0* < , *opt* < , *bic* < , *tc* < , *par* < , "ptit" > < , "grd" > < , "nlc" > < , "jacnlc" >);
- quadratic optimization method:
CALL NLP QUA(*rc*, *xr*, *quad*, *x0* < , *opt* < , *bic* < , *tc* < , *par* < , "ptit" > < , *lin* >);
- trust-region optimization method:
CALL NLP TR(*rc*, *xr*, "fun", *x0* < , *opt* < , *bic* < , *tc* < , *par* < , "ptit" > < , "grd" > < , "hes" >);

The following list shows the syntax for optimization subroutines that use least squares methods. Subsequent sections describe each subroutine in detail.

- hybrid quasi-Newton least squares methods:

CALL NLPHQN(*rc*, *xr*, "fun", *x0*, *opt* < , *blc* > < , *tc* > < , *par* > < , "ptit" > < , "jac" >);

- Levenberg-Marquardt least squares method:

CALL NLPLM(*rc*, *xr*, "fun", *x0*, *opt* < , *blc* > < , *tc* > < , *par* > < , "ptit" > < , "jac" >);

The following list shows the syntax for supplementary subroutines that are often used in conjunction with optimization subroutines. Subsequent sections describe each subroutine in detail.

- approximate derivatives by finite differences:

CALL NLPFDD(*f*, *g*, *h*, "fun", *x0* < , *par* > < , "grd" >);

- feasible point subject to constraints:

CALL NLPFEA(*xr*, *x0*, *blc* < , *par* >);

NOTE: The names of the optional arguments can be used as keywords. For example, the following statements are equivalent:

```
call nlpnrr(rc,xr,"fun",x0,,ter,, "grad");
call nlpnrr(rc,xr,"fun",x0) tc=ter grd="grad";
```

All the optimization subroutines require at least two input arguments:

- The **NLPQUA** subroutine requires the *quad* matrix argument, which specifies the symmetric matrix **G** of the quadratic problem. The input can be dense or sparse.
- Other optimization subroutines require the "fun" argument, which specifies a module that defines the objective function or functions. For least squares subroutines, the FUN module must return a column vector of length *m* that corresponds to the values of the *m* functions $f_1(x), \dots, f_m(x)$, each evaluated at the point $x = (x_1, \dots, x_n)$. For other subroutines, the FUN module must return the value of the objective function $f = f(x)$ evaluated at the point *x*.
- The argument *x0* specifies a row vector that defines the number of parameters *n*. If *x0* is a feasible point, it represents a starting point for the iterative optimization process. Otherwise, a linear programming algorithm is called at the start of each optimization subroutine to replace the input *x0* by a feasible starting point.

The other arguments that can be used as input are described in the following list. As indicated in the previous lists, not all input arguments apply to each subroutine.

Note that you can specify optional arguments with the *keyword=argument* syntax.

The following list describes each argument:

opt indicates an options vector that specifies details of the optimization process, such as particular updating techniques and whether the objective function is to be maximized instead of minimized. See the section "Options Vector" on page 356 for details.

<i>bic</i>	specifies a constraint matrix that defines lower and upper bounds for the n parameters in addition to general linear equality and inequality constraints. For details, see the section “ Parameter Constraints ” on page 354.
<i>tc</i>	specifies a vector of thresholds that correspond to the termination criteria tested in each iteration. See the section “ Termination Criteria ” on page 360 for details.
<i>par</i>	specifies a vector of control parameters that can be used to modify the algorithms if the default settings do not complete the optimization process successfully. For details, see the section “ Control Parameters Vector ” on page 367.
<i>“ptit”</i>	specifies a module that replaces the subroutine used to print the iteration history and test the termination criteria. If the <i>“ptit”</i> module is specified, the matrix specified by the <i>tc</i> argument has no effect. See the section “ Termination Criteria ” on page 360 for details.
<i>“grd”</i>	specifies a module that computes the gradient vector, $g = \nabla f$, at a given input point x . See the section “ Objective Function and Derivatives ” on page 347 for details.
<i>“hes”</i>	specifies a module that computes the $n \times n$ Hessian matrix, $G = \nabla^2 f$, at a given input point x . See the section “ Objective Function and Derivatives ” on page 347 for details.
<i>“jac”</i>	specifies a module that computes the $m \times n$ Jacobian matrix, $J = (\nabla f_i)$, of the m least squares functions at a given input point x . See the section “ Objective Function and Derivatives ” on page 347 for details.
<i>“nlc”</i>	specifies a module that computes general equality and inequality constraints. This is the method by which nonlinear constraints must be specified. For details, see the section “ Parameter Constraints ” on page 354.
<i>“jacnlc”</i>	specifies a module that computes the Jacobian matrix of first-order derivatives of the equality and inequality constraints specified by the NLC module. For details, see the section “ Parameter Constraints ” on page 354.
<i>lin</i>	specifies the linear part of the quadratic optimization problem. See the section “ NLPQUA Call ” on page 851 for details.

The modules that can be used as input arguments for the subroutines (*“fun,” “grd,” “hes,” “jac,” “ptit,” “nlc,”* and *“jacnlc”*) accept only a single input parameter $x = (x_1, \dots, x_n)$. You can provide more input parameters for these modules by using the GLOBAL clause. See the section “[Using the GLOBAL Clause](#)” on page 77 for an example.

All the optimization subroutines return the following results:

- The scalar return code *rc* indicates the reason for the termination of the optimization process. A return code $rc > 0$ indicates a successful termination that corresponds to one of the specified termination criteria. A return code $rc < 0$ indicates unsuccessful termination—that is, that the result *xr* is unreliable. See the section “[Definition of Return Codes](#)” on page 346 for more details.
- The row vector *xr*, which has length n , contains the optimal point when $rc > 0$.

NLPCG Call

CALL NLPCG(*rc*, *xr*, "fun", *x0* < , *opt* > < , *bic* > < , *tc* > < , *par* > < , "ptit" > < , "grd" >);

The NLPCG subroutine uses the conjugate gradient method to solve a nonlinear optimization problem.

See the section “[Nonlinear Optimization and Related Subroutines](#)” on page 823 for a listing of all NLP subroutines. See [Chapter 14](#) for a description of the arguments of NLP subroutines.

The NLPCG subroutine requires function and gradient calls; it does not need second-order derivatives. The gradient vector contains the first derivatives of the objective function f with respect to the parameters x_1, \dots, x_n , as follows:

$$g(x) = \nabla f(x) = \left(\frac{\partial f}{\partial x_j} \right)$$

If you do not specify a module with the “*grd*” argument, the first-order derivatives are approximated by finite difference formulas by using only function calls. The NLPCG algorithm can require many function and gradient calls, but it requires less memory than other subroutines for unconstrained optimization. In general, many iterations are needed to obtain a precise solution, but each iteration is computationally inexpensive. You can specify one of four update formulas for generating the conjugate directions with the fourth element of the *opt* input argument.

Value of <i>opt</i> [4]	Update Method
1	Automatic restart method of Powell (1977) and Beale (1972). This is the default.
2	Fletcher-Reeves update (Fletcher 1987)
3	Polak-Ribiere update (Fletcher 1987)
4	Conjugate-descent update of Fletcher (1987)

The NLPCG subroutine is useful for optimization problems with large n . For the unconstrained or boundary-constrained case, the NLPCG method requires less memory than other optimization methods. (The NLPCG method allocates memory proportional to n , whereas other methods allocate memory proportional to n^2 .) During n successive iterations, uninterrupted by restarts or changes in the working set, the conjugate gradient algorithm computes a cycle of n conjugate search directions. In each iteration, a line search is done along the search direction to find an approximate optimum of the objective function. The default line-search method uses quadratic interpolation and cubic extrapolation to obtain a step size α that satisfies the Goldstein conditions. One of the Goldstein conditions can be violated if the feasible region defines an upper limit for the step size. You can specify other line-search algorithms with the fifth element of the *opt* argument.

For an example of the NLPCG subroutine, see the section “[Constrained Betts Function](#)” on page 341.

NLPDD Call

CALL NLPDD(*rc*, *xr*, "fun", *x0* < , *opt* > < , *bic* > < , *tc* > < , *par* > < , "ptit" > < , "grd" >);

The NLPDD subroutine uses the double-dogleg method to solve a nonlinear optimization problem.

See the section “[Nonlinear Optimization and Related Subroutines](#)” on page 823 for a listing of all NLP subroutines. See [Chapter 14](#) for a description of the arguments of NLP subroutines.

The double-dogleg optimization method combines the ideas of the quasi-Newton and trust-region methods. In each iteration, the algorithm computes the step, $s^{(k)}$, as a linear combination of the steepest descent or ascent search direction, $s_1^{(k)}$, and a quasi-Newton search direction, $s_2^{(k)}$, as follows:

$$s^{(k)} = \alpha_1 s_1^{(k)} + \alpha_2 s_2^{(k)}$$

The step $s^{(k)}$ must remain within a specified trust-region radius (Fletcher 1987). Hence, the NLPDD subroutine uses the dual quasi-Newton update but does not perform a line search. You can specify one of two update formulas with the fourth element of the *opt* input argument.

Value of <i>opt</i> [4]	Update Method
1	Dual BFGS update of the Cholesky factor of the Hessian matrix. This is the default.
2	Dual DFP update of the Cholesky factor of the Hessian matrix.

The double-dogleg optimization technique works well for medium to moderately large optimization problems, in which the objective function and the gradient are much faster to compute than the Hessian. The implementation is based on Dennis and Mei (1979) and Gay (1983), but it is extended for boundary and linear constraints. The NLPDD subroutine generally needs more iterations than the techniques that require second-order derivatives ([NLPTR](#), [NLPNRA](#), and [NLPNRR](#)), but each of the NLPDD iterations is computationally inexpensive. Furthermore, the NLPDD subroutine needs only gradient calls to update the Cholesky factor of an approximate Hessian.

In addition to the standard iteration history, the NLPDD routine prints the following information:

- The heading *lambda* refers to the parameter λ of the double-dogleg step. A value of 0 corresponds to the full (quasi-) Newton step.
- The heading *slope* refers to $g^T s$, the slope of the search direction at the current parameter iterate $x^{(k)}$. For minimization, this value should be significantly smaller than zero.

The following statements invoke the NLPDD subroutine to solve the constrained Betts optimization problem (see the section “[Constrained Betts Function](#)” on page 341):

```
start F_BETTS(x);
    f = .01 * x[1] * x[1] + x[2] * x[2] - 100;
    return(f);
finish F_BETTS;

con = {  2 -50   .   .,
        50  50   .   .,
        10 -1   1  10};
x = {-1 -1};
opt = {0 1};
call nlpdd(rc, xres, "F_BETTS", x, opt, con);
```

[Figure 23.193](#) shows the iteration history. The optimization converged after six iterations.

Figure 23.193 Constrained Optimization

```

NOTE: Initial point was changed to be feasible for boundary and linear
      constraints.

      Double Dogleg Optimization

      Dual Broyden - Fletcher - Goldfarb - Shanno Update (DBFGS)

      Without Parameter Scaling
      Gradient Computed by Finite Differences

      Parameter Estimates          2
      Lower Bounds                 2
      Upper Bounds                 2
      Linear Constraints            1

      Optimization Start

Active Constraints          0  Objective Function          -98.5376
Max Abs Gradient Element  2  Radius                      1

      Iter      Rest      Func      Act      Objective  Obj Fun Gradient  Max Abs      Slope
      arts      Calls      Con      Function  Change  Element  Lambda      Search
      1         0         2         0      -99.54678   1.0092   0.1346   6.012   -1.805
      2         0         3         0      -99.59120   0.0444   0.1279    0   -0.0228
      3         0         5         0      -99.90252   0.3113   0.0624    0   -0.209
      4         0         6         1      -99.96000   0.0575   0.00432   0   -0.0975
      5         0         7         1      -99.96000   4.66E-6  0.000079   0  -458E-8
      6         0         8         1      -99.96000  1.559E-9    0    0  -16E-10

      Optimization Results

Iterations          6  Function Calls          9
Gradient Calls      8  Active Constraints       1
Objective Function  -99.96  Max Abs Gradient Element  0
Slope of Search Direction  -1.56621E-9  Radius          1

GCONV convergence criterion satisfied.

```

The optimal value for the function is returned in the **xres** vector, which is displayed in [Figure 23.194](#).

Figure 23.194 The Optimal Value

```

      xres

      2 -9.612E-8

```

NLPFDD Call

CALL NLPFDD(*f*, *g*, *h*, "fun", *x0*, <, *par*> <, "grd">);

The NLPFDD subroutine uses the finite-differences method to approximate derivatives.

See the section “[Nonlinear Optimization and Related Subroutines](#)” on page 823 for a listing of all NLP subroutines. See [Chapter 14](#) for a description of the arguments of NLP subroutines.

The NLPFDD subroutine can be used for the following tasks:

- If the module “*fun*” returns a scalar, the NLPFDD subroutine computes the function value *f*, the gradient vector *g*, and the Hessian matrix *h*, all evaluated at the point *x0*.
- If the module “*fun*” returns a column vector of *m* function values, the subroutine assumes that a least squares function is specified, and it computes the function vector *f*, the Jacobian matrix **J**, and the crossproduct of the Jacobian matrix **J’J** at the point *x0*. In this case, you must set the first element of the *par* argument to *m*.

If any of the results cannot be computed, the subroutine returns a missing value for that result.

You can specify the following input arguments with the NLPFDD subroutine:

- The “*fun*” argument refers to a module that returns either a scalar value or a column vector of length *m*. This module returns the value of the objective function or, for least squares problems, the values of the *m* functions that the objective function comprises.
- The *x0* argument is a vector of length *n* that defines the point at which the functions and derivatives should be computed.
- The *par* argument is a vector that defines options and control parameters. The *par* argument in the NLPFDD call is different from the one used in the optimization subroutines.
- The “*grd*” argument is optional and refers to a module that returns a vector that defines the gradient of the function at *x0*. If the “*fun*” argument returns a vector of values instead of a scalar, the “*grd*” argument is ignored.

If the “*fun*” module returns a scalar, the subroutine returns the following values:

- *f* is the value of the function at the point *x0*.
- *g* is a vector that contains the value of the gradient at the point *x0*. If you specify the “*grd*” argument, the gradient is computed from that module. Otherwise, the approximate gradient is computed by a finite difference approximation by using calls of the function module in a neighborhood of *x0*.
- *h* is a matrix that contains a finite difference approximation of the value of the Hessian at the point *x0*. If you specify the “*grd*” argument, the Hessian is computed by calls of that module in a neighborhood of *x0*. Otherwise, it is computed by calls of the function module in a neighborhood of *x0*.

If the “*fun*” module returns a vector, the subroutine returns the following values:

- f is a vector that contains the values of the m functions that comprise objective function at the point $x0$.
- g is the $m \times n$ Jacobian matrix \mathbf{J} , which contains the first-order derivatives of the functions with respect to the parameters, evaluated at $x0$. It is computed by finite difference approximations in a neighborhood of $x0$.
- h is the $n \times n$ crossproduct of the Jacobian matrix, $\mathbf{J}^T \mathbf{J}$. It is computed by finite difference approximations in a neighborhood of $x0$.

The *par* argument is a vector of length 3.

- *par*[1] corresponds to the *opt*[1] argument in the optimization subroutines. This argument is relevant only to least squares optimization methods, in which case it specifies the number of functions returned by the module “*fun*”. If *par*[1] is missing or is smaller than 1, it is set to 1.
- *par*[2] corresponds to the *opt*[8] argument in the optimization subroutines. It determines what type of approximation is to be used and how the finite difference interval, h , is to be computed. See the section “[Finite-Difference Approximations of Derivatives](#)” on page 352 for details.
- *par*[3] corresponds to the *par*[8] argument in the optimization subroutines. It specifies the number of accurate digits in evaluating the objective function. The default is $-\log_{10}(\epsilon)$, where ϵ is the machine precision.

If you specify a missing value in the *par* argument, the default value is used.

The NLPFDD subroutine is particularly useful for checking your analytical derivative specifications of the “*grd*”, “*hes*”, and “*jac*” modules. You can compare the results of the modules with the finite difference approximations of the derivatives of f at the point $x0$ to verify your specifications.

In the unconstrained Rosenbrock problem (see the section “[Unconstrained Rosenbrock Function](#)” on page 337), the objective function is

$$f(x) = 50(x_2 - x_1^2)^2 + \frac{1}{2}(1 - x_1)^2$$

The gradient and the Hessian are

$$g'(x, y) = \begin{bmatrix} \frac{\partial f}{\partial x_1} \\ \frac{\partial f}{\partial x_2} \end{bmatrix} = \begin{bmatrix} 200x_1^3 - 200x_1x_2 + x_1 - 1 \\ -100x_1^2 + 100x_2 \end{bmatrix}$$

$$\mathbf{H}(x, y) = \begin{bmatrix} \frac{\partial^2 f}{\partial x_1^2} & \frac{\partial^2 f}{\partial x_1 \partial x_2} \\ \frac{\partial^2 f}{\partial x_2 \partial x_1} & \frac{\partial^2 f}{\partial x_2^2} \end{bmatrix} = \begin{bmatrix} 600x_1^2 - 200x_2 + 1 & -200x_1 \\ -200x_1 & 100 \end{bmatrix}$$

At the point $x = (2, 7)$, these matrices evaluate to

$$g'(2, 7) = \begin{bmatrix} -1199 \\ 300 \end{bmatrix}$$

$$\mathbf{H}(2, 7) = \begin{bmatrix} 1001 & -400 \\ -400 & 100 \end{bmatrix}$$

The following statements define the Rosenbrock function and use the NLPFDD call to compute the gradient and the Hessian:

```
start F_ROSEN(x);
  y1 = 10 * (x[2] - x[1] * x[1]);
  y2 = 1 - x[1];
  f = 0.5 * (y1 * y1 + y2 * y2);
  return(f);
finish F_ROSEN;
x = {2 7};
call nlpfdd(crit, grad, hess, "F_ROSEN", x);
print grad;
print hess;
```

Figure 23.195 Gradient and Hessian at a Point

grad	
-1199	300.00001
hess	
1000.9998	-400.0018
-400.0018	99.999993

If the Rosenbrock problem is considered from a least squares perspective, the two functions are

$$f_1(x) = 10(x_2 - x_1^2)$$

$$f_2(x) = 1 - x_1$$

The Jacobian and the crossproduct of the Jacobian are

$$\mathbf{J} = \begin{bmatrix} \frac{\partial f_1}{\partial x_1} & \frac{\partial f_1}{\partial x_2} \\ \frac{\partial f_2}{\partial x_1} & \frac{\partial f_2}{\partial x_2} \end{bmatrix} = \begin{bmatrix} -20x_1 & 10 \\ -1 & 0 \end{bmatrix}$$

$$\mathbf{J}^T \mathbf{J} = \begin{bmatrix} 400x_1^2 + 1 & -200x_1 \\ -200x_1 & 100 \end{bmatrix}$$

At the point $x = (2, 7)$, these matrices evaluate to

$$\mathbf{J}(2, 7) = \begin{bmatrix} -40 & 10 \\ -1 & 0 \end{bmatrix}$$

$$\mathbf{J}^T \mathbf{J}|_{(2,7)} = \begin{bmatrix} 1601 & -400 \\ -400 & 100 \end{bmatrix}$$

The following statements define the Rosenbrock problem in a least squares framework and use the NLPFDD call to compute the Jacobian and the crossproduct matrix. Since the value of the PARMs variable, which is used for the *par* argument, is 2, the NLPFDD subroutine allocates memory for a least squares problem with two functions, $f_1(x)$ and $f_2(x)$.

```
start F_ROSEN(x);
  y = j(2, 1, 0);
  y[1] = 10 * (x[2] - x[1] * x[1]);
  y[2] = 1 - x[1];
  return(y);
finish F_ROSEN;
x      = {2 7};
parms = 2;
call nlpfdd(fun, jac, crpj, "F_ROSEN", x, parms);
print jac;
print crpj;
```

Figure 23.196 Jacobian and Crossproduct Matrix at a Point

jac	
-40	10
-1	0
crpj	
1601	-400
-400	100

NLPFEA Call

CALL NLPFEA(*xr*, *x0*, *btc* < , *par* >);

The NLPFEA subroutine computes feasible points subject to constraints.

See the section “[Nonlinear Optimization and Related Subroutines](#)” on page 823 for a listing of all NLP subroutines. See [Chapter 14](#) for a description of the arguments of NLP subroutines.

The NLPFEA subroutine tries to compute a point that is feasible subject to a set of boundary and linear constraints. You can specify boundary and linear constraints that define an empty feasible region, in which

case the subroutine returns missing values.

You can specify the following input arguments with the NLPFEA subroutine:

- *x0* is a row vector that defines the coordinates of a point that is not necessarily feasible for a set of linear and boundary constraints.
- *b1c* is an $m \times n$ matrix that defines a set of m boundary and linear constraints. See the section “[Parameter Constraints](#)” on page 354 for details.
- *par* is a vector of length two. The argument is different from the one used in the optimization subroutines. The first element sets the LCEPS parameter, which controls how precisely the returned point must satisfy the constraints. The second element sets the LCSING parameter, which specifies the criterion for deciding when constraints are considered linearly dependent. For details, see the section “[Control Parameters Vector](#)” on page 367.

The NLPFEA subroutine returns the *xr* argument. The result is a vector that contains either the n coordinates of a feasible point, which indicates that the subroutine was successful, or missing values, which indicates that the subroutine could not find a feasible point.

The following statements call the NLPFEA subroutine with the constraints from the Betts problem (see the section “[Constrained Betts Function](#)” on page 341) and an initial infeasible point $x_0 = (-17, -61)$. The subroutine returns the feasible point $(2, -50)$ as the vector XFEAS.

```
con = {  2 -50  .  . ,
        50  50  .  . ,
        10 -1  1  10};
x = {-17. -61};
call nlpfea(xfeas, x, con);
print xfeas;
```

Figure 23.197 Feasible Point

xfeas	
6.8	-40

NLPHQN Call

CALL NLPHQN(*rc*, *xr*, “*fun*”, *x0* < , *opt* < , *b1c* < , *tc* < , *par* < , “*ptit*” < , “*jac*” >);

The NLPHQN subroutine uses a hybrid quasi-Newton least squares method to compute an optimum value of a function.

See the section “[Nonlinear Optimization and Related Subroutines](#)” on page 823 for a listing of all NLP subroutines. See [Chapter 14](#) for a description of the arguments of NLP subroutines.

The NLPHQN subroutine uses one of the Fletcher and Xu (1987) hybrid quasi-Newton methods. Refer also

to Al-Baali and Fletcher (1985) and Al-Baali and Fletcher (1986). In each iteration, the subroutine uses a criterion to decide whether a Gauss-Newton or a dual quasi-Newton search direction is appropriate. You can choose one of three criteria (HY1, HY2, or HY3) proposed by Fletcher and Xu (1987) with the sixth element of the *opt* vector. The default is HY2. The subroutine computes the crossproduct Jacobian (for the Gauss-Newton step), updates the Cholesky factor of an approximate Hessian (for the quasi-Newton step), and performs a line search to compute an approximate minimum along the search direction. The default line-search technique used by the NLPHQN method is designed for least squares problems ((Lindström and Wedin 1984) and (Al-Baali and Fletcher 1986)), but you can specify a different line-search algorithm with the fifth element of the *opt* argument. See the section “Options Vector” on page 356 for details.

You can specify two update formulas with the fourth element of the *opt* argument as indicated in the following table.

Value of <i>opt</i> [4]	Update Method
1	Dual Broyden, Fletcher, Goldfarb, and Shanno (DBFGS) update of the Cholesky factor of the Hessian matrix. This is the default.
2	Dual Davidon, Fletcher, and Powell (DDFP) update of the Cholesky factor of the Hessian matrix.

The NLPHQN subroutine needs approximately the same amount of working memory as the [NLPLM subroutine](#), and in most applications, the latter seems to be superior. Hence, the NLPHQN method is recommended only when the [NLPLM method](#) encounters problems.

NOTE: In least squares subroutines, you must set the first element of the *opt* vector to *m*, the number of functions.

In addition to the standard iteration history, the NLPHQN subroutine prints the following information:

- Under the heading *Iter*, an asterisk (*) printed after the iteration number indicates that, on the basis of the Fletcher and Xu (1987) criterion, the subroutine used a Gauss-Newton search direction instead of a quasi-Newton search direction.
- The heading *alpha* is the step size, α , computed with the line-search algorithm.
- The heading *slope* refers to $g^T s$, the slope of the search direction at the current parameter iterate $x^{(k)}$. For minimization, this value should be significantly smaller than zero. Otherwise, the line-search algorithm has difficulty reducing the function value sufficiently.

The following statements use the NLPHQN call to solve the unconstrained Rosenbrock problem (see the section “[Unconstrained Rosenbrock Function](#)” on page 337).

```

title "Test of NLPHQN subroutine: No Derivatives";
start F_ROSEN(x);
  y = j(1, 2, 0);
  y[1] = 10 * (x[2] - x[1] * x[1]);
  y[2] = 1 - x[1];
  return(y);
finish F_ROSEN;

x = {-1.2 1};
opt = {2 2};
call nlphqn(rc, xr, "F_ROSEN", x, opt);

```

Figure 23.198 Optimization Results

Test of NLPHQN subroutine: No Derivatives		
Optimization Start		
Parameter Estimates		
		Gradient
		Objective
N Parameter	Estimate	Function
1 X1	-1.200000	-107.799999
2 X2	1.000000	-44.000000
Value of Objective Function = 12.1		
Test of NLPHQN subroutine: No Derivatives		
Hybrid Quasi-Newton LS Minimization		
Dual Broyden - Fletcher - Goldfarb - Shanno Update (DBFGS)		
Version HY2 of Fletcher & Xu (1987)		
Gradient Computed by Finite Differences		
CRP Jacobian Computed by Finite Differences		
Parameter Estimates	2	
Functions (Observations)	2	
Optimization Start		
Active Constraints	0	Objective Function
Max Abs Gradient Element	107.7999987	12.1

Figure 23.198 continued

ABSGCONV convergence criterion satisfied.		
Test of NLPQN subroutine: No Derivatives		
Optimization Results		
Parameter Estimates		
		Gradient
		Objective
N Parameter	Estimate	Function
1 X1	1.000000	1.816858E-10
2 X2	1.000000	-1.22069E-10
Value of Objective Function = 2.024647E-21		

NLPLM Call

CALL NLPLM(*rc*, *xr*, "fun", *x0*, *opt* < , *bic* > < , *tc* > < , *par* > < , "ptit" > < , "jac" >);

The NLPLM subroutine uses the Levenberg-Marquardt least squares method to compute an optimum value of a function.

See the section “Nonlinear Optimization and Related Subroutines” on page 823 for a listing of all NLP subroutines. See Chapter 14 for a description of the arguments of NLP subroutines.

The NLPLM subroutine uses the Levenberg-Marquardt method, which is an efficient modification of the trust-region method for nonlinear least squares problems and is implemented as in Moré (1978). This is the recommended algorithm for small to medium least squares problems. Large least squares problems can often be processed more efficiently with other subroutines, such as the NLPCG and NLPQN methods. In each iteration, the NLPLM subroutine solves a quadratically constrained quadratic minimization problem that restricts the step to the boundary or interior of an n -dimensional elliptical trust region.

The m functions $f_1(x), \dots, f_m(x)$ are computed by the module specified with the “fun” module argument. The $m \times n$ Jacobian matrix, **J**, contains the first-order derivatives of the m functions with respect to the n parameters, as follows:

$$\mathbf{J}(x) = (\nabla f_1, \dots, \nabla f_m) = \left(\frac{\partial f_i}{\partial x_j} \right)$$

You can specify **J** with the “jac” module argument; otherwise, the subroutine computes it with finite difference approximations. In each iteration, the subroutine computes the crossproduct of the Jacobian matrix, $\mathbf{J}^T \mathbf{J}$, to be used as an approximate Hessian.

NOTE: In least squares subroutines, you must set the first element of the *opt* vector to m , the number of functions.

In addition to the standard iteration history, the NLPLM subroutine also prints the following information:

- Under the heading *Iter*, an asterisk (*) printed after the iteration number indicates that the computed Hessian approximation was singular and had to be ridged with a positive value.
- The heading *lambda* represents the Lagrange multiplier, λ . This has a value of zero when the optimum of the quadratic function approximation is inside the trust region, in which case a trust-region-scaled Newton step is performed. It is greater than zero when the optimum is at the boundary of the trust region, in which case the scaled Newton step is too long to fit in the trust region and a quadratically constrained optimization is done. Large values indicate optimization difficulties, and as in Gay (1983), a negative value indicates the special case of an indefinite Hessian matrix.
- The heading *rho* refers to ρ , the ratio between the achieved and predicted difference in function values. Values that are much smaller than 1 indicate optimization difficulties. Values close to or larger than 1 indicate that the trust region radius can be increased.

See the section “[Unconstrained Rosenbrock Function](#)” on page 337 for an example that uses the NLPLM subroutine to solve the unconstrained Rosenbrock problem.

NLPNMS Call

CALL NLPNMS(*rc*, *xr*, “*fun*”, *x0* < , *opt* > < , *bic* > < , *tc* > < , *par* > < , “*ptit*” > < , “*nlc*” >);

The NLPNMS subroutine use the Nelder-Mead simplex method to compute an optimum value of a function.

See the section “[Nonlinear Optimization and Related Subroutines](#)” on page 823 for a listing of all NLP subroutines. See [Chapter 14](#) for a description of the arguments of NLP subroutines.

The Nelder-Mead simplex method is one of the subroutines that can solve optimization problems with nonlinear constraints. It does not use any derivatives, and it does not assume that the objective function has continuous derivatives. However, the objective function must be continuous. The NLPNMS technique uses a large number of function calls, and it can be unable to generate precise results when $n > 40$.

The NLPNMS subroutine uses the following simplex algorithms:

- For unconstrained or only boundary-constrained problems, the original Nelder-Mead simplex algorithm is implemented and extended to boundary constraints. This algorithm does not compute the objective for infeasible points, and it is invoked if the “*nlc*” module argument is not specified and the *bic* argument contains at most two rows (corresponding to lower and upper bounds).
- For linearly or nonlinearly constrained problems, a slightly modified version of Powell’s (1992) constrained optimization by linear approximations (COBYLA) implementation is used. This algorithm is invoked if the “*nlc*” module argument is specified or if at least one linear constraint is specified with the *bic* argument.

The original Nelder-Mead algorithm cannot be used for general linear or nonlinear constraints, but in the unconstrained or boundary-constrained cases, it can be faster. It changes the shape of the simplex by adapting the nonlinearities of the objective function; this contributes to an increased speed of convergence.

Powell's COBYLA Algorithm

Powell's COBYLA algorithm is a sequential trust-region algorithm that tries to maintain a regularly shaped simplex throughout the iterations. The algorithm uses a monotone-decreasing radius, ρ , of a spheric trust region. The modification implemented in the NLPNMS call permits an increase of the trust-region radius ρ in special situations. A sequence of iterations is performed with a constant trust-region radius ρ until the computed function reduction is much less than the predicted reduction. Then, the trust-region radius ρ is reduced. The trust-region radius is increased only if the computed function reduction is relatively close to the predicted reduction and if the simplex is well-shaped. The start radius, ρ_{beg} , can be specified with the second element of the *par* argument, and the final radius, ρ_{end} , can be specified with the ninth element of the *tc* argument. Convergence to small values of ρ_{end} , or high-precision convergence, can require many calls of the function and constraint modules and can result in numerical problems. The main reasons for the slow convergence of the COBYLA algorithm are as follows:

- Linear approximations of the objective and constraint functions are used locally.
- Maintaining the regularly shaped simplex and not adapting its shape to nonlinearities yields very small simplexes for highly nonlinear functions, such as fourth-order polynomials.

To allocate memory for the vector returned by the “*nlc*” module argument, you must specify the total number of nonlinear constraints with the tenth element of the *opt* argument. If any of the constraints are equality constraints, the number of equality constraints must be specified by the eleventh element of the *opt* argument. See the section “[Parameter Constraints](#)” on page 354 for details.

For more information about the special sets of termination criteria used by the NLPNMS algorithms, see the section “[Termination Criteria](#)” on page 360.

In addition to the standard iteration history, the NLPNMS subroutine prints the following information. For unconstrained or boundary-constrained problems, the subroutine also prints the following:

- *difcrit*, which, in this subroutine, refers to the difference between the largest and smallest function values of the $n + 1$ simplex vertices
- *std*, which is the standard deviation of the function values of the simplex vertices
- *deltax*, which is the vertex length of a restarted simplex. If there are convergence problems, the algorithm restarts the iteration process with a simplex of smaller vertex length.
- *size*, which is the average L_1 distance of the simplex vertex with the smallest function value to the other simplex vertices

For linearly and nonlinearly constrained problems, the subroutine prints the following:

- *conmax* is the maximum constraint violation.
- *meritf* is the value of the merit function, Φ .
- *difmerit* is the difference between adjacent values of the merit function.
- ρ is the trust-region radius.

The following statements use the NLPNMS call to solve the Rosen-Suzuki problem (see the section “Rosen-Suzuki Problem” on page 342), which has three nonlinear constraints. Figure 23.199 is a partial listing of the output:

```

start F_HS43(x);
  f = x*x` + x[3]*x[3] - 5*(x[1] + x[2]) - 21*x[3] + 7*x[4];
  return(f);
finish F_HS43;
start C_HS43(x);
  c = j(3,1,0.);
  c[1] = 8 - x*x` - x[1] + x[2] - x[3] + x[4];
  c[2] = 10 - x*x` - x[2]*x[2] - x[4]*x[4] + x[1] + x[4];
  c[3] = 5 - 2.*x[1]*x[1] - x[2]*x[2] - x[3]*x[3]
    - 2.*x[1] + x[2] + x[4];
  return(c);
finish C_HS43;

x = j(1, 4, 1);
opt = j(1, 11, .);
opt[2] = 3; opt[10] = 3; opt[11] = 0;
call nlpnms(rc, xres, "F_HS43", x, opt, , , , "C_HS43");

```

Figure 23.199 Nelder-Mead Simplex Optimization

Optimization Start		
Parameter Estimates		
N	Parameter	Estimate
1	X1	1.000000
2	X2	1.000000
3	X3	1.000000
4	X4	1.000000
Value of Objective Function = -19		
Values of Nonlinear Constraints		
Constraint		Residual
[1]	4.0000
[2]	6.0000
[3]	1.0000

Figure 23.199 *continued*

Nelder-Mead Simplex Optimization								
COBYLA Algorithm by M.J.D. Powell (1992)								
Minimum Iterations			0					
Maximum Iterations			1000					
Maximum Function Calls			3000					
Iterations Reducing Constraint Violation			0					
ABSFCNV Function Criterion			0					
FCONV Function Criterion			2.220446E-16					
FCONV2 Function Criterion			1E-6					
FSIZE Parameter			0					
ABSXCONV Parameter Change Criterion			0.0001					
XCONV Parameter Change Criterion			0					
XSIZE Parameter			0					
ABSCONV Function Criterion			-1.34078E154					
Initial Simplex Size (INSTEP)			0.5					
Singularity Tolerance (SINGULAR)			1E-8					
Nelder-Mead Simplex Optimization								
COBYLA Algorithm by M.J.D. Powell (1992)								
Parameter Estimates			4					
Nonlinear Constraints			3					
Optimization Start								
Objective Function			-29.5			Maximum Constraint Violation		4.5
								Ratio
								Between
								Actual
								and
								Predicted
								Change
Iter	Restarts	Function Calls	Objective Function	Maximum Constraint Violation	Merit Function	Merit Function Change		
1	0	12	-52.80342	4.3411	-42.3031	12.803		1.000
2	0	17	-39.51475	0.0227	-39.3797	-2.923		0.250
3	0	53	-44.02098	0.00949	-43.9727	4.593		0.0625
4	0	62	-44.00214	0.000833	-43.9977	0.0249		0.0156
5	0	72	-44.00009	0.000033	-43.9999	0.00226		0.0039
6	0	79	-44.00000	1.783E-6	-44.0000	0.00007		0.0010
7	0	90	-44.00000	1.363E-7	-44.0000	1.74E-6		0.0002
8	0	94	-44.00000	1.543E-8	-44.0000	5.33E-7		0.0001
Optimization Results								
Iterations			8	Function Calls			95	
Restarts			0	Objective Function			-44.00000003	
Maximum Constraint Violation			1.543059E-8	Merit Function			-43.99999999	
Actual Over Pred Change			0.0001					

Figure 23.199 *continued*

ABSXCONV convergence criterion satisfied.

WARNING: The point **x** is feasible only at the LCEPSILON= 1E-7 range.

Optimization Results	
Parameter Estimates	
N	Parameter Estimate
1	X1 -0.000034167
2	X2 1.000004
3	X3 2.000023
4	X4 -0.999971

Value of Objective Function = -44.00000003

Values of Nonlinear Constraints			
Constraint		Residual	
[1]	-1.54E-8	*?*
[2]	1.0000	
[3]	-1.5E-8	*?*

The 2 nonlinear constraints which are marked with *?* are not satisfied at the accuracy specified by the LCEPSILON= option. However, the default value of this option seems to be too strong to be applied to nonlinear constraints.

NLPNRA Call

CALL NLPNRA(*rc*, *xr*, "fun", *x0* < , *opt* < , *blc* < , *tc* < , *par* < , "ptit" < , "grd" < , "hes" >);

The NLPNRA subroutine uses the Newton-Raphson method to compute an optimum value of a function.

See the section “[Nonlinear Optimization and Related Subroutines](#)” on page 823 for a listing of all NLP subroutines. See [Chapter 14](#) for a description of the arguments of NLP subroutines.

The NLPNRA algorithm uses a pure Newton step at each iteration when both the Hessian is positive definite and the Newton step successfully reduces the value of the objective function. Otherwise, it performs a combination of ridging and line-search to compute successful steps. If the Hessian is not positive definite, a multiple of the identity matrix is added to the Hessian matrix to make it positive definite ((Eskow and Schnabel 1991)).

The subroutine uses the gradient $g^{(k)} = \nabla f(x^{(k)})$ and the Hessian matrix $G^{(k)} = \nabla^2 f(x^{(k)})$. It requires continuous first- and second-order derivatives of the objective function inside the feasible region. If second-

order derivatives are computed efficiently and precisely, the NLPNRA method does not need many function, gradient, and Hessian calls, and it can perform well for medium to large problems.

Using only function calls to compute finite difference approximations for second-order derivatives can be computationally very expensive and can contain significant rounding errors. If you use the “*grad*” input argument to specify a module that computes first-order derivatives analytically, you can reduce drastically the computation time for numerical second-order derivatives. The computation of the finite difference approximation for the Hessian matrix generally uses only n calls of the module that specifies the gradient.

In each iteration, a line search is done along the search direction to find an approximate optimum of the objective function. The default line-search method uses quadratic interpolation and cubic extrapolation. You can specify other line-search algorithms with the fifth element of the *opt* argument. See the section “Options Vector” on page 356 for details.

In unconstrained and boundary constrained cases, the NLPNRA algorithm can take advantage of diagonal or sparse Hessian matrices that are specified by the input argument “*hes*”. To use sparse Hessian storage, the value of the ninth element of the *opt* argument must specify the number of nonzero Hessian elements returned by the Hessian module. See the section “Objective Function and Derivatives” on page 347 for more details.

In addition to the standard iteration history, the NLPNRA subroutine prints the following information:

- The heading *alpha* is the step size, α , computed with the line-search algorithm.
- The heading *slope* refers to $g^T s$, the slope of the search direction at the current parameter iterate $x^{(k)}$. For minimization, this value should be significantly smaller than zero. Otherwise, the line-search algorithm has difficulty reducing the function value sufficiently.

The following statements invoke the NLPNRA subroutine to solve the constrained Betts optimization problem (see the section “Constrained Betts Function” on page 341). The iteration history follows.

```
start F_BETTS(x);
    f = .01 * x[1] * x[1] + x[2] * x[2] - 100;
    return(f);
finish F_BETTS;

con = {  2 -50  .  . ,
        50  50  .  . ,
        10 -1  1  10};
x = {-1 -1};
opt = {0 2};
call nlpnra(rc, xres, "F_BETTS", x, opt, con);
```

Figure 23.200 Newton-Raphson Optimization

NOTE: Initial point was changed to be feasible for boundary and linear constraints.

Figure 23.200 continued

Optimization Start								
Parameter Estimates								
N Parameter	Estimate	Gradient	Lower	Upper				
		Objective Function	Bound Constraint	Bound Constraint				
1 X1	6.800000	0.136000	2.000000	50.000000				
2 X2	-1.000000	-2.000000	-50.000000	50.000000				
Value of Objective Function = -98.5376								
Linear Constraints								
1	59.00000 :	10.0000	<= + 10.0000 * X1	- 1.0000 * X2				
Newton-Raphson Optimization with Line Search								
Without Parameter Scaling								
Gradient Computed by Finite Differences								
CRP Jacobian Computed by Finite Differences								
Parameter Estimates		2						
Lower Bounds		2						
Upper Bounds		2						
Linear Constraints		1						
Optimization Start								
Active Constraints		0	Objective Function	-98.5376				
Max Abs Gradient Element		2						
Iter	Rest arts	Func Calls	Act Con	Objective Function	Obj Fun Change	Max Abs Gradient Element	Step Size	Slope Search Direc
1	0	2	0	-98.81551	0.2779	1.8000	0.100	-2.925
2*	0	3	0	-99.40840	0.5929	1.2713	0.294	-2.365
3*	0	4	1	-99.87460	0.4662	0.5845	0.540	-1.182
4	0	5	1	-99.96000	0.0854	0.000025	1.000	-0.171
5	0	6	1	-99.96000	1.54E-10	0	1.000	-31E-11
Optimization Results								
Iterations		5	Function Calls	7				
Hessian Calls		6	Active Constraints	1				
Objective Function		-99.96	Max Abs Gradient Element	0				
Slope of Search Direction		-3.07388E-10	Ridge	0				
GCONV convergence criterion satisfied.								

Figure 23.200 continued

Optimization Results			
Parameter Estimates			
N Parameter	Estimate	Gradient Objective Function	Active Bound Constraint
1 X1	2.000000	0.040000	Lower BC
2 X2	-4.860653E-9	0	
Value of Objective Function = -99.96			
Linear Constraints Evaluated at Solution			
1	10.00000	= -10.0000 + 10.0000 * X1	- 1.0000 * X2

NLPNRR Call

CALL NLPNRR(*rc*, *xr*, "fun", *x0* < , *opt* < , *blc* < , *tc* < , *par* < , "ptit" < , "grd" < , "hes" >);

The NLPNRR subroutine uses a Newton-Raphson ridge method to compute an optimum value of a function.

See the section “Nonlinear Optimization and Related Subroutines” on page 823 for a listing of all NLP subroutines. See Chapter 14 for a description of the arguments of NLP subroutines.

The NLPNRR algorithm uses a pure Newton step when both the Hessian is positive definite and the Newton step successfully reduces the value of the objective function. Otherwise, a multiple of the identity matrix is added to the Hessian matrix.

The subroutine uses the gradient $g^{(k)} = \nabla f(x^{(k)})$ and the Hessian matrix $\mathbf{G}^{(k)} = \nabla^2 f(x^{(k)})$. It requires continuous first- and second-order derivatives of the objective function inside the feasible region.

Note that using only function calls to compute finite difference approximations for second-order derivatives can be computationally very expensive and can contain significant rounding errors. If you use the “grd” input argument to specify a module that computes first-order derivatives analytically, you can reduce drastically the computation time for numerical second-order derivatives. The computation of the finite difference approximation for the Hessian matrix generally uses only n calls of the module that specifies the gradient.

The NLPNRR method performs well for small- to medium-sized problems, and it does not need many function, gradient, and Hessian calls. However, if the gradient is not specified analytically by using the “grd” module argument, or if the computation of the Hessian module specified with the “hes” argument is computationally expensive, one of the (dual) quasi-Newton or conjugate gradient algorithms might be more efficient.

In addition to the standard iteration history, the NLPNRR subroutine prints the following information:

- The heading *ridge* refers to the value of the nonnegative ridge parameter. A value of zero indicates that a Newton step is performed. A value greater than zero indicates either that the Hessian approximation is zero or that the Newton step fails to reduce the optimization criterion. A large value can indicate optimization difficulties.
- The heading *rho* refers to ρ , the ratio of the achieved difference in function values and the predicted difference, based on the quadratic function approximation. A value that is much smaller than 1 indicates possible optimization difficulties.

The following statements invoke the NLPNRR subroutine to solve the constrained Betts optimization problem (see the section “[Constrained Betts Function](#)” on page 341). The iteration history follows.

```
start F_BETTS(x);
  f = .01 * x[1] * x[1] + x[2] * x[2] - 100;
  return(f);
finish F_BETTS;

con = {  2 -50  .  . ,
        50  50  .  . ,
        10 -1  1  10};
x = {-1 -1};
opt = {0 2};
call nlpnrr(rc, xres, "F_BETTS", x, opt, con);
```

Figure 23.201 Newton-Raphson Optimization

NOTE: Initial point was changed to be feasible for boundary and linear constraints.				
Optimization Start				
Parameter Estimates				
		Gradient	Lower	Upper
		Objective	Bound	Bound
N Parameter	Estimate	Function	Constraint	Constraint
1 X1	6.800000	0.136000	2.000000	50.000000
2 X2	-1.000000	-2.000000	-50.000000	50.000000
Value of Objective Function = -98.5376				
Linear Constraints				
1	59.00000 :	10.0000	<= + 10.0000 * X1	- 1.0000 *
	X2			

Figure 23.201 *continued*

Newton-Raphson Ridge Optimization									
Without Parameter Scaling									
Gradient Computed by Finite Differences									
CRP Jacobian Computed by Finite Differences									
Parameter Estimates				2					
Lower Bounds				2					
Upper Bounds				2					
Linear Constraints				1					
Optimization Start									
Active Constraints				0	Objective Function				-98.5376
Max Abs Gradient Element				2					
Iter	Rest arts	Func Calls	Act Con	Objective Function	Obj Fun Change	Max Abs Gradient Element	Ridge	Actual Over Pred Change	
1	0	2	1	-99.87337	1.3358	0.5887	0	0.706	
2	0	3	1	-99.96000	0.0866	0.000040	0	1.000	
3	0	4	1	-99.96000	4.07E-10	0	0	1.014	
Optimization Results									
Iterations				3	Function Calls				5
Hessian Calls				4	Active Constraints				1
Objective Function				-99.96	Max Abs Gradient Element				0
Ridge				0	Actual Over Pred Change				1.0135158294
GCONV convergence criterion satisfied.									
Optimization Results									
Parameter Estimates									
				Gradient		Active			
				Objective		Bound			
				Function		Constraint			
N	Parameter	Estimate							
1	X1	2.000000		0.040000		Lower BC			
2	X2	0.000000134		0					
Value of Objective Function = -99.96									
Linear Constraints Evaluated at Solution									
1	10.00000	=	-10.0000	+	10.0000 * X1	-	1.0000 * X2		

NLPQN Call

```
CALL NLPQN(rc, xr, "fun", x0 <, opt <, blc <, tc <, par <, "ptit" > <, "grd" > <, "nlc" > <,
           "jacnlc" > );
```

The NLPQN subroutine uses a quasi-Newton method to compute an optimum value of a function.

See the section “[Nonlinear Optimization and Related Subroutines](#)” on page 823 for a listing of all NLP subroutines. See [Chapter 14](#) for a description of the arguments of NLP subroutines.

The NLPQN subroutine uses (dual) quasi-Newton optimization techniques, and it is one of the two available subroutines that can solve problems with nonlinear constraints. These techniques work well for medium to moderately large optimization problems where the objective function and the gradient are much faster to compute than the Hessian matrix. The NLPQN subroutine does not need to compute second-order derivatives, but it generally requires more iterations than the techniques that compute second-order derivatives.

The two categories of problems solved by the NLPQN subroutine are unconstrained or linearly constrained problems and nonlinearly constrained problems. Unconstrained or linearly constrained problems do not use the “*nlc*” or “*jacnlc*” module arguments, whereas nonlinearly constrained problems use the arguments to specify the nonlinear constraints and the Jacobian matrix of their first-order derivatives, respectively.

The type of optimization problem specified determines the algorithm that the subroutine invokes. The algorithms are very different, and they use different sets of termination criteria. For more details, see the section “[Termination Criteria](#)” on page 360.

Unconstrained or Linearly Constrained Quasi-Newton Optimization

The NLPQN subroutine invokes this algorithm if you do not specify the “*nlc*” argument. Using the fourth element of the *opt* argument, you can specify two update formulas for either the original quasi-Newton algorithm or the dual quasi-Newton algorithm, as indicated in the following table:

Value of <i>opt</i> [4]	Update Method
1	Dual Broyden, Fletcher, Goldfarb, and Shanno (DBFGS) update of the Cholesky factor of the Hessian matrix. This is the default.
2	Dual Davidon, Fletcher, and Powell (DDFP) update of the Cholesky factor of the Hessian matrix.
3	Original Broyden, Fletcher, Goldfarb, and Shanno (BFGS) update of the inverse Hessian matrix.
4	Original Davidon, Fletcher, and Powell (DFP) update of the inverse Hessian matrix.

In each iteration, a line search is performed along the search direction to find an approximate optimum of the objective function. The default line-search method uses quadratic interpolation and cubic extrapolation to obtain a step size that satisfies the Goldstein conditions. One of the Goldstein conditions can be violated if the feasible region defines an upper limit of the step size. Violating the left-side Goldstein condition can affect the positive definiteness of the quasi-Newton update. In these cases, either the update is skipped or the iterations are restarted with an identity matrix that results in the steepest descent or ascent search direction. You can specify line-search algorithms different from the default method with the fifth element of the *opt* argument.

The following statements invoke the NLPQN subroutine to solve the Rosenbrock problem (see the section “Unconstrained Rosenbrock Function” on page 337):

```
start F_ROSEN(x);
  y1 = 10 * (x[2] - x[1] * x[1]);
  y2 = 1 - x[1];
  f = 0.5 * (y1 * y1 + y2 * y2);
  return(f);
finish F_ROSEN;
x = {-1.2 1};
opt = {0 2 . 2};
call nlpqn(rc, xr, "F_ROSEN", x, opt);
```

Since $opt[4]=2$, the DDFP update is performed. The gradient is approximated by finite differences since no module is specified that computes the first-order derivatives. Part of the iteration history follows. In addition to the standard iteration history, the NLPQN subroutine prints the following information for unconstrained or linearly constrained problems:

- The heading *alpha* is the step size, α , computed with the line-search algorithm.
- The heading *slope* refers to $g^T s$, the slope of the search direction at the current parameter iterate $x^{(k)}$. For minimization, this value should be significantly smaller than zero. Otherwise, the line-search algorithm has difficulty reducing the function value sufficiently.

Figure 23.202 Quasi-Newton Optimization

Optimization Start			
Parameter Estimates			
N	Parameter	Estimate	Gradient Objective Function
1	X1	-1.200000	-107.799989
2	X2	1.000000	-43.999999
Value of Objective Function = 12.1			
Dual Quasi-Newton Optimization			
Dual Davidon - Fletcher - Powell Update (DDFP)			
Gradient Computed by Finite Differences			
Parameter Estimates			2
Optimization Start			
Active Constraints		0	Objective Function
Max Abs Gradient Element		107.79998927	12.1

Figure 23.202 *continued*

Iter	Rest arts	Func Calls	Act Con	Objective Function	Obj Fun Change	Max Abs Gradient Element	Step Size	Slope Search Direc
1	0	4	0	2.06405	10.0359	0.7917	0.0340	-628.8
2	0	7	0	1.92035	0.1437	8.6301	6.557	-0.0363
3	0	10	0	1.78089	0.1395	11.0943	8.193	-0.0288
4	0	13	0	1.33331	0.4476	7.6069	33.376	-0.0269
5	0	17	0	1.13400	0.1993	0.9386	15.438	-0.0260
6	0	22	0	0.93915	0.1948	3.5290	11.537	-0.0233
7	0	24	0	0.84821	0.0909	4.8308	8.124	-0.0193
8	0	30	0	0.54334	0.3049	4.1770	35.143	-0.0186
9	0	32	0	0.46593	0.0774	0.9479	8.708	-0.0178
10	0	37	0	0.35322	0.1127	2.5981	10.964	-0.0147
11	0	40	0	0.26381	0.0894	3.3028	13.590	-0.0121
12	0	41	0	0.20282	0.0610	0.6451	10.000	-0.0116
13	0	46	0	0.11714	0.0857	1.6603	11.395	-0.0102
14	0	51	0	0.07149	0.0456	2.4050	11.559	-0.0074
15	0	53	0	0.04746	0.0240	0.5628	6.868	-0.0071
16	0	58	0	0.02759	0.0199	1.3282	5.365	-0.0055
17	0	60	0	0.01625	0.0113	1.9246	5.882	-0.0035
18	0	62	0	0.00475	0.0115	0.6357	8.068	-0.0032
19	0	66	0	0.00167	0.00307	0.4810	2.336	-0.0022
20	0	70	0	0.0005952	0.00108	0.6043	3.287	-0.0006
21	0	72	0	0.0000771	0.000518	0.0289	2.329	-0.0004
22	0	76	0	1.92121E-6	0.000075	0.0365	1.772	-0.0001
23	0	78	0	2.39914E-8	1.897E-6	0.00158	1.159	-331E-8
24	0	80	0	5.0936E-11	2.394E-8	0.000016	0.967	-46E-9
25	0	119	0	3.9538E-11	1.14E-11	7.962E-7	1.061	-19E-13

Optimization Results

Iterations	25	Function Calls	120
Gradient Calls	107	Active Constraints	0
Objective Function	3.953804E-11	Max Abs Gradient Element	7.9622469E-7
Slope of Search Direction	-1.88032E-12		

ABSGCONV convergence criterion satisfied.

Optimization Results
Parameter Estimates

N Parameter	Estimate	Gradient Objective Function
1 X1	0.999991	-0.000000796
2 X2	0.999982	0.000000430

Value of Objective Function = 3.953804E-11

Nonlinearly Constrained Quasi-Newton Optimization

The algorithm used for nonlinearly constrained quasi-Newton optimization is an efficient modification of Powell's (1978a, 1982b) variable metric constrained watchdog (VMCWD) algorithm. A similar but older algorithm (VF02AD) is part of the Harwell library. Both the VMCWD and VF02AD algorithms use Fletcher's VE02AD algorithm, which is also part of the Harwell library, for positive definite quadratic programming. This **NLPQN** implementation uses a quadratic programming subroutine that updates and downdates the Cholesky factor when the active set changes (Gill et al. 1984). The nonlinear **NLPQN** algorithm is not a feasible point algorithm, and the value of the objective function is not required to decrease monotonically. Instead, the algorithm tries to reduce a linear combination of objective function and constraint violations.

The following are similarities and differences between this algorithm and Powell's VMCWD algorithm:

- You can use the sixth element of the *opt* argument to modify the algorithm used by the **NLPQN** subroutine. If you specify *opt*[6]= 2, which is the default, the evaluation of the Lagrange vector μ is performed the same way as described in Powell (1982). However, the VMCWD program seems to have a bug in the implementation of formula (4.4) in Powell (1982). If you specify *opt*[6]= 1, the original update of μ used in the VF02AD algorithm in Powell (1978) is performed.
- Instead of updating an approximate Hessian matrix, this algorithm uses the dual BFGS or dual DFP update that updates the Cholesky factor of an approximate Hessian. If the condition of the updated matrix gets too bad, the algorithm restarts with a positive diagonal matrix. At the end of the first iteration after each restart, the Cholesky factor is scaled.
- The Cholesky factor is loaded into the quadratic programming subroutine, which ensures positive definiteness of the problem. During the quadratic programming step, the Cholesky factor of the projected Hessian matrix $Z_k^T G Z_k$ is updated simultaneously with QT decomposition when the active set changes. See Gill et al. (1984) for more information.
- The line-search strategy is very similar to that of Powell's algorithm, but this algorithm does not call for derivatives during the line search. Therefore, this algorithm generally needs fewer derivative calls than function calls, whereas the VMCWD algorithm always requires the same number of derivative calls as function calls. Also, Powell's line-search method sometimes uses steps that are too long during the early iterations. In those cases, you can use the second element of the *par* argument to restrict the step length α in the first five iterations. See the section "Control Parameters Vector" on page 367 for more details.
- The watchdog strategy is also similar to that of Powell's algorithm. However, this algorithm does not return automatically after a fixed number of iterations to a previous, more optimal point. A return to such a point is further delayed if the observed function reduction is close to the expected function reduction of the quadratic model.
- Although Powell's termination criterion, the FTOL2 criterion, can still be used, the **NLPQN** implementation uses, by default, two other termination criteria (GTOL and ABSGTOL).

This algorithm is automatically invoked if the "*n/c*" argument is specified. The module specified with the "*n/c*" argument must return a vector of length n_c , where n_c is the total number of constraints. Letting n_e be the number of equality constraints, the constraints must be of the following form:

$$\begin{aligned} c_i(x) &= 0, & i &= 1, \dots, n_e \\ c_i(x) &\geq 0, & i &= n_e + 1, \dots, n_c \end{aligned}$$

The first n_c elements of the returned vector contain the c_i for the equality constraints, and the remaining elements contain the c_i for the inequality constraints.

NOTE: You must specify the total number of constraints with the tenth element of the *opt* argument, and if there are any equality constraints, you must specify their number, n_e , with the eleventh element of the *opt* argument.

The nonlinear **NLPQN** algorithm requires the Jacobian matrix of the first-order derivatives of the n_c constraints returned by the module specified by the “*nlc*” argument. You can provide these derivatives by specifying a module with the “*jacnlc*” argument. This module must return the Jacobian matrix **J** of first-order partial derivatives. That is, **J** is an $n_c \times n$ matrix such that the entry in the i th row and j th column is given by

$$\mathbf{J}(i, j) = \frac{\partial c_i}{\partial x_j}$$

If you specify an “*nlc*” module without specifying a “*jacnlc*” argument, finite difference approximations of the first-order derivatives of the constraints are used. You can use the ninth element of the *par* argument to specify the number of accurate digits used in evaluating the constraints.

You can specify two update formulas with the fourth element of the *opt* argument as indicated in the following table:

Value of <i>opt</i> [4]	Update Method
1	Dual Broyden, Fletcher, Goldfarb, and Shanno (DBFGS) update of the Cholesky factor of the Hessian matrix. This is the default.
2	Dual Davidon, Fletcher, and Powell (DDFP) update of the Cholesky factor of the Hessian matrix.

This algorithm uses its own line-search technique. None of the options and parameters that control the line search in the other algorithms apply in the nonlinear **NLPQN** algorithm, with the exception of the second element of the *par* vector, which can be used to restrict the length of the step size in the first five iterations.

See [Example 14.8](#) for an example where you need to specify a value for the second element of the *par* argument. The values of the fourth, fifth, and sixth elements of the *par* vector, which control the processing of linear and boundary constraints, are valid only for the quadratic programming subroutine used in each iteration of the **NLPQN** call. For a simple example of the **NLPQN** subroutine, see the section “[Rosen-Suzuki Problem](#)” on page 342.

NLPQUA Call

CALL NLPQUA(*rc, xr, quad, x0* < , *opt* < , *bic* < , *tc* < , *par* < , “*ptit*” < , *lin* >);

The NLPQUA subroutine computes an optimum value of a quadratic objective function.

See the section “[Nonlinear Optimization and Related Subroutines](#)” on page 823 for a listing of all NLP subroutines. See [Chapter 14](#) for a description of the arguments of NLP subroutines.

The NLPQUA subroutine uses a fast algorithm for maximizing or minimizing the quadratic objective func-

tion

$$\frac{1}{2}x^T \mathbf{G}x + g^T x + con$$

subject to boundary constraints and general linear equality and inequality constraints. The algorithm is memory-consuming for problems with general linear constraints.

The matrix \mathbf{G} must be symmetric but not necessarily positive definite (or negative definite for maximization problems). The constant term *con* affects only the value of the objective function, not its derivatives or the optimal point x^* .

The algorithm is an active-set method in which the update of active boundary and linear constraints is done separately. The QT decomposition of the matrix A_k of active linear constraints is updated iteratively (Gill et al. 1984). If n_f is the number of free parameters (that is, n minus the number of active boundary constraints) and n_a is the number of active linear constraints, then \mathbf{Q} is an $n_f \times n_f$ orthogonal matrix that contains null space Z in its first $n_f - n_a$ columns and range space Y in its last n_a columns. The matrix \mathbf{T} is an $n_a \times n_a$ triangular matrix of the form $t_{ij} = 0$ for $i < n - j$. The Cholesky factor of the projected Hessian matrix $Z_k^T \mathbf{G} Z_k$ is updated simultaneously with the QT decomposition when the active set changes.

The objective function is specified by the input arguments *quad* and *lin*, as follows:

- The *quad* argument specifies the symmetric $n \times n$ Hessian matrix, \mathbf{G} , of the quadratic term. The input can be in dense or sparse form. In dense form, all n^2 entries of the *quad* matrix must be specified. If $n \leq 3$, the dense specification must be used. The sparse specification can be useful when \mathbf{G} has many zero elements. You can specify an $nn \times 3$ matrix in which each row represents one of the nn nonzero elements of \mathbf{G} . The first column specifies the row location in \mathbf{G} , the second column specifies the column location, and the third column specifies the value of the nonzero element.
- The *lin* argument specifies the linear part of the quadratic optimization problem. It must be a vector of length n or $n + 1$. If *lin* is a vector of length n , it specifies the vector g of the linear term, and the constant term *con* is considered zero. If *lin* is a vector of length $n + 1$, then the first n elements of the argument specify the vector g and the last element specifies the constant term *con* of the objective function.

As in the other optimization subroutines, you can use the *b/c* argument to specify boundary and general linear constraints, and you must provide a starting point *x0* to determine the number of parameters. If *x0* is not feasible, a feasible initial point is computed by linear programming, and the elements of *x0* can be missing values.

Assuming nonnegativity constraints $x \geq 0$, the quadratic optimization problem is solved with the LCP call, which solves the linear complementarity problem.

Choosing a sparse (or dense) input form of the *quad* argument does not mean that the algorithm used in the NLPQUA subroutine is necessarily sparse (or dense). If the following conditions are satisfied, the NLPQUA algorithm stores and processes the matrix \mathbf{G} as sparse:

- No general linear constraints are specified.
- The memory needed for the sparse storage of \mathbf{G} is less than 80% of the memory needed for dense storage.

- **G** is not a diagonal matrix. If **G** is diagonal, it is stored and processed as a diagonal matrix.

The sparse NLPQUA algorithm uses a modified form of minimum degree Cholesky factorization (George and Liu 1981).

In addition to the standard iteration history, the NLPNRA subroutine prints the following information:

- The heading *alpha* is the step size, α , computed with the line-search algorithm.
- The heading *slope* refers to $g^T s$, the slope of the search direction at the current parameter iterate $x^{(k)}$. For minimization, this value should be significantly smaller than zero. Otherwise, the line-search algorithm has difficulty reducing the function value sufficiently.

The Betts problem (see the section “[Constrained Betts Function](#)” on page 341) can be expressed as a quadratic problem in the following way:

$$x = \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}, \quad G = \begin{bmatrix} 0.02 & 0 \\ 0 & 2 \end{bmatrix}, \quad g = \begin{bmatrix} 0 \\ 0 \end{bmatrix}, \quad con = -100$$

Then

$$\frac{1}{2}x^T Gx - g^T x + con = 0.5[0.02x_1^2 + 2x_2^2] - 100 = 0.01x_1^2 + x_2^2 - 100$$

The following statements use the NLPQUA subroutine to solve the Betts problem:

```
lin = { 0. 0. -100};
quad = { 0.02 0.0 ,
        0.0 2.0 };
c = { 2. -50. . . ,
      50. 50. . . ,
      10. -1. 1. 10.};
x = { -1. -1.};
opt = {0 2};
call nlpqua(rc, xres, quad, x, opt, c, , , , lin);
```

The *quad* argument specifies the **G** matrix, and the *lin* argument specifies the *g* vector with the value of *con* appended as the last element. The matrix **c** specifies the boundary constraints and the general linear constraint.

The iteration history follows.

Figure 23.203 Quadratic Optimization

NOTE: Initial point was changed to be feasible for boundary and linear constraints.				
Optimization Start Parameter Estimates				
N Parameter	Estimate	Gradient Objective Function	Lower Bound Constraint	Upper Bound Constraint
1 x1	6.800000	0.136000	2.000000	50.000000
2 x2	-1.000000	-2.000000	-50.000000	50.000000

Figure 23.203 continued

```

Value of Objective Function = -98.5376

Linear Constraints
1  59.00000 :    10.0000 <= +  10.0000 * X1      -  1.0000 *
X2

Null Space Method of Quadratic Problem

Parameter Estimates          2
Lower Bounds                 2
Upper Bounds                 2
Linear Constraints           1
Using Sparse Hessian         -

Optimization Start

Active Constraints            0 Objective Function          -98.5376
Max Abs Gradient Element    2

Iter   Rest   Func   Act   Objective   Obj Fun   Max Abs   Step   Slope
      arts  Calls  Con   Function   Change   Element   Size   Search
      1     0     2     1   -99.87349   1.3359   0.5882   0.706   -2.925
      2     0     3     1   -99.96000   0.0865     0   1.000   -0.173

Optimization Results

Iterations                    2 Function Calls              4
Gradient Calls                3 Active Constraints          1
Objective Function            -99.96 Max Abs Gradient Element  0
Slope of Search Direction    -0.173010381

ABSGCONV convergence criterion satisfied.

Optimization Results
Parameter Estimates
N Parameter   Estimate   Gradient   Active
              Estimate   Objective   Bound
              Estimate   Function   Constraint

1 X1          2.000000    0.040000   Lower BC
2 X2          0          0

Value of Objective Function = -99.96

Linear Constraints Evaluated at Solution

1  10.00000 = -10.0000 +  10.0000 * X1      -  1.0000 * X2

```

NLPTR Call

CALL NLPTR(*rc*, *xr*, "fun", *x0* < , *opt* > < , *bic* > < , *tc* > < , *par* > < , "ptit" > < , "grd" > < , "hes" >);

The NLPTR subroutine uses a trust-region method to compute an optimum value of a function.

See the section “Nonlinear Optimization and Related Subroutines” on page 823 for a listing of all NLP subroutines. See Chapter 14 for a description of the arguments of NLP subroutines.

The NLPTR subroutine is a trust-region method. The algorithm uses the gradient $g^{(k)} = \nabla f(x^{(k)})$ and Hessian matrix $G^{(k)} = \nabla^2 f(x^{(k)})$ and requires that the objective function $f = f(x)$ has continuous first- and second-order derivatives inside the feasible region.

The $n \times n$ Hessian matrix G contains the second derivatives of the objective function f with respect to the parameters x_1, \dots, x_n , as follows:

$$G(x) = \nabla^2 f(x) = \left(\frac{\partial^2 f}{\partial x_j \partial x_k} \right)$$

The trust-region method works by optimizing a quadratic approximation to the nonlinear objective function within a hyperelliptic trust region. This trust region has a radius, Δ , that constrains the step size that corresponds to the quality of the quadratic approximation. The method is implemented by using Dennis, Gay, and Welsch (1981), Gay (1983), and Moré and Sorensen (1983).

Finite difference approximations for second-order derivatives that use only function calls are computationally very expensive. If you specify first-order derivatives analytically with the “grd” module argument, you can drastically reduce the computation time for numerical second-order derivatives. Computing the finite difference approximation for the Hessian matrix G generally uses only n calls of the module that computes the gradient analytically.

The NLPTR method performs well for small- to medium-sized problems and does not need many function, gradient, and Hessian calls. However, if the gradient is not specified by using the “grd” argument or if the computation of the Hessian module, as specified by the “hes” module argument, is computationally expensive, one of the (dual) quasi-Newton or conjugate gradient algorithms might be more efficient.

In addition to the standard iteration history, the NLPTR subroutine prints the following information:

- Under the heading *Iter*, an asterisk (*) printed after the iteration number indicates that the computed Hessian approximation was singular and had to be ridged with a positive value.
- The heading *lambda* represents the Lagrange multiplier, λ . This has a value of zero when the optimum of the quadratic function approximation is inside the trust region, in which case a trust-region-scaled Newton step is performed. It is greater than zero when the optimum is at the boundary of the trust region, in which case the scaled Newton step is too long to fit in the trust region and a quadratically constrained optimization is done. Large values indicate optimization difficulties, and as in Gay (1983), a negative value indicates the special case of an indefinite Hessian matrix.
- The heading *radius* refers to Δ , the radius of the trust region. Small values of the radius combined with large values of λ in subsequent iterations indicate optimization problems.

For an example of the use of the NLPTR subroutine, see the section “[Unconstrained Rosenbrock Function](#)” on page 337.

NORMAL Function

NORMAL(*seed*);

The NORMAL function generates pseudorandom numbers from the standard normal distribution. The *seed* argument is a numeric matrix or literal. The elements of the *seed* argument can be any integer value up to $2^{31} - 1$.

The NORMAL function returns pseudorandom numbers from a normal distribution with a mean of 0 and a standard deviation of 1. The NORMAL function returns a matrix with the same dimensions as the argument. The first argument on the first call is used for the seed; if that value is 0, the system time is used for the seed. This function is equivalent to the DATA step function RANNOR.

The Box-Muller transformation of the [UNIFORM function](#) deviates is used to generate the numbers. The following statements produce the output shown in [Figure 23.204](#):

```
seed = 123456;
c = j(5, 1, seed);      /* generate 5 number from the same seed */
b = normal(c);
print b;
```

Figure 23.204 Random Values Generated from a Normal Distribution

b
-0.109483
-0.348785
1.1202546
-2.513766
1.3630022

For generating millions of pseudorandom numbers, use the [RANDGEN](#) subroutine.

NROW Function

NROW(*matrix*);

The NROW function returns the number of rows in its matrix argument. If the matrix has not been given a value, the NROW function returns a value of 0.

For example, following statements display the number of rows of the matrix *m*:

```
m = {1 2 3, 4 5 6, 3 2 1, 4 3 2, 5 4 3};
```



```
n = nrow(m);
print n;
```

Figure 23.205 Number of Rows in a Matrix

n
5

NUM Function

NUM(*matrix*);

The NUM function produces a numeric representation of elements in a character matrix. If you have a character matrix for which each element is a string representation of a number, the NUM function produces a numeric matrix with dimensions that are the same as the dimensions of the argument and with elements that are the numeric representations (double-precision floating-point) of the corresponding elements of the argument.

For example, following statements display the result of converting a character matrix to a numeric matrix:

```
c = {"1" "2" "3"};
reset print;          /* display values and type of matrices */
m = num(c);
```

Figure 23.206 Numeric Matrix

m	1 row	3 cols	(numeric)
	1	2	3

You can also use the PUTN function in Base SAS software to apply a SAS format to each element of a numeric matrix. The resulting matrix is character-valued.

See also the description of the [CHAR function](#), which converts numeric matrices into character matrices.

ODE Call

CALL ODE(*r*, "dername", *c*, *t*, *h* < , **J**="jacobian"> < , **EPS**=*eps*> < , "SAS-data-set">);

The ODE subroutine performs numerical integration of first-order vector differential equations of the form

$$\frac{dy}{dt} = f(t, y(t)) \quad \text{with } y(0) = c$$

The ODE subroutine returns the following values:

r is a numeric matrix that contains the results of the integration over connected subintervals. The number of columns in *r* is equal to the number of subintervals of integration as defined by the argument *t*. In case of any error in the integration on any subinterval, partial results are not reported in *r*.

The input arguments to the ODE subroutine are as follows:

“dename” specifies the name of a module used to evaluate the integrand.

c specifies an initial value vector for the variable *y*.

t specifies a sorted vector that describes the limits of integration over connected subintervals. The simplest form of the vector *t* contains only the limits of the integration on one interval. The first component of *t* should contain the initial value, and the second component should be the final value of the independent variable. For more advanced usage of the ODE subroutine, the vector *t* can contain more than two components. The components of the vector must be sorted in ascending order. Two consecutive components of the vector *t* are interpreted as a subinterval. The ODE subroutine reports the final result of integration at the right endpoint of each subinterval. This information is vital if $f(\cdot)$ has internal points of discontinuity. To produce accurate solutions, it is essential that you provide the location of these points in the variable *t*. The continuity of the forcing function is vital to the internal control of error.

h specifies a numeric vector that contains three components: the minimum allowable step size, *hmin*; the maximum allowable step size, *hmax*; and the initial step size to start the integration process, *hinit*.

“jacobian” optionally specifies the name of a module that is used to evaluate the Jacobian analytically. The Jacobian is the matrix *J*, with

$$J_{ij} = \frac{\partial f_i}{\partial y_j}$$

If the *“jacobian”* module is not specified, the ODE subroutine uses a finite-difference method to approximate the Jacobian. The keyword for this option is *J*.

eps specifies a scalar that indicates the required accuracy. It has a default value of 1E–4. The keyword for this option is *EPS*.

SAS-data-set is an optional argument that specifies the name of a valid predefined SAS data set name. The data set is used to save the successful independent and dependent variables of the integration at each step. The keyword for this option is *DATA*.

The ODE subroutine is an adaptive, variable-order, variable-step-size, stiff integrator based on implicit backward-difference methods. See Aiken (1985), Bickart and Picel (1973), Donelson and Hansen (1971), Gaffney (1984), and Shampine (1978). The integrator is an implicit predictor-corrector method that locally attempts to maintain the prescribed precision *eps* relative to

$$d = \max_{0 \leq t \leq T} (\|y(t)\|_{\infty}, 1)$$

As you can see from the expression, this quantity is dynamically updated during the integration process and can help you to understand the validity of the results reported by the subroutine.

A Linear Differential Equation

Consider the differential equation

$$\frac{dy}{dt} = -ty \text{ with } y = 0.5 \text{ at } t = 0$$

The following statements attempt to find the solution at $t = 1$:

```
/* Define the integrand */
start fun(t,y);
    v = -t*y;
    return(v);
finish;

/* Call ODE */
c  = 0.5;
t  = {0 1};
h  = {1E-12 1 1E-5};
call ode(r1, "FUN", c, t, h);
print r1[format=E21.14];
```

Figure 23.207 Solution to a Differential Equation at $t = 1$

r1
3.03432290135600E-01

In this case, the integration is carried out over $(0, 1)$ to give the value of y at $t = 1$. The optional parameter *eps* has not been specified, so it is internally set to $1\text{E}-4$. Also, the optional parameter “*jacobian*” has not been specified, so finite-difference methods are used to estimate the Jacobian. The accuracy of the answer can be increased by specifying *eps*. For example, set $\text{EPS}=1\text{E}-7$, as follows:

```
call ode(r2, "FUN", c, t, h) eps=1E-7;
print r2[format =E21.14];
```

Figure 23.208 A Solution with Increased Accuracy

r2
3.03265687354960E-01

Compare this value to $0.5e^{-0.5} = 3.03265329856310\text{E}-01$ and observe that the result is correct through the sixth decimal digit and has an error relative to 1 that is $O(1\text{E}-7)$.

If the solution was desired at 1 and 2 with an accuracy of $1\text{E}-7$, you would use the following statements:

```
t  = {0 1 2};
h  = {1E-12 1 1E-5};
call ode(r3, "FUN", c, t, h) eps=1E-7;
print r3[format=E21.14];
```

Figure 23.209 A Solution at Two Times

r3	
3.03265687354960E-01	6.76677185425360E-02

Note that **r3** contains the solution at $t = 1$ in the first column and at $t = 2$ in the second column.

A Discontinuous Forcing Function

Now consider the smoothness of the forcing function $f(\cdot)$. For the purpose of estimating errors, adaptive methods require some degree of smoothness in the function $f(\cdot)$. If this smoothness is not present in $f(\cdot)$ over the interior and including the left endpoint of the subinterval, the reported result does not have the desired accuracy. The function $f(\cdot)$ must be at least continuous. If the function does not meet this requirement, you should specify the discontinuity as an intermediate point. For example, consider the differential equation

$$\frac{dy}{dt} = \begin{cases} t & \text{if } t < 1 \\ 0.5t^2 & \text{if } t \geq 1 \end{cases}$$

To find the solution at $t = 2$, use the following statements:

```
/* Define the integrand */
start fun(t,y);
  if t < 1 then v = t;
  else v = .5*t*t;
  return(v);
finish;

c   = 0;
t   = {0 2};
h   = {1E-12 1. 1E-5};
call ode(r1, "FUN", c, t, h) eps=1E-12;
print r1[format=E21.14];
```

Figure 23.210 Numerical Solution Across a Discontinuity

r1	
1.66666626639430E+00	

In the preceding case, the integration is carried out over a single interval, $(0, 2)$. The optional parameter *eps* is specified to be $1\text{E}-12$. The optional parameter “jacobian” is not specified, so finite-difference methods are used to estimate the Jacobian.

Note that the value of **r1** does not have the required accuracy (it should contain a 12 decimal-place representation of $5/3$), although no error message is produced. The reason is that the function is not continuous at

the point $t = 1$. Even the lowest-order method cannot produce a local reliable error estimate near the point of discontinuity. To avoid this problem, you can create subintervals so that the integration is carried out first over $(0, 1)$ and then over $(1, 2)$. The following statements implement this method:

```
c    = 0;
t    = {0 1 2};
h    = {1E-12 1 1E-5};
call ode(r2, "FUN", c, t, h) eps=1E-12;
print r2[format=E21.14];
```

Figure 23.211 Numerical Solution on Subintervals

r2	
5.00000000003280E-01	1.66666666667280E+00

The variable **r2** contains the solutions at both $t = 1$ and $t = 2$, and the errors are of the specified order. Although there is no interest in the solution at the point $t = 1$, the advantage of specifying subintervals with no discontinuities is that the function $f(\cdot)$ is infinitely differentiable in each subinterval.

A Piecewise Continuous Forcing Function

When $f(\cdot)$ is continuous, the ODE subroutine can compute the integration to the specified precision, even if the function is defined piecewise. Consider the differential equation

$$\frac{dy}{dt} = \begin{cases} t & \text{if } t < 1 \\ t^2 & \text{if } t \geq 1 \end{cases}$$

The following statements find the solution at $t = 2$. Since the function $f(\cdot)$ is continuous, the requirements for error control are satisfied.

```
/* Define the integrand */
start fun(t,y);
  if t < 1 then v = t;
  else v = t*t;
  return(v);
finish;

c    = 0.5;
t    = {0 2};
h    = {1E-12 1 1E-5};
call ode(r, "FUN", c, t, h) eps=1E-12;
print r[format=E21.14];
```

Figure 23.212 Numerical Solution Across a Discontinuity

r
3.333333333334290E+00

Figure 23.212 *continued*

count	
437	
z1	
1.85787839378720E-06	6.58580950202810E-06
-1.76251639451200E-03	-6.35540294085790E-03
-1.56685625917120E-03	-5.72429205508220E-03
1.01207878768800E-03	3.73655890904620E-03

Comparing Numerical Integration with an Eigenvalue Decomposition

This example compares the ODE subroutine to an eigenvalue decomposition for stiff-linear systems. In the problem

$$\frac{dy}{dt} = Ay \text{ with } y(0) = c$$

where A is a symmetric constant matrix, the solution can be written in terms of the eigenvalue decomposition as

$$y(t) = Ue^{Dt}U'c$$

where U is the matrix of eigenvectors and D is a diagonal matrix with the eigenvalues on its diagonal.

The following statements produce two solutions, one by using the ODE subroutine and the other by using the eigenvalue decomposition:

```

/* Define the integrand */
start fun(t,x) global(a,count);
  count = count+1;
  v = a*x;
  return(v);
finish;

/* Define the Jacobian */
start jac(t,x) global(a);
  return(a);
finish;

a = {-1000 -1 -2 -3,
      -1 -2 3 -1,
      -2 3 -4 -3,
      -3 -1 -3 -5 };

count = 0;
t = {0 1 2};
h = {1E-12 1 1E-5};
eps = 1E-9;

```

```

c = {1, 0, 0, 0 };
call ode(z, "FUN", c, t, h)  eps=eps j="JAC";
print z[format=E21.14];
print count;

```

Figure 23.213 Numerical Integration of a Linear System

```

              z
1.85787365492010E-06  6.58581431443360E-06
-1.76251618648210E-03 -6.35540480231360E-03
-1.56685608329260E-03 -5.72429355490000E-03
1.01207978491490E-03  3.73655984699120E-03

              count
437

              z1
1.85787839378720E-06  6.58580950202810E-06
-1.76251639451200E-03 -6.35540294085790E-03
-1.56685625917120E-03 -5.72429205508220E-03
1.01207878768800E-03  3.73655890904620E-03

```

```

/* Do the eigenvalue decomposition */
start eval(t) global(d,u,c);
  v = u*diag(exp(d*t))*u`*c;
  return(v);
finish;

call eigen(d,u,a);
free z1;
do i = 1 to nrow(t)*ncol(t)-1;
  z1 = z1 || (eval(t[i+1]));
end;
print z1[format=E21.14];

```

Figure 23.214 Analytic Solution of a Linear System

```

              z
1.85787365492010E-06  6.58581431443360E-06
-1.76251618648210E-03 -6.35540480231360E-03
-1.56685608329260E-03 -5.72429355490000E-03
1.01207978491490E-03  3.73655984699120E-03

              count
437

```

Figure 23.214 *continued*

z1	
1.85787839378720E-06	6.58580950202810E-06
-1.76251639451200E-03	-6.35540294085790E-03
-1.56685625917120E-03	-5.72429205508220E-03
1.01207878768800E-03	3.73655890904620E-03

Is this an $O(1E-9)$ result? Note that for the problem

$$d = \max_{0 \leq t \leq T} (\|y(t)\|_{\infty}, 1) = 1$$

with the $1E-6$ result, the ODE subroutine should attempt to maintain an accuracy of $1E-9$ relative to 1. Therefore, the $1E-6$ result should have almost three correct decimal places. At $t = 2$, the first component of **z** is $6.58597048842310E-06$, while its more accurate value is $6.58580950203220E-06$, showing an $O(1E-10)$ error.

Troubleshooting

The ODE subroutine can fail for problems with unusual qualitative properties, such as finite escape time in the interval of integration (that is, the solution goes towards infinity at some finite time). In such cases, try testing with different subintervals and different levels of accuracy to gain some qualitative information about the behavior of the solution of the differential equation.

ODSGRAPH Call

CALL ODSGRAPH(*name*, *template*, *matrix1* <, *matrix2*, ..., *matrix13* >);

The ODSGRAPH subroutine renders an ODS statistical graph that is defined by a template.

The input arguments to the ODSGRAPH subroutine are as follows:

- name* is a character matrix or quoted literal that assigns a name to the graph. The name is used to identify the output graph in the SAS Results window.
- template* is a character matrix or quoted literal that names the template used to render the graph.
- matrix* is a matrix whose columns are supplied to the template. You can specify up to 13 arguments. The name of each column must be specified by using the **MATTRIB statement** or the COLNAME= option in a **READ statement**.

The ODSGRAPH subroutine (which requires a SAS/GRAPH license) renders a graph defined by the input template. Data for the graph are in the columns of the matrix arguments. Column names are assigned to the matrices by using the MATTRIB statement or by using the COLNAME= option in a READ statement. This is illustrated in the following example, which produces a three-dimensional surface plot:


```

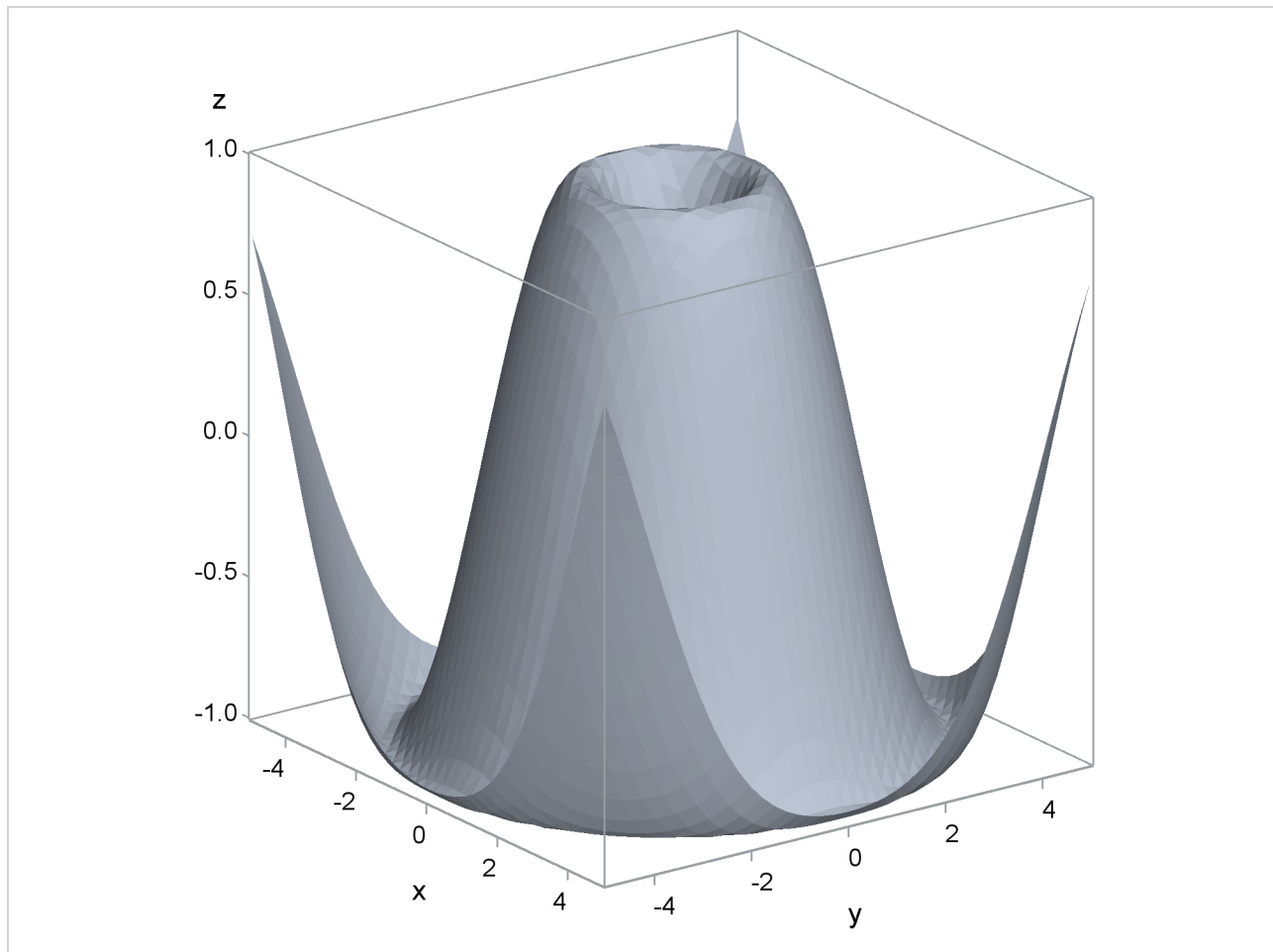
proc template;
  define statgraph SurfacePlot;
    BeginGraph;
    layout overlay3d;
      surfaceplotparm x=x y=y z=z / surfacetype=fill;
    endlayout;
    EndGraph;
  end;
run;

ods graphics on;
title "Surface Plot";

proc iml;
XDiv = do( -5, 5, 0.25 );
YDiv = do( -5, 5, 0.25 );
nX = ncol(XDiv);
nY = ncol(YDiv);
x = shape(repeat(XDiv, nY, 1), 0, 1);
y = shape(repeat(YDiv, 1, nX), 0, 1);
z = sin( sqrt( x##2 + y##2 ) );
matrix = x || y || z;
mattrib matrix colname={"x" "y" "z"};
call odsgraph("surface", "SurfacePlot", matrix);
quit;

ods graphics off;

```

Figure 23.215 ODS Graphic

In the example, the `TEMPLATE` procedure defines a template for a surface plot. The `ODSGRAPH` subroutine calls ODS to render the graph by using the layout in the template. (You can render the graph in any ODS destination.) The data for the graph are contained in a matrix. The `MATTRIB` statement associates the columns of the matrix with the variable names required by the template.

You can also create graphs from data that are read from a data set. If `x`, `y`, and `z` are variables in a data set, then the following statements plot these variables:

```
use myData;
read all into matrix[colname = c];
call odsgraph("surface", "SurfacePlot", matrix);
```

Since column names created via a `READ` statement are permanently associated with the `INTO` matrix, you do not need to use a `MATTRIB` statement for this example.

The sample programs distributed with SAS/IML software include other examples of plots that are available by using ODS Statistical Graphics.

OPSCAL Function

OPSCAL(*mlevel*, *quanti* < , *qualit* >);

The OPSCAL function rescales qualitative data to be a least squares fit to quantitative data.

The arguments to the OPSCAL function are as follows:

<i>mlevel</i>	specifies a scalar that has one of two values. When <i>mlevel</i> is 1, the <i>qualit</i> matrix is at the nominal measurement level; when <i>mlevel</i> is 2, it is at the ordinal measurement level.
<i>quanti</i>	specifies an $m \times n$ matrix of quantitative information assumed to be at the interval level of measurement.
<i>qualit</i>	specifies an $m \times n$ matrix of qualitative information whose level of measurement is specified by <i>mlevel</i> . When <i>qualit</i> is omitted, <i>mlevel</i> must be 2 and a temporary <i>qualit</i> is constructed that contains the integers from 1 to n in the first row, from $n + 1$ to $2n$ in the second row, from $2n + 1$ to $3n$ in the third row, and so forth, up to the integers $(m - 1)n$ to mn in the last(<i>m</i> th) row. You cannot specify <i>qualit</i> as a character matrix.

The result of the OPSCAL function is the optimal scaling transformation of the qualitative (nominal or ordinal) data in *qualit*. The optimal scaling transformation that results has the following properties:

- It is a least squares fit to the quantitative data in *quanti*.
- It preserves the qualitative measurement level of *qualit*.

When *qualit* is at the nominal level of measurement, the optimal scaling transformation result is a least squares fit to *quanti*, given the restriction that the category structure of *qualit* must be preserved. If element *i* of *qualit* is in category *c*, then element *i* of the optimum scaling transformation result is the mean of all those elements of *quanti* that correspond to elements of *qualit* that are in category *c*.

For example, the following statements create the vector shown in Figure 23.216:

```
quanti = {5  4  6  7  4  6  2  4  8  6};
qualit = {6  6  2 12  4 10  4 10  8  6};
os = opscal(1, quanti, qualit);
print os;
```

Figure 23.216 Optimal Scaling Transformation of Nominal Data

	COL1	COL2	COL3	COL4	COL5
ROW1	5	5	6	7	3
	COL6	COL7	COL8	COL9	COL10
ROW1	5	3	5	8	5

The optimal scaling transformation result is said to preserve the nominal measurement level of *qualit* because wherever there was a *qualit* category *c*, there is now a result category label *v*. The transformation is least squares because the result element *v* is the mean of appropriate elements of *quanti*. This is Young's (1981) discrete-nominal transformation.

When *qualit* is at the ordinal level of measurement, the optimal scaling transformation result is a least squares fit to *quanti*, given the restriction that the ordinal structure of *qualit* must be preserved. This is done by determining blocks of elements of *qualit* so that if element *i* of *qualit* is in block *b*, then element *i* of the result is the mean of all those *quanti* elements that correspond to block *b* elements of *qualit* so that the means are (weakly) in the same order as the elements of *qualit*.

For example, consider these statements, which produce the transformation shown in Figure 23.217:

```
os2 = opscal(2, quanti, qualit);
print os2;
```

Figure 23.217 Optimal Scaling Transformation of Ordinal Data

	os2				
	COL1	COL2	COL3	COL4	COL5
ROW1	5	5	4	7	4
	os2				
	COL6	COL7	COL8	COL9	COL10
ROW1	6	4	6	6	5

This transformation preserves the ordinal measurement level of *qualit* because the elements of *qualit* and the result are (weakly) in the same order. It is least squares because the result elements are the means of appropriate elements of *quanti*. By comparing this result to the nominal one, you see that categories whose means are incorrectly ordered have been merged together to form correctly ordered blocks. This is known as Kruskal's (1964) least squares monotonic transformation.

You can omit the *qualit* argument, as shown in the following statements:

```
quanti = {5 3 6 7 5 7 8 6 7 8};
os3 = opscal(2, quanti);
print os3;
```

These statements are equivalent to specifying

```
qualit = 1:10;
```

The result is shown in Figure 23.218.

Figure 23.218 Optimal Scaling Transformation

		os3			
	COL1	COL2	COL3	COL4	COL5
ROW1	4	4	6	6	6
		os3			
	COL6	COL7	COL8	COL9	COL10
ROW1	7	7	7	7	8

ORPOL Function

ORPOL(*x* <, *maxdegree* > <, *weights* >);

The ORPOL function generates orthogonal polynomials on a discrete set of points.

The arguments to the ORPOL function are as follows:

- x* is an $n \times 1$ vector of values on which the polynomials are to be defined.
- maxdegree* specifies the maximum degree polynomial to be computed. If *maxdegree* is omitted, the default value is $\min(n, 19)$. If *weights* is specified, you must also specify *maxdegree*.
- weights* specifies an $n \times 1$ vector of nonnegative weights associated with the points in *x*. If you specify *weights*, you *must* also specify *maxdegree*. If *maxdegree* is not specified or is specified incorrectly, the default weights (all weights are 1) are used.

The ORPOL matrix function generates orthogonal polynomials evaluated at the n points contained in *x* by using the algorithm of Emerson (1968). The result is a column-orthonormal matrix **P** with n rows and *maxdegree*+1 columns such that $\mathbf{P}'\text{diag}(\text{weights})\mathbf{P} = \mathbf{I}$. The result of evaluating the polynomial of degree $j - 1$ at the i th element of *x* is stored in **P**[i, j].

The maximum number of nonzero orthogonal polynomials (r) that can be computed from the vector and the weights is the number of distinct values in the vector, ignoring any value associated with a zero weight.

The polynomial of maximum degree has degree of $r - 1$. If the value of *maxdegree* exceeds $r - 1$, then columns $r + 1, r + 2, \dots, \text{maxdegree} + 1$ of the result are set to 0. In this case,

$$\mathbf{P}'\text{diag}(\text{weights})\mathbf{P} = \begin{bmatrix} I(r) & 0 \\ 0 & 0 \end{bmatrix}$$

The following statements create a matrix with three orthogonal columns, as shown in [Figure 23.219](#):

```
x = T(1:5);
P = orpol(x,2);
print P;
```

Figure 23.219 Orthogonal Polynomials

P		
0.4472136	-0.632456	0.5345225
0.4472136	-0.316228	-0.267261
0.4472136	1.755E-17	-0.534522
0.4472136	0.3162278	-0.267261
0.4472136	0.6324555	0.5345225

The first column is a polynomial of degree 0 (a constant polynomial) evaluated at each point of x . The second column is a polynomial of degree 1 evaluated at each point of x . The third column is a polynomial of degree 2 evaluated at each point of x .

Normalization of the Polynomials

The columns of **P** are orthonormal with respect to the inner product

$$\langle f, g \rangle = \sum_{i=1}^n f(x_i)g(x_i)w_i$$

as shown by the following statements:

```
reset fuzz;          /* print tiny numbers as zero */
w = j(ncol(x),1,1); /* default weight is all ones */
/* Verify orthonormal */
L = P`*diag(w)*P;
print L;
```

Some reference books on orthogonal polynomials do not normalize the columns of the matrix that represents the orthogonal polynomials. For example, a textbook might give the following as a fourth-degree polynomial evaluated on evenly spaced data:

```
textbookPoly = { 1 -2  2 -1  1,
                  1 -1 -1  2 -4,
                  1  0 -2  0  6,
                  1  1 -1 -2 -4,
                  1  2  2  1  1 };
```

To compare this representation to the normalized representation that the ORPOL function produces, use the following program:

```
/* Normalize the columns of textbook representation */
normalPoly = textbookPoly;
do i = 1 to ncol( normalPoly );
    v = normalPoly[,i];
    norm = sqrt(v[##]);
    normalPoly[,i] = v / norm;
end;

/* Compare the normalized matrix with ORPOL */
x = T(1:5); /* Any evenly spaced data gives the same answer */
```

```

imlPoly = orpol( x, 4 );

diff = imlPoly - normalPoly;
maxDiff = abs(diff)[<>];
reset fuzz; /* print tiny numbers as zero */
print maxDiff;

```

Figure 23.220 Normalizing a Matrix

maxDiff
0

Polynomial Regression

A typical use for orthogonal polynomials is to fit a polynomial to a set of data. Given a set of points (x_i, y_i) , $i = 1, \dots, m$, the classical theory of orthogonal polynomials says that the best approximating polynomial of degree d is given by

$$f_d = \sum_{i=1}^{d+1} c_i P_i$$

where $c_i = \langle y, P_i \rangle / \langle P_i, P_i \rangle$ and where P_i is the i th column of the matrix \mathbf{P} returned by ORPOL. But the matrix is orthonormal with respect to the inner product, so $\langle P_i, P_i \rangle = 1$ for all i . Thus you can easily compute a regression onto the span of polynomials.

In the following program, the weight vector is used to overweight or underweight particular data points. The researcher has reasons to doubt the accuracy of the first measurement. The last data point is also underweighted because it is a leverage point and is believed to be an outlier. The second data point was measured twice and is overweighted. (Rerunning the program with a weight vector of all ones and examining the new values of the `fit` variable is a good way to understand the effect of the weight vector.)

```

x = {0.1, 2, 3, 5, 8, 10, 20};
y = {0.5, 1, 0.1, -1, -0.5, -0.8, 0.1};

/* The second measurement was taken twice.
   The first and last data points are underweighted
   because of uncertainty in the measurements. */
w = {0.5, 2, 1, 1, 1, 1, 0.2};
maxDegree = 4;
P = orpol(x, maxDegree, w);

/* The best fit by a polynomial of degree k is
   Sum c_i P_i where c_i = <f, P_i> */
start InnerProduct(f, g, w);
  h = f#g#w;
  return (h[+]);
finish;

c = j(1, maxDegree+1);
do i = 1 to maxDegree+1;

```

```

    c[i] = InnerProduct(y, P[,i], w);
end;

FitResults = j(maxDegree+1,2);
do k = 1 to maxDegree+1;
    fit = P[,1:k] * c[1:k];
    resid = y - fit;
    FitResults[k,1] = k-1;      /* degree of polynomial */
    FitResults[k,2] = resid[##]; /* sum of square errors */
end;
print FitResults[colname={"Degree" "SSE"}];

```

Figure 23.221 Statistics for an Orthogonal Polynomial Regression

FitResults	
Degree	SSE
0	3.1733014
1	4.6716722
2	1.3345326
3	1.3758639
4	0.8644558

Testing Linear Hypotheses

The ORPOL function can also be used to test linear hypotheses. Suppose you have an experimental design with k factor levels. (The factor levels can be equally or unequally spaced.) At the i th level, you record n_k observations, $i = 1 \dots k$. If $n_1 = n_2 = \dots = n_k$, then the design is said to be *balanced*; otherwise it is *unbalanced*. You want to fit a polynomial model to the data and then ask how much variation in the data is explained by the linear component, how much variation is explained by the quadratic component after the linear component is taken into account, and so on for the cubic, quartic, and higher-level components.

To be completely concrete, suppose you have four factor levels (1, 4, 6, and 10) and that you record seven measurements at first level, two measurements at the second level, three measurements at the third level, and four measurements at the fourth level. This is an example of an unbalanced and unequally spaced factor-level design. The following program uses orthogonal polynomials to compute the Type I sum of squares for the linear hypothesis. (The program works equally well for balanced designs and for equally spaced factor levels.)

The following program calls the ORPOL function to generate the orthogonal polynomial matrix **P**, and uses it to form the Type I hypothesis matrix **L**. The program then uses the **DESIGN** function to generate **X**, the design matrix associated with the experiment. The program then computes **b**, the estimated parameters of the linear model. Since **L** was expressed in terms of the orthogonal polynomial matrix **P**, the computations involved in forming the Type I sum of squares are considerably simplified.

```

/* unequally spaced and unbalanced factor levels */
levels = { 1,1,1,1,1,1,1,
          4,4,
          6,6,6,
          10,10,10,10};

```



```

/* data for y. Make sure the data are sorted
   according to the factor levels */
y = {2.804823, 0.920085, 1.396577, -0.083318,
      3.238294, 0.375768, 1.513658,
      3.913391, 3.405821,
      6.031891, 5.262201, 5.749861,
      10.685005, 9.195842, 9.255719, 9.204497 /* level 10 */
};

a      = {1,4,6,10}; /* spacing */
trials = {7,2,3,4}; /* sample sizes */
maxDegree = 3; /* model with Intercept,a,a##2,a##3 */

P = orpol(a,maxDegree,trials);

/* Test linear hypotheses:
   How much variation is explained by the
   i_th polynomial component after components
   0..(i-1) have been taken into account? */

/* the columns of L are the coefficients of the
   orthogonal polynomial contrasts */
L = diag(trials)*P;

/* form design matrix */
x = design(levels);

/* compute b, the estimated parameters of the
   linear model. b is the mean of the y values
   at each level.
   b = ginv(x'*x) * x' * y
   but since x is the output from DESIGN, then
   x'*x = diag(trials) and so
   ginv(x'*x) = diag(1/trials) */
b = diag(1/trials)*x'*y;

/* (L'*b)[i] is the best linear unbiased estimated
   (BLUE) of the corresponding orthogonal polynomial
   contrast */
blue = L'*b;

/* The variance of (L'*b) is
   var(L'*b) = L'*ginv(x'*x)*L
               = [P'*diag(trials)]*diag(1/trials)*[diag(trials)*P]
               = P'*diag(trials)*P
               = Identity          (by definition of P)

   Therefore the standardized square of
   (L'*b) is computed as
   SS1[i] = (blue[i]*blue[i])/var(L'*b)[i,i]
            = (blue[i])##2
*/

SS1 = blue # blue;
rowNames = {"Intercept" "Linear" "Quadratic" "Cubic"};

```

```
print SS1[rowname=rowNames format=11.7 label="Type I SS"];
```

Figure 23.222 indicates that most of the variation in the data can be explained by a first-degree polynomial.

Figure 23.222 Statistics for an Orthogonal Polynomial Regression

Type I SS	
Intercept	331.8783538
Linear	173.4756050
Quadratic	0.4612604
Cubic	0.0752106

Generating Families of Orthogonal Polynomials

There are classical families of orthogonal polynomials (for example, Legendre, Laguerre, Hermite, and Chebyshev) that arise in the study of differential equations and mathematical physics. These “named” families are orthogonal on particular intervals (a, b) with respect to the inner product $\int_b^a f(x)g(x)w(x) dx$. The functions returned by the ORPOL function are *different* from these named families because the ORPOL function uses a different inner product. There are no built-in functions that can automatically generate these families; however, you can write a program to generate them.

Each named polynomial family $\{p_j\}$, $j \geq 0$ satisfies a three-term recurrence relation of the form

$$p_j = (A_j + xB_j)p_{j-1} - C_j p_{j-2}$$

where the constants A_j , B_j , and C_j are relatively simple functions of j . To generate these “named” families, use the three-term recurrence relation for the family. The recurrence relations are found in references such as Abramowitz and Stegun (1972) or Thisted (1988).

For example, the so-called Legendre polynomials (represented P_j for the polynomial of degree j) are defined on $(-1, 1)$ with the weight function $w(x) = 1$. They are standardized by requiring that $P_j(1) = 1$ for all $j \geq 0$. Thus $P_0(x) = 1$. The linear polynomial $P_1(x) = a + bx$ is orthogonal to P_0 so that

$$\int_{-1}^1 P_1(x)P_0(x) dx = \int_{-1}^1 a + bx dx = 0$$

which implies $a = 0$. The standardization $P_1(1) = 1$ implies that $P_1(x) = x$. The remaining Legendre polynomials can be computed by looking up the three-term recurrence relation: $A_j = 0$, $B_j = (2j - 1)/j$, and $C_j = (j - 1)j$. The following program computes Legendre polynomials evaluated at a set of points:

```
maxDegree = 6;
/* evaluate polynomials at these points */
x = T( do(-1,1,0.05) );

/* define the standard Legendre Polynomials
Using the 3-term recurrence with
A[j]=0, B[j]=(2j-1)/j, and C[j]=(j-1)/j
and the standardization P_j(1)=1
which implies P_0(x)=1, P_1(x)=x. */
legendre = j(nrow(x), maxDegree+1);
legendre[,1] = 1; /* P_0 */
```

```

legendre[,2] = x; /* P_1 */

do j = 2 to maxDegree;
    legendre[,j+1] = (2*j-1)/j # x # legendre[,j] -
                    (j-1)/j # legendre[,j-1];
end;

```

ORTVEC Call

CALL ORTVEC(*w*, *r*, *rho*, *lindep*, *v* <, *q* >);

The ORTVEC subroutine provides columnwise orthogonalization and stepwise QR decomposition by using the Gram-Schmidt process.

The ORTVEC subroutine returns the following values:

w is an $m \times 1$ vector. If the Gram-Schmidt process converges (*lindep*=0), *w* is orthonormal to the columns of *Q*, which is assumed to have $n \leq m$ (nearly) orthonormal columns. If the Gram-Schmidt process does not converge (*lindep*=1), *w* is a vector of missing values. For stepwise QR decomposition, *w* is the $(n + 1)$ th orthogonal column of the matrix *Q*. If the *q* argument is not specified, *w* is the normalized value of the vector *v*,

$$w = \frac{v}{\sqrt{v'v}}$$

r is a $n \times 1$ vector. If the Gram-Schmidt process converges (*lindep*=0), *r* contains Fourier coefficients. If the Gram-Schmidt process does not converge (*lindep*=1), *r* is a vector of missing values. If the *q* argument is not specified, *r* is a vector with zero dimension. For stepwise QR decomposition, *r* contains the *n* upper triangular elements of the $(n + 1)$ th column of *R*.

rho is a scalar value. If the Gram-Schmidt process converges (*lindep*=0), *rho* specifies the distance from *w* to the range of *Q*. Even if the Gram-Schmidt process converges, if *rho* is sufficiently small, the vector *v* can be linearly dependent on the columns of *Q*. If the Gram-Schmidt process does not converge (*lindep*=1), *rho* is set to 0. For stepwise QR decomposition, *rho* contains the diagonal element of the $(n + 1)$ th column of *R*. In formulas, the value *rho* is denoted by ρ .

lindep returns a value of 1 if the Gram-Schmidt process does not converge in 10 iterations. A value of 1 often indicates that the input vector *v* is linearly dependent on the *n* columns of the input matrix *Q*. In that case, *rho* is set to 0, and the results *w* and *r* contain missing values. If *lindep*=0, the Gram-Schmidt process did converge, and the results *w*, *r*, and *rho* are computed.

The input arguments to the ORTVEC subroutine are as follows:

v specifies an $m \times 1$ vector *v* that is to be orthogonalized to the *n* columns of *Q*. For stepwise QR decomposition of a matrix, *v* is the $(n + 1)$ th matrix column before its orthogonalization.

q specifies an optional $m \times n$ matrix Q that is assumed to have $n \leq m$ (nearly) orthonormal columns. Thus, the $n \times n$ matrix $Q'Q$ should approximate the identity matrix. The column orthonormality assumption is not tested in the ORTVEC call. If it is violated, the results are not predictable. The argument q can be omitted or can have zero rows and columns. For stepwise QR decomposition of a matrix, q contains the first n matrix columns that are already orthogonal.

The relevant formula for the ORTVEC subroutine is

$$v = Qr + \rho w$$

In the formula, if the $m \times n$ matrix Q has n (nearly) orthonormal columns, the vector v is orthogonal to the columns of Q and ρ is the distance from w to the range of Q .

There are two special cases:

- If $m > n$, ORTVEC normalizes the result w , so that $w'w = 1$.
- If $m = n$, the output vector w is the null vector.

The case $m < n$ is not possible since Q is assumed to have n (nearly) orthonormal columns.

To initialize a stepwise QR decomposition, the ORTVEC subroutine can be called to normalize v only (that is, to compute $w = v/\sqrt{v'v}$ and $\rho = \sqrt{v'v}$). There are two ways of using the ORTVEC subroutine for this reason:

- Omit the last argument q , as in `call ortvec(w, r, rho, lind, v);`.
- Provide a matrix q with zero rows and columns (for example, by using the `free q;` command).

In both cases, r is a column vector with zero rows.

The ORTVEC subroutine is useful for the following applications:

- performing stepwise QR decomposition. Compute Q and R , so that $A = QR$, where Q is column orthonormal, $Q'Q = I$, and R is upper triangular. The j th step is applied to the j th column, v , of A , and it computes the j th column w of Q and the j th column, $(r \ \rho \ 0)'$, of R .
- computing the $m \times (m - n)$ null space matrix, Q_2 , that corresponds to an $m \times n$ range space matrix, Q_1 ($m > n$), by the following stepwise process:
 1. Set $v = e_i$ (where e_i is the i th unit vector) and try to make it orthogonal to all column vectors of Q_1 and the already generated Q_2 .
 2. If the subroutine is successful, append w to Q_2 ; otherwise, try $v = e_{i+1}$.

The 4×3 matrix Q contains the unit vectors e_1, e_3 , and e_4 . The column vector v is pairwise linearly independent with the three columns of Q . As expected, the ORTVEC subroutine computes the vector w as the unit vector e_2 with $u = (1, 1, 1)$ and $\rho = 1$.

```

q = { 1  0  0,
      0  0  0,
      0  1  0,
      0  0  1 };
v = { 1, 1, 1, 1 };
call ortvec(w,u,rho,lindep,v,q);
print rho u w;

```

Figure 23.223 Matrix Orthogonalization

	rho	u	w
	1	1	0
		1	1
		1	0
			0

Stepwise QR Decomposition Example

You can perform the QR decomposition of the linearly independent columns of an $m \times n$ matrix **A** with the following statements:

```

a = {1  2  1,
      2  4  2,
      1  4 -1,
      1  0  3}; /* use any matrix A */
nind = 0;  ndep = 0;  dmax = 0.;
n = ncol(a);  m = nrow(a);  ind = j(1,n,0);
free q;
do j = 1 to n;
  v = a[ ,j];
  call ortvec(w,u,rho,lindep,v,q);
  aro = abs(rho);
  if aro > dmax then dmax = aro;
  if aro <= 1.e-10 * dmax then lindep = 1;
  if lindep = 0 then do;
    nind = nind + 1;
    q = q || w;
    if nind = n then r = r || (u // rho);
    else r = r || (u // rho // j(n-nind,1,0.));
  end;
  else do;
    print "Column " j " is linearly dependent.";
    ndep = ndep + 1;  ind[ndep] = j;
  end;
end;
print q r;

```

Figure 23.224 QR Decomposition of Independent Columns

q		r	
0.3779645	0	2.6457513	5.2915026
0.7559289	0	0	2.8284271
0.3779645	0.7071068	0	0
0.3779645	-0.707107		

Next, process the remaining (dependent) columns of **A**:

```

do j = 1 to ndep;
  k = ind[ndep-j+1];
  v = a[ ,k];
  call ortvec(w,u,rho,lindep,v,q);
  if lindep = 0 then do;
    nind = nind + 1;
    q = q || w;
    if nind = n then r = r || (u // rho);
    else r = r || (u // rho // j(n-nind,1,0.));
  end;
end;
print q r;

```

Figure 23.225 QR Decomposition of Dependent Columns

q			r		
0.3779645	0	-0.239046	2.6457513	5.2915026	2.6457513
0.7559289	0	-0.478091	0	2.8284271	-2.828427
0.3779645	0.7071068	0.5976143	0	0	1.327E-16
0.3779645	-0.707107	0.5976143			

You can also use the **ORTVEC** subroutine to compute the null space in the last columns of **Q**:

```

do i = 1 to m;
  if nind < m then do;
    v = j(m,1,0.); v[i] = 1.;
    call ortvec(w,u,rho,lindep,v,q);
    aro = abs(rho);
    if aro > dmax then dmax = aro;
    if aro <= 1.e-10 * dmax then lindep = 1;
    if lindep = 0 then do;
      nind = nind + 1;
      q = q || w;
    end;
    else print "Unit vector" i "linearly dependent.";
  end;
end;
if nind < m then do;
  print "This is theoretically not possible.";
end;

```

```
print q;
```

Figure 23.226 Final Orthogonal Matrix

q				
0.3779645	0	-0.239046	0.8944272	
0.7559289	0	-0.478091	-0.447214	
0.3779645	0.7071068	0.5976143		0
0.3779645	-0.707107	0.5976143		-3.1E-17

In the example, if you define \mathbf{Q}_2 to be the last two columns of \mathbf{Q} , then $\mathbf{Q}_2' \mathbf{A} = \mathbf{0}$.

PAUSE Statement

PAUSE <expression> <*> ;

The PAUSE statement interrupts the execution of a module.

The arguments to the PAUSE statement are as follows:

expression is a character matrix or quoted literal that contains a message to print.

* suppresses any messages.

The PAUSE statement stops execution of a module, saves the calling chain so that execution can resume later (by a [RESUME statement](#)), prints a pause message that you can specify, and puts you in immediate mode so you can enter more statements.

You can specify an operand in the PAUSE statement to supply a message to be printed for the pause prompt. If no operand is specified, the following default message is printed:

Paused in module XXX.

In this case, XXX is the name of the module that contains the pause. If you want to suppress all messages in a PAUSE statement, use an asterisk as the operand, as follows:

pause *;

The PAUSE statement should be specified only in modules. It generates a warning if executed in immediate mode.

When an error occurs while executing inside a module, PROC IML automatically behaves as though a PAUSE statement was issued. The following note is displayed in the SAS Log:

Paused in module XXX.

PROC IML also enters “immediate mode” within the module environment. You can correct the error and then resume execution by issuing a **RESUME** command.

PROC IML supports pause processing of both subroutine and function modules. See also the description of the **SHOW statement** which uses the PAUSE option.

PGRAF Call

CALL PGRAF(*xy* < , *id* > < , *xlabel* > < , *ylabel* > < , *title* >);

The PGRAF subroutine displays a low-resolution scatter plot, sometimes called a “line-printer plot.”

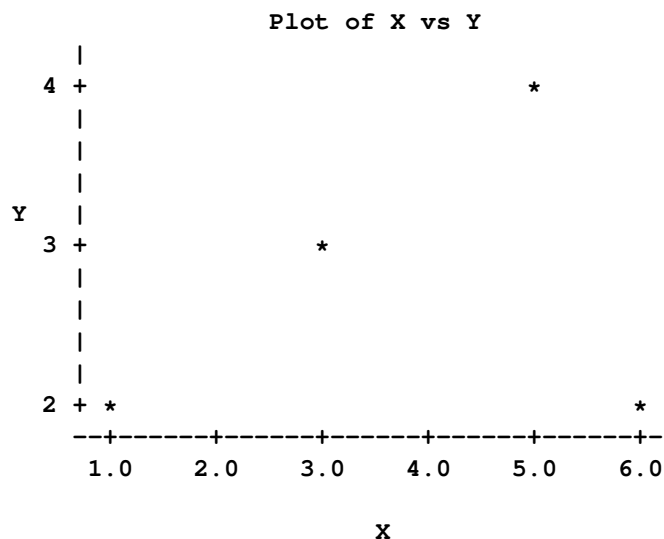
The arguments to the PGRAF subroutine are as follows:

<i>xy</i>	is an $n \times 2$ matrix of (x , y) points.
<i>id</i>	is an $n \times 1$ character matrix of labels for each point. The PGRAF subroutine uses up to 8 characters per point. If <i>id</i> is a scalar (1×1), then the same label is used for all of the points. The label is centered over the actual point location. If you do not specify <i>id</i> , ‘x’ is the default character for labeling the points.
<i>xlabel</i>	is a character scalar or quoted literal that labels the x axis (centered beneath the x axis).
<i>ylabel</i>	is a character scalar or quoted literal that labels the y axis (printed vertically to the left of the y axis).
<i>title</i>	is a character scalar or quoted literal printed above the graph.

The PGRAF subroutine produces a scatter plot suitable for display on a line printer or similar device.

The following statements specify a plotting symbol, axis labels, and a title to produce the plot shown.

```
xy={1 2, 3 3, 5 4, 6 2};
call pgraf(xy,"*", "X", "Y", "Plot of X vs Y");
```



POLYROOT Function

POLYROOT(*vector*);

The POLYROOT function computes the zeros of a real polynomial. The *vector* argument is an $n \times 1$ (or $1 \times n$) vector that contains the coefficients of an $(n - 1)$ degree polynomial with the coefficients arranged in order of decreasing powers.

The POLYROOT function returns the array *r*, which is an $(n - 1) \times 2$ matrix that contains the roots of the polynomial. The first column of *r* contains the real part of the complex roots, and the second column contains the imaginary part. If a root is real, the imaginary part is 0.

The POLYROOT function finds the real and complex roots of a polynomial with real coefficients.

The POLYROOT function uses an algorithm proposed by Jenkins and Traub (1970) to find the roots of the polynomial. The algorithm is not guaranteed to find all roots of the polynomial. An appropriate warning message is issued when one or more roots cannot be found. If *r* is given as a root of the polynomial $P(x)$, then $1 + P(R) = 1$, based on the rounding error of the computer that is employed.

For example, you can use the following statements to find the roots of the polynomial

$$P(x) = 0.2567x^4 + 0.1570x^3 + 0.0821x^2 - 0.3357x + 1$$

```
p = {0.2567 0.1570 0.0821 -0.3357 1};
r = polyroot(p);
print r;
```

Figure 23.227 Roots of a Quartic Polynomial

<i>r</i>	
0.8383029	0.8514519
0.8383029	-0.851452
-1.144107	1.1914525
-1.144107	-1.191452

The polynomial has two conjugate pairs of roots that, within machine precision, are given by $r = 0.8383029 \pm 0.8514519i$ and $r = -1.144107 \pm 1.1914525i$.

PRINT Statement

PRINT < *matrices* > < (*expression*) > < "message" > < *pointer-controls* > < [*options*] > ;

The PRINT statement displays the values of matrices or literals.

The arguments to the PRINT statement are as follows:

<i>matrices</i>	are the names of matrices.
<i>(expression)</i>	is an expression in parentheses that is evaluated. The result of the evaluation is printed. The evaluation of a subscripted matrix used as an expression results in printing the submatrix.
<i>"message"</i>	is a message in quotes.
<i>pointer-controls</i>	control the pointer for printing. For example, a comma (,) skips a single line and a slash (/) skips to a new page.
<i>options</i>	are described in the following list.

The following *options* can appear in the PRINT statement. They are specified in brackets after the matrix name to which they apply.

COLNAME=*matrix*

specifies the name of a character matrix whose first *ncol* elements are to be used for the column labels of the matrix to be printed, where *ncol* is the number of columns in the matrix. You can also use the [RESET AUTONAME statement](#) to automatically label columns as COL1, COL2, and so on.

FORMAT=*format*

specifies a valid SAS or user-defined format to use in printing the values of the matrix. For example:

```
print x[format=5.3];
```

LABEL=*label*

specifies the name of a scalar character matrix or literal to use as a label when printing the matrix. For example:

```
print x[label="Net Pay"];
```

ROWNAME=*matrix*

specifies the name of a character matrix whose first *nrow* elements are to be used for the row labels of the matrix to be printed, where *nrow* is the number of rows in the matrix and where the scan to find the first *nrow* elements goes across row 1, then across row 2, and so forth through row *n*. You can also use the following [RESET AUTONAME statement](#) to automatically label rows as ROW1, ROW2, and so on:

```
reset autoname;
```

For example, the following statements print a matrix in the 12.2 format with column and row labels:

```
x = {45.125 50.500,
      75.375 90.825};
r = {"Div A"  "Div B"};
c = {"Amount" "Net Pay"};
print x[rowname=r colname=c format=12.2];
```

Figure 23.228 Matrix with Row and Column Labels

	x	
	Amount	Net Pay
Div A	45.13	50.50
Div B	75.38	90.83

To permanently associate the preceding options with a matrix name, see the description of the [MATTRIB statement](#).

If there is not enough room to print all the matrices across the page, then one or more matrices are printed out in the next group. If there is not enough room to print all the columns of a matrix across the page, then the columns are continued on a subsequent line.

The spacing between adjacent matrices can be controlled by the SPACES= option of the [RESET statement](#). The FW= option of the [RESET statement](#) can be used to control the number of print positions used to print each numeric element. For more print-related options, including the PRINTADV option, see the description of the [RESET statement](#).

To print part of a matrix or a temporary expression, enclose the expression in parentheses:

```
y=1:10;
print (y[1:3])[format=5.1]; /* prints first few elements */
print (sum(y))[label="sum"];
```

Figure 23.229 Printing Temporary Matrices

	x	
	Amount	Net Pay
Div A	45.13	50.50
Div B	75.38	90.83
	1.0	
	2.0	
	3.0	
	sum	
	55	

PROD Function

PROD(*matrix1* <, *matrix2*, ..., *matrix15* >);

The PROD function returns as a single numeric value the product of all nonmissing elements in all arguments. You can pass in as many as 15 numeric matrices as arguments. The PROD function checks for missing values and does not include them in the product. It returns missing if all values are missing.

For example, consider the following statements:

```
a = {2 1, . 3};
b = prod(a);
print b;
```

Figure 23.230 Output from the PROD Function

	b
	6

For a single argument with at least one nonmissing value, the PROD function is identical to the subscript reduction operator that computes the product. That is, `prod(x)` and `x[#]` both compute the product of the elements of `x`. See the section “[Subscript Reduction Operators](#)” on page 59 for more information about subscript reduction operators.

PRODUCT Function

PRODUCT(*a*, *b* <, *dim*>);

The PRODUCT function multiplies matrices of polynomials.

The arguments to the PRODUCT function are as follows:

- a* is an $m \times (ns)$ numeric matrix. The first $m \times n$ submatrix contains the constant terms of the polynomials, the second $m \times n$ submatrix contains the first-order terms, and so on.
- b* is an $n \times (pt)$ matrix. The first $n \times p$ submatrix contains the constant terms of the polynomials, the second $n \times p$ submatrix contains the first-order terms, and so on.
- dim* is a 1×1 matrix, with value $p > 0$. The value of this matrix is used to set the dimension p of the matrix *b*. If omitted, the value of p is set to 1.

The PRODUCT function multiplies matrices of polynomials. The value returned is the $m \times (p(s + t - 1))$ matrix of the polynomial products. The first $m \times p$ submatrix contains the constant terms, the second $m \times p$ submatrix contains the first-order terms, and so on.

The PRODUCT function can be used to multiply the matrix operators employed in a multivariate time series model of the form

$$\Phi_1(B)\Phi_2(B)Y_t = \Theta_1(B)\Theta_2(B)\epsilon_t$$

where $\Phi_1(B)$, $\Phi_2(B)$, $\Theta_1(B)$, and $\Theta_2(B)$ are matrix polynomial operators whose first matrix coefficients are identity matrices. Often $\Phi_2(B)$ and $\Theta_2(B)$ represent seasonal components that are isolated in the modeling process but multiplied with the other operators when forming predictors or estimating parameters. The [RATIO function](#) is often employed in a time series context as well.

For example, the following statements demonstrate the PRODUCT function:

```

m1 = {1 2 3 4,
      5 6 7 8};
m2 = {1 2 3,
      4 5 6};
r = product(m1, m2, 1);
print r;

```

Figure 23.231 A Product of Matrices of Polynomials

r			
9	31	41	33
29	79	105	69

PURGE Statement

PURGE ;

The PURGE data processing statement is used to remove observations marked for deletion and to renumber the remaining observations. This closes the gaps created by deleted records. Execution of this statement can be time-consuming because it involves rewriting the entire data set.

CAUTION: Any indexes associated with the data set are lost after a purge.

When you quit PROC IML, observations marked for deletion are *not* automatically purged.

The following example creates a data set named A. The EDIT statement opens the data set for editing. The DELETE statement marks several observations for deletion. As shown in [Figure 23.232](#), the observations are not removed and renumbered until the PURGE statement executes.

```

data a;
do i=1 to 10;
  output;
end;
run;

proc iml;
edit a;
pts = 3:8;
delete point pts;
list all;

purge;
list all;

```

Figure 23.232 Deleting and Purging Observations

OBS	i
1	1.0000
2	2.0000
9	9.0000
10	10.0000

OBS	i
1	1.0000
2	2.0000
3	9.0000
4	10.0000

PUSH Call

CALL PUSH(*argument1* < , *argument2* , ... , *argument15* >);

The PUSH subroutine pushes character arguments that contain valid SAS statements (usually SAS/IML statements or global statements) to the input command stream. You can specify up to 15 arguments. Any statements in the input command queue are executed when the module is paused (see the [PAUSE statement](#)), which happens when one of the following occurs:

- An execution error occurs within a module.
- An interrupt is issued.
- A PAUSE statement executes.

The pushed string is read before any other lines of input. If you call the PUSH subroutine several times, the strings pushed each time are ahead of the less recently pushed strings. If you would rather place the lines after others in the input stream, then use the [QUEUE](#) command instead.

The strings you push do not appear on the log.

CAUTION: Do not push too many statements at one time. Pushing too many statements causes problems that can result in exiting the SAS System.

For more information about the input command stream, see [Chapter 18](#).

An example that uses the PUSH subroutine follows:

```
start;
  code='reset pagesize=25;';
  call push(code, 'resume;');
  pause;
```

```

/* show that pagesize was set to 25 during */
/* a PAUSE state of a module */
show options;
finish;
run main;

```

Figure 23.233 Result of a PUSH Statement

```

Options: noautoname center noclip
         deflib=WORK (system-specific-pathname)
         nodetails noflow nofuzz fw=9
         imlmlib=SASHELP.IMLMLIB linesize=80 nolog
         name pagesize=25 noprint noprintall spaces=1
         userlib=WORK.IMLSTOR(not open)

```

PUT Statement

PUT <operand> <record-directives> <positionals> <format> ;

The PUT statement writes data to an external file.

The arguments to the PUT statement are as follows:

<i>operand</i>	specifies the value you want to output to the current position in the record. The <i>operand</i> can be either a variable name, a literal value, or an expression in parentheses. The <i>operand</i> can be followed immediately by an output format specification.						
<i>record-directives</i>	start new records. There are three types: <table> <tr> <td><i>holding @</i></td><td>is used at the end of a PUT statement to hold the current record so that you can continue to write more data to the record with later PUT statements. Otherwise, the next record is used for the next PUT statement.</td></tr> <tr> <td><i>/</i></td><td>writes out the current record and begins forming a new record.</td></tr> <tr> <td><i>> operand</i></td><td>specifies that the next record written start at the indicated byte position in the file (for RECFM=N files only). The <i>operand</i> is a literal number, a variable name, or an expression in parentheses. For example:</td></tr> </table> <pre>put >3 x 3.2;</pre>	<i>holding @</i>	is used at the end of a PUT statement to hold the current record so that you can continue to write more data to the record with later PUT statements. Otherwise, the next record is used for the next PUT statement.	<i>/</i>	writes out the current record and begins forming a new record.	<i>> operand</i>	specifies that the next record written start at the indicated byte position in the file (for RECFM=N files only). The <i>operand</i> is a literal number, a variable name, or an expression in parentheses. For example:
<i>holding @</i>	is used at the end of a PUT statement to hold the current record so that you can continue to write more data to the record with later PUT statements. Otherwise, the next record is used for the next PUT statement.						
<i>/</i>	writes out the current record and begins forming a new record.						
<i>> operand</i>	specifies that the next record written start at the indicated byte position in the file (for RECFM=N files only). The <i>operand</i> is a literal number, a variable name, or an expression in parentheses. For example:						
<i>positionals</i>	specify the column on the record to which the PUT statement should go. There are two types of positionals: <table> <tr> <td><i>@ operand</i></td><td>specifies to go to the indicated column, where <i>operand</i> is a literal number, a variable name, or an expression in parentheses. For example, @30 means to go to column 30.</td></tr> </table>	<i>@ operand</i>	specifies to go to the indicated column, where <i>operand</i> is a literal number, a variable name, or an expression in parentheses. For example, @30 means to go to column 30.				
<i>@ operand</i>	specifies to go to the indicated column, where <i>operand</i> is a literal number, a variable name, or an expression in parentheses. For example, @30 means to go to column 30.						

+ *operand* specifies that the indicated number of columns are to be skipped, where *operand* is a literal number, a variable name, or an expression in parentheses.

format specifies a valid SAS or user-defined output format. These are of the form *w.d* or *\$w.* for standard numeric and character formats, respectively, where *w* is the width of the field and *d* is the decimal parameter, if any. They can also be a named format of the form *NAMEw.d*, where *NAME* is the name of the format. If the width is unspecified, then a default width is used; this is 9 for numeric variables.

The PUT statement writes to the file specified in the previously executed FILE statement, putting the values from matrices. The statement is described in detail in [Chapter 8](#).

The PUT statement is a sequence of positionals and record directives, variables, and formats. An example that uses the PUT statement follows:

```
/* output variable A in column 1 using a 6.4 format */
/* Skip 3 columns and output X using an 8.4 format */
put @1 a 6.4 +3 x 8.4;
```

PV Function

PV(*times,flows,freq,rates*);

The PV function returns a scalar that contains the present value of the cash flows based on the specified frequency and rates.

The arguments to the function are as follows:

<i>times</i>	is an $n \times 1$ column vector of times. Elements should be nonnegative.
<i>flows</i>	is an $n \times 1$ column vector of cash flows.
<i>freq</i>	is a scalar that represents the base of the rates to be used for discounting the cash flows. If positive, it represents discrete compounding as the reciprocal of the number of compoundings per period. If zero, it represents continuous compounding. If -1 , the rates represent per-period discount factors. No other negative values are accepted.
<i>rates</i>	is an $n \times 1$ column vector of rates to be used for discounting the cash flows. Elements should be positive.

A general present value relationship can be written as

$$P = \sum_{k=1}^K c(k)D(t_k)$$

where P is the present value of the asset, $\{c(k)\}$, $k = 1, \dots, K$, is the sequence of cash flows from the asset, t_k is the time to the k th cash flow in periods from the present, and $D(t)$ is the discount function for time t . The discount factors are as follows:

- with per-unit-time-period discount factors d_t :

$$D(t) = d_t^t$$

- with continuous compounding:

$$D(t) = e^{-r_t t}$$

- with discrete compounding:

$$D(t) = (1 + fr)^{-t/f}$$

where $f > 0$ is the frequency, the reciprocal of the number of compoundings per unit time period.

The following statements present an example of using the PV function in the DATA step:

```
data a;
  pv = mort(., 438.79, 0.10/12, 30*12);
run;
proc print data=a; run;
```

Figure 23.234 Present Value Computation (DATA Step)

	OBS	pv
	1	50000.48

You can do the same computation by using the PV function in SAS/IML software. The first example uses a monthly rate; the second example uses an annual rate.

```
proc iml;
/* If rate is specified as annual rate divided by 12 and FREQ=1,
 * then results are equal to those computed by the MORT function. */
timesn = t(1:360);
flows = repeat(438.79, 360);
rate = repeat(0.10/12, 360);
freq = 1;
pv = pv(timesn, flows, freq, rate);
print pv;

/* If rate is specified as annual rate, then the cash flow TIMES
 * need to be specified in 1/12 increments and the FREQ=1/12.
 * This produces the same result as the previous PV call. */
timesn = t(do(1/12, 30, 1/12));
flows = repeat(438.79, 360);
rate = repeat(0.10, 360); /* specify annual rate */
freq = 1/12;             /* 12 compoundings annually */
pv = pv(timesn, flows, freq, rate);
print pv;
```

Figure 23.235 Present Value Computation (PROC IML)

	p_v
	50000.48
	p_v
	50000.48

QNTL Call

CALL QNTL(*q*, *x*, <, *probs*> <, *method*>);

The QNTL subroutine computes sample quantiles for data. The arguments are as follows:

<i>q</i>	specifies a matrix to contain the quantiles of the <i>x</i> matrix.
<i>x</i>	specifies an $n \times p$ numerical matrix of data. The QNTL subroutine computes quantiles for each column of the matrix.
<i>probs</i>	specifies a numeric vector of probabilities used to compute the quantiles. If this option is not specified, the vector {0.25, 0.5, 0.75} is used, resulting in the quartiles of the data.
<i>method</i>	specifies the method used to compute the quantiles. These methods correspond to those defined by using the PCTLDEF= option in the UNIVARIATE procedure. For details, see the section “Calculating Percentiles” of the documentation for the CORR procedure in the <i>Base SAS Procedures Guide: Statistical Procedures</i> .

The following values are valid:

1	specifies that quantiles are computed according to a weighted average.
2	specifies that quantiles are computed by choosing an observation closest to some quantity.
3	specifies that quantiles are computed by using the empirical distribution function.
4	specifies that quantiles are computed according to a different weighted average.
5	specifies that quantiles are computed by using average values of the empirical distribution function. This is the default value.

If *x* is an $n \times p$ matrix, the QNTL subroutine computes a $k \times p$ matrix where *k* is the dimension of the PROBS= option. The quantiles are returned in the *q* matrix, as shown in the following example:

```
x = {5 1 10,
      6 2 3,
      6 8 5,
      6 7 9,
      7 2 13};
```

```
call qntl(q, x);
print q[rowname={"P25", "P50", "P75"}];
```

Figure 23.236 Quantiles

	q		
P25	6	2	5
P50	6	2	9
P75	6	7	10

You can use the MATTRIB statement to permanently assign row names to the matrix that contains the quantiles, as shown in the following statements:

```
p = {0.25 0.50 0.75};
labels = "P" + strip(putn(100*p, "best5."));
mattrib q rowname=labels;
print q;
```

Figure 23.237 Rownames for Quantiles

	q		
P25	6	2	5
P50	6	2	9
P75	6	7	10

You can specify the optional arguments in either of two ways: by specifying an argument positionally or by specifying a keyword/value pair, as shown in the following statements.

```
x = T(1:100);
p = do(0.1, 0.9, 0.1);
call qntl(q1, x, p);
call qntl(q2, x) probs=p; /* equivalent */
```

QR Call

CALL QR(*q*, *r*, *piv*, *lindep*, *a* <, *ord* > <, *b* >);

The QR subroutine produces the QR decomposition of a matrix by using Householder transformations.

The QR subroutine returns the following values:

q specifies an orthogonal matrix **Q** that is the product of the Householder transformations applied to the $m \times n$ matrix **A**, if the *b* argument is not specified. In this case, the $\min(m, n)$ Householder transformations are applied, and *q* is an $m \times m$ matrix. If the *b* argument is specified, *q* is the $m \times p$ matrix **Q'B** that has the transposed Householder transformations **Q'** applied on the *p* columns of the argument matrix **B**.

- r* specifies a $\min(m, n) \times n$ upper triangular matrix \mathbf{R} that is the upper part of the $m \times n$ upper triangular matrix $\tilde{\mathbf{R}}$ of the QR decomposition of the matrix \mathbf{A} . The matrix $\tilde{\mathbf{R}}$ of the QR decomposition can be obtained by vertical concatenation (by using the operator `//`) of the $(m - \min(m, n)) \times n$ zero matrix to the result matrix \mathbf{R} .
- piv* specifies an $n \times 1$ vector of permutations of the columns of \mathbf{A} ; that is, on return, the QR decomposition is computed, not of \mathbf{A} , but of the permuted matrix whose columns are $[\mathbf{A}_{piv[1]} \dots \mathbf{A}_{piv[n]}]$. The vector *piv* corresponds to an $n \times n$ permutation matrix $\mathbf{\Pi}$.
- lindep* is the number of linearly dependent columns in matrix \mathbf{A} detected by applying the $\min(m, n)$ Householder transformations in the order specified by the argument vector *piv*.

The input arguments to the QR subroutine are as follows:

- a* specifies an $m \times n$ matrix \mathbf{A} that is to be decomposed into the product of the orthogonal matrix \mathbf{Q} and the upper triangular matrix $\tilde{\mathbf{R}}$.
- ord* specifies an optional $n \times 1$ vector that specifies the order of Householder transformations applied to matrix \mathbf{A} . When you specify the *ord* argument, the columns of \mathbf{A} can be divided into the following groups:
- | | |
|--------------------|---|
| <i>ord[j]>0</i> | Column <i>j</i> of \mathbf{A} is an <i>initial column</i> , meaning it has to be processed at the start in increasing order of <i>ord[j]</i> . This specification defines the first n_l columns of \mathbf{A} that are to be processed. |
| <i>ord[j]=0</i> | Column <i>j</i> of \mathbf{A} is a <i>pivot column</i> , meaning it is to be processed in order of decreasing residual Euclidean norms. The pivot columns of \mathbf{A} are processed after the n_l initial columns and before the n_u final columns. |
| <i>ord[j]<0</i> | Column <i>j</i> of \mathbf{A} is a <i>final column</i> , meaning it has to be processed at the end in decreasing order of <i>ord[j]</i> . This specification defines the last n_u columns of \mathbf{A} that are to be processed. If $n > m$, some of these columns are not processed. |
- The default is *ord[j]=j*, in which case the Householder transformations are processed in the same order in which the columns are stored in matrix \mathbf{A} (without pivoting).
- b* specifies an optional $m \times p$ matrix \mathbf{B} that is to be multiplied by the transposed $m \times m$ matrix \mathbf{Q}' . If *b* is specified, the result *q* contains the $m \times p$ matrix $\mathbf{Q}'\mathbf{B}$. If *b* is not specified, the result *q* contains the $m \times m$ matrix \mathbf{Q} .

The QR subroutine decomposes an $m \times n$ matrix \mathbf{A} into the product of an $m \times m$ orthogonal matrix \mathbf{Q} and an $m \times n$ upper triangular matrix $\tilde{\mathbf{R}}$, so that

$$\mathbf{A}\mathbf{\Pi} = \mathbf{Q}\tilde{\mathbf{R}}, \mathbf{Q}'\mathbf{Q} = \mathbf{Q}\mathbf{Q}' = \mathbf{I}_m$$

by means of $\min(m, n)$ Householder transformations.

The $m \times m$ orthogonal matrix \mathbf{Q} is computed only if the last argument *b* is not specified, as in the following example:

```
call qr(q, r, piv, lindep, a, ord);
```

In many applications, the number of rows, m , is very large. In these cases, the explicit computation of the $m \times m$ matrix \mathbf{Q} might require too much memory or time.

In the usual case where $m > n$,

$$\mathbf{A} = \begin{bmatrix} * & * & * \\ * & * & * \\ * & * & * \\ * & * & * \\ * & * & * \end{bmatrix} \quad \mathbf{Q} = \begin{bmatrix} * & * & * & * & * \\ * & * & * & * & * \\ * & * & * & * & * \\ * & * & * & * & * \\ * & * & * & * & * \end{bmatrix}$$

$$\tilde{\mathbf{R}} = \begin{bmatrix} * & * & * \\ 0 & * & * \\ 0 & 0 & * \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix} \quad \mathbf{R} = \begin{bmatrix} * & * & * \\ 0 & * & * \\ 0 & 0 & * \end{bmatrix}$$

$$\mathbf{Q} = [\mathbf{Q}_1 \ \mathbf{Q}_2], \quad \tilde{\mathbf{R}} = \begin{bmatrix} \mathbf{R} \\ \mathbf{0} \end{bmatrix}$$

where \mathbf{R} is the result returned by the QR subroutine.

The n columns of matrix \mathbf{Q}_1 provide an orthonormal basis for the n columns of \mathbf{A} and are called the *range space* of \mathbf{A} . Since the $m - n$ columns of \mathbf{Q}_2 are orthogonal to the n columns of \mathbf{A} , $\mathbf{Q}_2' \mathbf{A} = \mathbf{0}$, they provide an orthonormal basis for the orthogonal complement of the columns of \mathbf{A} and are called the *null space* of \mathbf{A} .

In the case where $m < n$,

$$\mathbf{A} = \begin{bmatrix} * & * & * & * & * \\ * & * & * & * & * \\ * & * & * & * & * \end{bmatrix} \quad \mathbf{Q} = \begin{bmatrix} * & * & * \\ * & * & * \\ * & * & * \end{bmatrix}$$

$$\tilde{\mathbf{R}} = \mathbf{R} = \begin{bmatrix} * & * & * & * & * \\ 0 & * & * & * & * \\ 0 & 0 & * & * & * \end{bmatrix}$$

Specifying the argument *ord* as an n vector lets you specify a special order of the columns in matrix \mathbf{A} on which the Householder transformations are applied. There are two special cases:

- If you do not specify the *ord* argument, the default values $\text{ord}[j] = j$ are used. In this case, Householder transformations are done in the same order in which the columns are stored in \mathbf{A} (without pivoting).
- If you set all components of *ord* to zero, the Householder transformations are done in order of decreasing Euclidean norms of the columns of \mathbf{A} .

To check the QR decomposition, use the following statements to compute the three residual sum of squares (represented by the variables SS0, SS1, and SS2), which should be close to zero:

```
a = shape(1:20, 5);
m = nrow(a); n = ncol(a);
ord = j(1, n, 0);
call qr(q, r, piv, lindep, a);
ss0 = ssq(a[ ,piv] - q[,1:n] * r);
ss1 = ssq(q * q` - i(m));
ss2 = ssq(q` * q - i(m));
print ss0 ss1 ss2;
```

Figure 23.238 Result of a QR Decomposition

ss0	ss1	ss2
6.231E-28	2.948E-31	2.862E-31

If the QR subroutine detects linearly dependent columns while processing matrix **A**, the column order given in the result vector *piv* can differ from an explicitly specified order in the argument vector *ord*. If a column of **A** is found to be linearly dependent on columns already processed, this column is swapped to the end of matrix **A**. The order of columns in the result matrix **R** corresponds to the order of columns processed in **A**. The swapping of a linearly dependent column of **A** to the end of the matrix corresponds to the swapping of the same column in **R** and leads to a zero row at the end of the upper triangular matrix **R**.

The scalar result *lindep* counts the number of linearly dependent columns that are detected in constructing the first min(*m*, *n*) Householder transformations in the order specified by the argument vector *ord*. The test of linear dependence depends on the singularity criterion, which is 1E-8 by default.

Solving the linear system $Rx = Q'b$ with an upper triangular matrix **R** whose columns are permuted corresponding to the result vector *piv* leads to a solution *x* with permuted components. You can reorder the components of *x* by using the index vector *piv* at the left-hand side of an expression, as follows:

```
a = {3  0  0 -1,
      0  1  2  0,
      4 -4 -1  1,
      -1 2  3  4};
b = {-1, 8, -3, 28};

n = ncol(a); p = ncol(b);
ord = j(1, n, 0);
call qr(qtb, r, piv, lindep, a, ord, b);
print piv;

x = j(n,1);
x[piv] = inv(r) * qtb[1:n, 1:p];
print x;
```

Figure 23.239 Solution to a Linear System

piv			
1	4	2	3

Figure 23.239 continued

x	
	1
	2
	3
	4

The Full-Rank Linear Least Squares Problem

This example solves the full-rank linear least squares problem. Specify the argument b as an $m \times p$ matrix B , as follows:

```
call qr(q, r, piv, lindep, a, ord, b);
```

When you specify the b argument, the QR subroutine computes the matrix $Q'B$ (instead of Q) as the result q . Now you can compute the p least squares solutions x_k of an overdetermined linear system with an $m \times n, m > n$ coefficient matrix A , $\text{rank}(A) = n$, and p right-hand sides b_k stored as the columns of the $m \times p$ matrix B :

$$\min_{x_k} \|Ax_k - b_k\|^2, k = 1, \dots, p$$

where $\|\cdot\|$ is the Euclidean vector norm. This is accomplished by solving the p upper triangular systems with back substitution:

$$x_k = P' R^{-1} Q_1' b_k, k = 1, \dots, p$$

For most applications, the number of rows of A , m , is much larger than n , the number of columns of A , or p , the number of right-hand sides. In these cases, you are advised not to compute the large $m \times m$ matrix Q (which can consume too much memory and time) if you can solve your problem by computing only the smaller $m \times p$ matrix $Q'B$ implicitly.

For example, use the first five columns of the 6×6 Hilbert matrix A , as follows:

```
a= { 36      -630      3360      -7560      7560      -2772,
     -630     14700     -88200     211680     -220500     83160,
     3360     -88200     564480    -1411200     1512000     -582120,
    -7560     211680    -1411200     3628800    -3969000     1552320,
     7560    -220500     1512000    -3969000     4410000    -1746360,
    -2772     83160     -582120     1552320    -1746360     698544 };
aa = a[, 1:5];
b= { 463, -13860, 97020, -258720, 291060, -116424};

m = nrow(aa); n = ncol(aa); p = ncol(b);
call qr(qtb, r, piv, lindep, aa, , b);

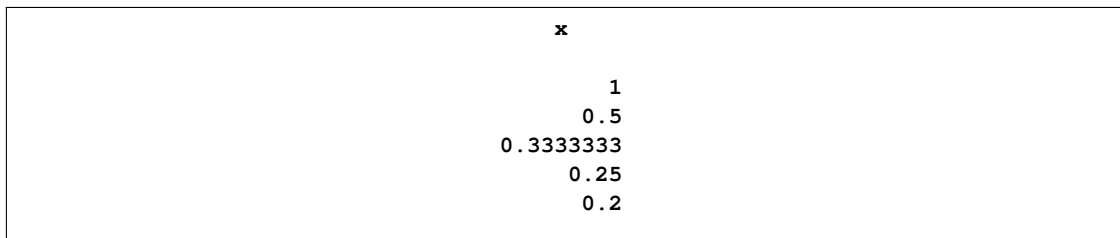
if lindep=0 then do;
```

```

    x=inv(r)*qtb[1:n];
    print x; /* x solves aa*x=b */
end;
else /* handle linear dependence */;

```

Figure 23.240 Solution to Least Squares Problem



Note that you are using only the first n rows, $Q_1^T B$, of the `qtb` matrix. The **IF-THEN** statement of the preceding example can be replaced by the more efficient **TRISOLV** function:

```

if lndep=0 then
    x = trisolv(1, r, qtb[1:n], piv);

```

For information about solving rank-deficient linear least squares problems, see the **RZLIND** call.

QUAD Call

```

CALL QUAD(r, "fun", points < , eps > < , peak > < , scale > < , msg > < , cycles > );

```

The QUAD subroutine performs numerical integration of scalar functions in one dimension over infinite, connected semi-infinite, and connected finite intervals.

The QUAD subroutine returns the following value:

r is a numeric vector that contains the results of the integration. The size of *r* is equal to the number of subintervals defined by the argument *points*. If the numerical integration fails on a particular subinterval, the corresponding element of *r* is set to missing.

The input arguments to the QUAD subroutine are as follows:

"fun" specifies the name of a module used to evaluate the integrand.

points specifies a sorted vector that provides the limits of integration over connected subintervals. The simplest form of the vector provides the limits of the integration on one interval. The first element of *points* should contain the left limit. The second element should be the right limit. A missing value of `.M` in the left limit is interpreted as $-\infty$, and a missing value of `.P` is interpreted as $+\infty$. For more advanced usage of the QUAD call, *points* can contain more than two elements. The elements of the vector must be sorted in an ascending order. Each two consecutive elements in *points* defines a subinterval, and the subroutine reports the integration over each specified subinterval. The use of subintervals is important because the presence of internal points of discontinuity in the integrand hinders the algorithm.

<i>eps</i>	is an optional scalar that specifies the desired relative accuracy. It has a default value of 1E-7. You can specify <i>eps</i> by using the EPS= keyword.
<i>peak</i>	is an optional scalar that is the approximate location of a maximum of the integrand. By default, it has a location of 0 for infinite intervals, a location that is one unit away from the finite boundary for semi-infinite intervals, and a centered location for bounded intervals. You can specify <i>peak</i> by using the PEAK= keyword.
<i>scale</i>	is an optional scalar that is the approximate estimate of any scale in the integrand along the independent variable (see the examples). It has a default value of 1. You can specify <i>scale</i> by using the SCALE= keyword.
<i>msg</i>	is an optional character scalar that restricts the number of messages produced by the QUAD subroutine. If <i>msg</i> = "NO" then it does not produce any warning messages. You can specify <i>msg</i> by using the MSG= keyword.
<i>cycles</i>	is an optional integer that indicates the maximum number of refinements the QUAD subroutine can make in order to achieve the required accuracy. It has a default value of 8. You can specify <i>cycles</i> by using the CYCLES= keyword.

If the dimensions of any optional argument are 0×0 , the QUAD subroutine uses its default value.

The QUAD subroutine is a numerical integrator based on adaptive Romberg-type integration techniques. See Rice (1973), Sikorsky (1982), Sikorsky and Stenger (1984), Stenger (1973a), Stenger (1973b), and Stenger (1978). Many adaptive numerical integration methods (Ralston and Rabinowitz 1978) start at one end of the interval and proceed towards the other end, working on subintervals while locally maintaining a certain prescribed precision. This is not the case with the QUAD call. The QUAD subroutine is an adaptive global-type integrator that produces a quick, rough estimate of the integration result and then refines the estimate until it achieves the prescribed accuracy. This gives the subroutine an advantage over Gauss-Hermite and Gauss-Laguerre quadratures (Ralston and Rabinowitz 1978; Squire 1987), particularly for infinite and semi-infinite intervals, because those methods perform only a single evaluation.

A Simple Example

Consider the integral

$$\int_0^{\infty} e^{-t} dt$$

The following statements evaluate this integral:

```
/* Define the integrand */
start fun(t);
  v = exp(-t);
  return(v);
finish;

a = {0 .P};
call quad(z, "fun", a);
print z[format=E21.14];
```

Figure 23.241 Result of Numerical Integration on a Semi-Infinite Domain

z
9.99999999595190E-01

The integration is carried out over the interval $(0, \infty)$, as specified by the **a** variable. The missing value in the second element of **a** is interpreted as ∞ . The values of EPS=1E-7, PEAK=1, SCALE=1, and CYCLES=8 are used by default.

The following statements integrate the same exponential function over two subintervals:

```
a = {0 3 .P };
call quad(z2, "fun", a);
print z2[format=E21.14];
```

Figure 23.242 Result of Numerical Integration on Two Intervals

z2
9.50212930994570E-01
4.97870683477090E-02

Notice that the elements of **a** are in ascending order. The integration is carried out over $(0, 3)$ and $(3, \infty)$, and the corresponding results are shown in the output. The values of EPS=1E-7, PEAK=1, SCALE=1, and CYCLES=8 are used by default. To obtain the results of integration over $(0, \infty)$, use the **SUM function** on the elements of the **z2** vector, as follows:

```
b = sum(z2);
print b[format=E21.14];
```

Figure 23.243 Result of Numerical Integration on Two Intervals

b
9.99999999342280E-01

Using the PEAK= Option

The *peak* and *scale* options enable you to avoid analytically changing the variable of the integration in order to produce a well-conditioned integrand that permits the numerical evaluation of the integration.

Consider the integration

$$\int_0^{\infty} e^{-10000t} dt$$

The following statements evaluate this integral:

```

start fun2(t);
    v = exp(-10000*t);
    return(v);
finish;

a = {0 .P};
/* Either syntax can be used */
/* call quad(z, "fun2", a, 1E-10, 0.0001); or */
call quad(z3, "fun2", a) eps=1E-10 peak=0.0001;
print z3[format=E21.14];

```

Figure 23.244 Result of Specifying PEAK= Option

z3
9.99999999998990E-05

The integration is performed over the semi-infinite interval $(0, \infty)$. The default values of `SCALE=1` and `CYCLES=8` are used. However, the default value of *peak* is 1 for this semi-infinite interval, which is not a good estimate of the location of the function's maximum. If you do not specify a *peak* value, the integration cannot be evaluated to the desired accuracy, a message is printed to the LOG, and a missing value is returned. Note that *peak* can still be set to $1E-7$ and the integration will be successful.

The evaluation of the integrand at *peak* must be nonzero for the computation to continue. You should adjust the value of *peak* to get a nonzero evaluation at *peak* before trying to adjust *scale*. Reducing *scale* decreases the initial step size and can lead to an increase in the number of function evaluations per step at a linear rate.

Using the SCALE= Option

Consider the integration

$$\int_{-\infty}^{\infty} e^{-100000(t-3)^2} dt$$

The integrand is essentially zero except on a small interval close to $t = 3$. The following statements evaluate this integral:

```

/* Define the integrand */
start fun3(t);
    v = exp(-100000*(t-3)*(t-3));
    return(v);
finish;

a = { .M .P };
call quad(z4, "fun", a) eps=1E-10 peak=3 scale=0.001;
print z4[format=E21.14];

```

The integration is carried out over the infinite interval $(-\infty, \infty)$. The default value of `CYCLES=8` has been used. The integrand has its maximum value at $t = 3$, so the `PEAK=3` option is specified.

If you use the default value of *scale*, the integral cannot be evaluated to the desired accuracy, and a missing value is returned. The variables *scale* and *cycles* can be used to increase the number of possible function evaluations; the number of possible function evaluations increases linearly with the reciprocal of *scale*, but it potentially increases in an exponential manner when *cycles* is increased. Increasing the number of function evaluations increases execution time.

Two-Dimensional Integration

When you perform double integration, you must separate the variables between the iterated integrals. There should be a clear distinction between the variable of the one-dimensional integration and the parameters that are passed to the integrand. Another important consideration is specifying the correct limits of integration.

For example, suppose you want to compute probabilities for the standard bivariate normal distribution with correlation ρ . In particular, if an observation (x, y) is drawn from the distribution, what is probability that $x \leq a$ and $y \leq b$ for given values of a and b ?

The bivariate normal probability is given by the following double integral:

$$\text{probnrm}(a, b, \rho) = \frac{1}{2\pi\sqrt{1-\rho^2}} \int_{-\infty}^a \int_{-\infty}^b \exp\left(-\frac{x^2 - 2\rho xy + y^2}{2(1-\rho^2)}\right) dy dx$$

The inner integral is

$$g(x, b, \rho) = \frac{1}{2\pi\sqrt{1-\rho^2}} \int_{-\infty}^b \exp\left(-\frac{x^2 - 2\rho xy + y^2}{2(1-\rho^2)}\right) dy$$

with parameters x and ρ , and the limits of integration are from $-\infty$ to b . The outer integral is then

$$\text{probnrm}(a, b, \rho) = \int_{-\infty}^a g(x, b, \rho) dx$$

with the limits from $-\infty$ to a .

You can write a function module with parameters a, b, ρ that computes the bivariate normal probability. In the following statements, the function module is called NORCDF2 because it compute the CDF of the bivariate normal distribution. The NORCDF2 module calls the QUAD subroutine on the MARGINAL module, which computes the outer integral. The MARGINAL module, in turn, uses the QUAD function to evaluate inner integral. The integrand of the inner integral is defined in the NORPDF2 module.

```

/*-----*/
/* This function is the density function and requires */
/* the variable T (passed in the argument)           */
/* and a list of global parameters, YV, RHO, COUNT   */
/*-----*/
start norpdf2(t) global(yv,rho,count);
  count = count+1;
  q=(t#t-2#rho#t#yv+yv#yv)/(1-rho#rho);
  p=exp(-q/2);
  return(p);
finish;

```

```

/*-----*/
/* The outer integral */
/* The limits of integration are .M to YY */
/* YV is passed as a parameter to the inner integral*/
/*-----*/
start marginal(v) global(yy,yv,eps);
  interval = .M || yy;
  if ( v < -12 ) then return(0);
  yv = v;
  call quad(pm, "NORPDF2", interval) eps=eps;
  return(pm);
finish;

/*-----*/
/* Global parameters: YY, RHO, EPS */
/* EPS is set from IML */
/*-----*/
start norcdf2(a, b, rrho) global(yy,rho,eps);
  rho = rrho; /* copy arguments (local variables) to global list */
  yy = b;

  interval= .M || a; /* upper/lower limits for outer integral */
  call quad(p,"MARGINAL",interval) eps=eps;

  pi = constant("Pi");
  per = p / (2#pi#sqrt(1-rho#rho)); /* scale the value from QUAD */
  return(per);
finish;

/*-----*/
/* Main Program: set up global constants and call QUAD */
/*-----*/
count = 0;
eps = 1E-11;

p = norcdf2(2, 1, 0.1);
print p[format=E21.14], count;

```

Figure 23.245 Result of Numerical Integration of a Double Iterated Integral

P
8.23640898880300E-01
count
250453

The variable COUNT contains the number of times the NORPDF2 module is called. Note that the value computed by the NORCDF2 module is very close to that returned by the PROBBNRM function, which computes probabilities for the bivariate normal model, as shown by the following statements:

```

/* Compute the value with the PROBBNRM function */
pp = probbnrm(2,1,0.1);
print pp[format=E21.14];

```

Figure 23.246 Result of Numerical Integration of a Double Iterated Integral

PP
8.23640898880500E-01

Note the following:

- The iterated inner integral cannot have a left endpoint of $-\infty$. For large values of v , the inner integral does not contribute to the answer but still needs to be computed to the required relative accuracy. Therefore, either cut off the function (when $v \leq -12$), as in the MARGINAL module in the preceding example, or have the intervals start from a reasonable cutoff value. In addition, the QUAD subroutine stops if the integrands appear to be identically 0 (probably caused by underflow) over the interval of integration.
- This method of integration (iterated, one-dimensional integrals) is extremely conservative and requires unnecessary function evaluations. In this example, the QUAD subroutine for the inner integration lacks information about the final value that the QUAD subroutine for the outer integration is trying to refine. The lack of communication between the two QUAD routines can cause useless computations to be performed in the inner integration.

To illustrate this idea, let the relative error be $1\text{E}-11$ and let the answer delivered by the outer integral be close to 0.8, as in this example. Any computation of the inner execution of the QUAD call that yields $0.8\text{E}-11$ or less does not contribute to the final answer of the QUAD subroutine for the outer integral. However, the inner integral lacks this information, and for a given value of the parameter yv , it attempts to compute an answer with much more precision than is necessary. The lack of communication between the two QUAD subroutines prevents the introduction of better cutoffs. Although this method can be inefficient, the final calculations are accurate.

QUEUE Call

CALL QUEUE(*argument1* <, *argument2*, ..., *argument15* >);

The QUEUE subroutine places character arguments that contain valid SAS statements (usually SAS/IML statements or global statements) at the end of the input command stream. You can specify up to 15 arguments. Each argument to the QUEUE subroutine is a character matrix or quoted literal that contains valid SAS statements.

The queued string is read after other lines of input already in the queue. If you want to push the lines in front of other lines already in the queue, use the [PUSH subroutine](#) instead. Any statements queued to the input command queue get executed when the module is paused (see the [PAUSE statement](#)), which happens when one of the following occurs:

- An execution error occurs within a module.
- An interrupt is issued.
- A PAUSE statement executes.

The strings you queue do not appear on the log.

CAUTION: Do not queue too many statements at one time. Queuing too many statements can cause problems that can result in exiting the SAS System.

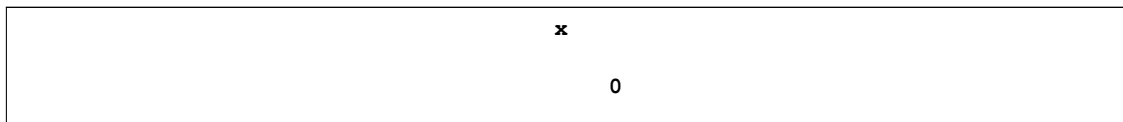
For more examples, see [Chapter 18](#).

An example that uses the QUEUE subroutine follows:

```
start mod(x);
  code="x=0;";
  call queue (code,"resume;");
  pause;
finish;

x=1;
run mod(x);
print x;
```

Figure 23.247 Result of Evaluating Queued Statements



QUIT Statement

QUIT ;

Use the QUIT statement to exit PROC IML. If a DATA or PROC statement is encountered, QUIT is implied. The QUIT statement is executed immediately; therefore, you cannot use QUIT as an executable statement (that is, as part of a module or conditional clause). However, you can use the [ABORT statement](#) as an executable statement.

PROC IML closes all open data sets and files when a QUIT statement is encountered. Workspace and symbol spaces are freed up. If you need to use any matrix values or any module definitions in a later session, you must store them in a storage library before you quit.

RANCOMB Function

RANCOMB(*n*, *k* <, *numcomb*>);

RANCOMB(*set*, *k* <, *numcomb*>);

The RANCOMB function generates random combinations of *k* elements taken from a set of *n* elements. The random number seed is set by the [RANDSEED](#) subroutine.

The first argument, *set*, can be a scalar or a vector. If *set* is a scalar, the function returns indices in the range 1–*n*. If *set* is a vector, the number of elements of the vector determines *n* and the RANCOMB function returns elements of *set*.

By default, the RANCOMB function returns a single random combination with one row and *k* columns. If the *numcomb* argument is specified, the function returns a matrix with *numcomb* rows and *k* columns. Each row of the returned matrix represents a single combination.

The following statements generate five random combinations of two elements from the set {1, 2, 3, 4}:

```
n = 4;
k = 2;
call randseed(1234);
c = rancomb(n, k, 5);
print c;
```

Figure 23.248 Random Pairwise Combinations of Four Items

c	
1	4
1	2
2	4
2	3
1	3

The function can return combinations for arbitrary numerical or character matrices. For example, the following statements generate five random pairwise combinations of four elements:

```
d = rancomb({A B C D}, 2, 5);
print d;
```

Figure 23.249 Random Pairwise Combinations of Four Characters

d	
A D	
A B	
A D	
B D	
A B	

RANDGEN Call

CALL RANDGEN(*result*, *distname* < , *parm1* > < , *parm2* > < , *parm3* >);

The RANDGEN subroutine generates random numbers from a specified distribution.

The input arguments to the RANDGEN subroutine are as follows:

result is a matrix that is to be filled with random samples from the specified distribution.
distname is the name of the distribution that is to be sampled.
parm1 is a distribution shape parameter.
parm2 is a distribution shape parameter.
parm3 is a distribution shape parameter.

The RANDGEN subroutine generates random numbers by using the same numerical method as the RAND function in Base SAS software, with the efficiency optimized for matrices. You can initialize the random number stream that is used by RANDGEN by calling the [RANDSEED subroutine](#). The *result* parameter should be preallocated to a size equal to the number of samples you want to generate. If *result* is not initialized, then it receives a single random sample.

The following distributions can be sampled.

Bernoulli Distribution

The random sample x is from the probability density function:

$$f(x) = \begin{cases} 1 & \text{for } p = 0, x = 0 \\ p^x(1-p)^{1-x} & \text{for } 0 < p < 1, x = 0, 1 \\ 1 & \text{for } p = 1, x = 1 \end{cases}$$

x is in the range: $x = 0, 1$

p is the success probability, with range: $0 \leq p \leq 1$

Beta Distribution

The random sample x is from the probability density function:

$$f(x) = \frac{\Gamma(a+b)}{\Gamma(a)\Gamma(b)} x^{a-1} (1-x)^{b-1}$$

x is in the range: $0 < x < 1$

a and b are shape parameters, with range: $a > 0$ and $b > 0$

Binomial Distribution

The random sample x is from the probability density function:

$$f(x) = \begin{cases} 1 & \text{for } p = 0, x = 0 \\ nxp^x(1-p)^{1-x} & \text{for } 0 < p < 1, x = 0, \dots, n \\ 1 & \text{for } p = 1, x = 1 \end{cases}$$

x is in the range: $x = 0, 1, \dots, n$

p is the success probability, with range: $0 \leq p \leq 1$

n specifies the number of independent trials, with range: $n = 1, 2, \dots$

Cauchy Distribution

The random sample x is from the probability density function:

$$f(x) = \frac{1}{\pi(1+x^2)}$$

x is in the range: $-\infty < x < \infty$

Chi-Square Distribution

The random sample x is from the probability density function:

$$f(x) = \frac{2^{-df/2}}{\Gamma(\frac{df}{2})} x^{df/2-1} e^{-x/2}$$

x is in the range: $x > 0$

df is degrees of freedom, with range: $df > 0$

Erlang Distribution

The random sample x is from the probability density function:

$$f(x) = \frac{1}{\Gamma(a)} x^{a-1} e^{-x}$$

x is in the range: $x > 0$

a is an integer shape parameter, with range: $a = 1, 2, \dots$

Exponential Distribution

The random sample x is from the probability density function:

$$f(x) = e^{-x}$$

x is in the range: $x > 0$

F Distribution ($F_{n,d}$)

The random sample x is from the probability density function:

$$f(x) = \frac{\Gamma(\frac{n+d}{2})n^{\frac{n}{2}}d^{\frac{d}{2}}x^{\frac{n}{2}-1}}{\Gamma(\frac{n}{2})\Gamma(\frac{d}{2})(d+nx)^{\frac{n+d}{2}}}$$

x is in the range: $x > 0$

n and d are degrees of freedom, with range: $n > 0$ and $d > 0$

Gamma Distribution

The random sample x is from the probability density function:

$$f(x) = \frac{x^{a-1}}{\Gamma(a)}e^{-x}$$

x is in the range: $x > 0$

a is a shape parameter: $a > 0$

Geometric Distribution

The random sample x is from the probability density function:

$$f(x) = \begin{cases} (1-p)^{x-1}p & \text{for } 0 < p < 1, x = 1, 2, \dots \\ 1 & \text{for } p = 1, x = 1 \end{cases}$$

x is in the range: $x = 1, 2, \dots$

p is the success probability, with range: $0 < p \leq 1$

Hypergeometric Distribution

The random sample x is from the probability density function:

$$f(x) = \frac{RxN - Rn - x}{Nn}$$

x is in the range: $x = \max(0, (n - (N - R))), \dots, \min(n, R)$

N is the population size, with range: $N = 1, 2, \dots$

R is the size of the category of interest, with range: $R = 0, 1, \dots, N$

n is the sample size, with range: $n = 0, 1, \dots, N$

Lognormal Distribution

The random sample x is from the probability density function:

$$f(x) = \frac{e^{-\ln^2(x)/2}}{x\sqrt{2\pi}}$$

x is in the range: $x \geq 0$

Negative Binomial Distribution

The random sample x is from the probability density function:

$$f(x) = \begin{cases} x + k - 1k - 1(1 - p)^x p^k & \text{for } 0 < p < 1, x = 0, 1, \dots \\ 1 & \text{for } p = 1, x = 0 \end{cases}$$

x is in the range: $x = 0, 1, \dots$

p is the success probability with range: $0 < p \leq 1$

k is an integer number that counts the number of successes, with range: $k = 1, 2, \dots$

Normal Distribution

The random sample x is from the probability density function:

$$f(x) = \frac{1}{\lambda\sqrt{2\pi}} \exp\left(-\frac{(x - \theta)^2}{2\lambda^2}\right)$$

x is in the range: $-\infty < x < \infty$

θ is the mean, with range: $-\infty < \theta < \infty$. This parameter is optional and defaults to 0.

λ is the standard deviation, with range: $\lambda > 0$. This parameter is optional and defaults to 1.

Poisson Distribution

The random sample x is from the probability density function:

$$f(x) = \frac{m^x e^{-m}}{x!}$$

x is in the range: $x = 0, 1, \dots$

m is the mean, with range $m > 0$

t Distribution

The random sample x is from the probability density function:

$$f(x) = \frac{\Gamma\left(\frac{df+1}{2}\right)}{\sqrt{df\pi} \Gamma\left(\frac{df}{2}\right)} \left(1 + \frac{x^2}{df}\right)^{-\frac{df+1}{2}}$$

x is in the range: $-\infty < x < \infty$

df is the degrees of freedom, with the range: $df > 0$

Table Distribution

The random sample i is from the probability density function:

$$f(i) = \begin{cases} p_i & \text{for } i = 1, 2, \dots, n \\ 1 - \sum_{j=1}^n p_j & \text{for } i = n + 1 \end{cases}$$

where p is a vector of probabilities, such that $0 \leq p \leq 1$, and n is the largest integer such that $n \leq \text{size of } p$ and

$$\sum_{j=1}^n p_j \leq 1$$

Triangle Distribution

The random sample x is from the probability density function:

$$f(x) = \begin{cases} \frac{2x}{h} & \text{for } 0 \leq x \leq h \\ \frac{2(1-x)}{1-h} & \text{for } h < x \leq 1 \end{cases}$$

x is in the range: $0 \leq x \leq 1$

h is the horizontal location of the peak of the triangle, with range: $0 \leq h \leq 1$

Uniform Distribution

The random sample x is from the probability density function:

$$f(x) = 1$$

x is in the range: $0 < x < 1$

Weibull Distribution

The random sample x is from the probability density function:

$$f(x) = \frac{a}{b^a} x^{a-1} e^{-\left(\frac{x}{b}\right)^a}$$

x is in the range: $x \geq 0$

a and b are shape parameters, with range $a > 0$ and $b > 0$

The following table describes how parameters of the RANDGEN call correspond to the distribution parameters.

Table 23.1 Parameter Assignments for Distributions

Distribution	<i>distname</i>	<i>parm1</i>	<i>parm2</i>	<i>parm3</i>
Bernoulli	'BERNOULLI'	p		
Beta	'BETA'	a	b	
Binomial	'BINOMIAL'	p	n	
Cauchy	'CAUCHY'			
Chi-Square	'CHISQUARE'	df		
Erlang	'ERLANG'	a		
Exponential	'EXPONENTIAL'			
$F_{n,d}$	'F'	n	d	

Gamma	'GAMMA'	a		
Geometric	'GEOMETRIC'	p		
Hypergeometric	'HYPERGEOMETRIC'	N	R	n
Lognormal	'LOGNORMAL'			
Negative Binomial	'NEGBINOMIAL'	p	k	
Normal	'NORMAL' or 'GAUSSIAN'	θ	λ	
Poisson	'POISSON'	m		
t	'T'	df		
Table	'TABLE'	p		
Triangle	'TRIANGLE' or 'TRIANGULAR'	h		
Uniform	'UNIFORM'			
Weibull	'WEIBULL'	a	b	

The *distname* argument can be in lowercase or uppercase, and you need to specify only enough letters to distinguish one distribution from the others, as shown by the following statements:

```
/* generate 10 samples from a Bernoulli distribution */
r = j(10, 1, .);          /* allocate room for samples */
call randgen(r, "ber", 0.5);
```

Except for the normal distribution, you must specify the parameters listed for each of the preceding distributions. For the normal distribution, default values of $\theta = 0$ and $\lambda = 1$ are used if no values are supplied.

The following example illustrates the use of the RANDGEN call:

```
call randseed(12345);

/* get four random observations from each distribution */
x = j(1, 4, .);
/* each row of m comes from a different distribution */
m = j(20, 4, .);
call randgen(x, 'BERN', 0.75);      m[ 1, ] = x;
call randgen(x, 'BETA', 3, 0.1);    m[ 2, ] = x;
call randgen(x, 'BINOM', 0.75, 10); m[ 3, ] = x;
call randgen(x, 'CAUCHY');          m[ 4, ] = x;
call randgen(x, 'CHISQ', 22);       m[ 5, ] = x;
call randgen(x, 'ERLANG', 7);       m[ 6, ] = x;
call randgen(x, 'EXPO');            m[ 7, ] = x;
call randgen(x, 'F', 12, 322);      m[ 8, ] = x;
call randgen(x, 'GAMMA', 7.25);     m[ 9, ] = x;
call randgen(x, 'GEOM', 0.02);      m[10, ] = x;
call randgen(x, 'HYPER', 10, 3, 5); m[11, ] = x;
call randgen(x, 'LOGN');            m[12, ] = x;
call randgen(x, 'NEGB', 0.8, 5);    m[13, ] = x;
call randgen(x, 'NORMAL');          m[14, ] = x;
call randgen(x, 'POISSON', 6.1);    m[15, ] = x;
call randgen(x, 'T', 4);            m[16, ] = x;
p = {0.1 0.2 0.25 0.1 0.15 0.1 0.1};
call randgen(x, 'TABLE', p);       m[17, ] = x;
```

```

call randgen(x, 'TRIANGLE', 0.7);      m[18, ] = x;
call randgen(x, 'UNIFORM');            m[19, ] = x;
call randgen(x, 'WEIB', 0.25, 2.1);    m[20, ] = x;

dist = {'BERN', 'BETA', 'BINOM', 'CAUCHY', 'CHISQ', 'ERLANG', 'EXPO',
        'F', 'GAMMA', 'GEOM', 'HYPER', 'LOGN', 'NEGB', 'NORMAL',
        'POISSON', 'T', 'TABLE', 'TRIANGLE', 'UNIFORM', 'WEIB'};
print m[rowname=dist];

```

Figure 23.250 Random Numbers from Various Distributions

m				
BERN	1	0	1	0
BETA	1	0.9999234	0.9842784	0.9997739
BINOM	7	8	5	10
CAUCHY	-1.209834	3.9732282	-0.048339	-1.337284
CHISQ	30.300691	20.653151	27.301922	26.878221
ERLANG	10.636299	4.6455449	7.5284821	2.5558646
EXPO	0.2449632	2.7656037	4.2254588	0.2866158
F	0.7035829	1.2676112	0.9806787	1.4811389
GAMMA	8.475216	8.8723256	8.2993617	8.0409742
GEOM	109	4	33	30
HYPER	1	1	2	1
LOGN	0.7784513	0.9792472	0.6018993	0.3643607
NEGB	3	2	0	2
NORMAL	0.0053637	1.4026784	-0.271338	-0.416685
POISSON	5	11	8	4
T	1.3237918	0.0505162	-0.660845	-0.634447
TABLE	2	3	2	3
TRIANGLE	0.5270875	0.6909336	0.8607548	0.5450831
UNIFORM	0.4064393	0.7464901	0.3463207	0.2615394
WEIB	0.4183405	0.9981923	16.812803	0.0001131

RANPERM Function

RANPERM(*n*);

RANPERM(*set*, <, *numperm*>);

The RANPERM function generates random permutations of a set with *n* elements. The random number seed is set by the [RANDSEED](#) subroutine.

The first argument, *set*, can be a scalar or a vector. If *set* is a scalar, the function returns indices in the range 1–*n*. If *set* is a vector, the number of elements of the vector determines *n* and the RANPERM function returns elements of *set*, which can be numeric or character.

By default, the RANPERM function returns a single random combination with one row and *n* columns. If the *numperm* argument is specified, the function returns a matrix with *numperm* rows and *n* columns. Each row of the returned matrix represents a single permutation.

The following statements generate five random permutations of the set {1, 2, 3}:


```
call randseed(1234);
n = 3;
p = ranperm(n, 5);
print p;
```

Figure 23.251 Random Permutations of Three Items

p		
1	2	3
3	2	1
3	2	1
3	1	2
3	1	2

Alternatively, the following statements compute five random permutations of an unsorted character vector:

```
a = ranperm({C B A}, 5);
print a;
```

Figure 23.252 Random Permutations of a Character Vector

a
B C A
B A C
C B A
B C A
B C A

RANDSEED Call

CALL RANDSEED(*seed* < , *reinit* >);

The RANDSEED subroutine sets the initial random seed for the RANDGEN subroutine.

The input arguments to the RANDSEED call are as follows:

- seed* is a number to be used to initialize the RANDGEN random number generator.
- reinit* specifies whether the random number stream can be reinitialized after the first initialization, within the same PROC IML session.

The RANDSEED subroutine creates an initial random seed for subsequent RANDGEN calls. If RANDSEED is not called, an initial seed is generated from the system clock. This subroutine is normally used when it is desirable to reproduce the same random number stream in different PROC IML sessions. The optional *reinit* parameter controls whether the seed is reinitialized within the same PROC IML session. If it is set to one, identical seeds produce the same random number sequence; otherwise a second call to RAND-

SEED within the same PROC IML session is ignored. Normally you should not specify *reinit*, or you should set it to zero to ensure that you are working with an independent random number stream within your PROC IML session.

RANGE Function

RANGE(*matrix1* <, *matrix2*, ..., *matrix15*>);

The RANGE function returns the range of values of a numerical matrix or set of matrices.

Missing values are excluded in the computation. When the arguments contain at least one nonmissing value, the range is defined as the maximum value minus the minimum value. If all arguments are missing, the RANGE function returns a missing value.

The following example uses the RANGE function:

```
c = {1 -123 13 56 128 -81 12};
r = range(c);
print r;
```

Figure 23.253 Range of Values

r	
	251

RANK Function

RANK(*matrix*);

The RANK function creates a new matrix that contains elements that are the ranks of the corresponding elements of the numerical argument, *matrix*. The rank of a missing value is a missing value. The ranks of tied values are assigned arbitrarily. (See the description of the [RANKTIE function](#) for alternate approaches.)

For example, the following statements produce the ranks of a vector:

```
x = {2 2 1 0 5};
r = rank(x);
print r;
```

Figure 23.254 Ranks of a Vector

r				
3	4	2	1	5

Provided that a vector, **x**, does not contain missing values, the RANK function can be used to sort the vector, as shown in the following statements:

```
b = x;
x[,rank(x)] = b;
print x;
```

Figure 23.255 Sorted Vector

x				
0	1	2	2	5

You can also sort a matrix by using the **SORT** subroutine. The SORT subroutine handles missing values in the data.

The RANK function can also be used to find anti-ranks of **x**, as follows:

```
x = {2 2 1 0 5};
r = rank(x);
a = r;
a[,r] = 1:ncol(x);
print a;
```

Figure 23.256 Anti-Ranks of a Vector

a				
4	3	1	2	5

Although the RANK function ranks only the elements of numerical matrices, you can rank the elements of a character matrix by using the **UNIQUE** function, as demonstrated by the following statements:

```
/* Create RANK-like functionality for character matrices */
start rankc(x);
  s = unique(x);          /* the unique function returns a sorted list */
  idx = j(nrow(x), ncol(x));
  ctr = 1;                /* there can be duplicate values in x */
  do i = 1 to ncol(s);    /* for each unique value */
    t = loc(x = s[i]);
    nDups = ncol(t);
    idx[t] = ctr : ctr+nDups-1;
    ctr = ctr + nDups;
  end;
  return (idx);
finish;

/* call the RANKC module */
x = {every good boy does fine and good and well every day};
rc = rankc(x);
print rc[colnam=x];
```

```

/* Notice that ranking is in ASCII order, in which capital
   letters precede lower case letters. To get case-insensitive
   behavior, transform the matrix before comparison */
x = {"a" "b" "X" "Y" };
asciiOrder = rankc(x);
alphaOrder = rankc(upcase(x));
print x, asciiOrder, alphaOrder;

```

Figure 23.257 Ranks of Character Matrices

	EVERY	GOOD	rc BOY	DOES	FINE	AND
ROW1	6	9	3	5	8	1

	GOOD	rc AND	WELL	EVERY	DAY
ROW1	10	2	11	7	4

	x
	a b X Y
	asciiOrder
	3 4 1 2
	alphaOrder
	1 2 3 4

There is no SAS/IML function that directly computes the linear algebraic rank of a matrix. In linear algebra, the rank of a matrix is the maximal number of linearly independent columns (or rows). You can use the following technique to compute the numerical rank of matrix **a**:

```

/* Only four linearly independent columns */
A = {1 0 1 0 0,
     1 0 0 1 0,
     1 0 0 0 1,
     0 1 1 0 0,
     0 1 0 1 0,
     0 1 0 0 1 };
rank = round(trace(ginv(a)*a));
print rank;

```

Figure 23.258 Numerical Rank of a Matrix

rank
4

Another common technique used to examine the rank of a matrix is to look at the number of nonzero singular values in the singular value decomposition of a matrix (see the [SVD call](#)). However, keep in mind that numerical computations might result in singular values for a rank-deficient matrix that are small but nonzero.

RANKTIE Function

RANKTIE(*matrix* < , *method* >);

The RANKTIE function creates a new matrix that contains elements that are the ranks of the corresponding elements of *matrix*. The rank of a missing value is a missing value. The ranks of tied values are computed by using one of several methods.

The arguments to the function are as follows:

<i>matrix</i>	specifies the data.
<i>method</i>	specifies the method used to compute the ranking of tied values. These methods correspond to those defined by using the TIES= option in the RANK procedure. For details, see the “Concepts” section of the documentation for the RANK procedure in the <i>Base SAS Procedures Guide</i> .

The following values are valid:

“Mean”	specifies that tied elements are assigned rankings equal to the mean of the tied elements. This is the default method. This method is known as a fractional competition ranking.
“Low”	specifies that tied elements are assigned rankings equal to the minimum order rank of the tied elements. This method is known as a standard competition ranking.
“High”	specifies that tied elements are assigned rankings equal to the maximum rank of the tied elements. This method is known as a modified competition ranking.
“Dense”	specifies that ranks are consecutive integers that begin with 1 and end with the number of unique, nonmissing values. Tied values are assigned the same rank. This method is known as a dense ranking.

The RANKTIE function differs from the [RANK function](#) in that the [RANK](#) function breaks ties arbitrarily.

For example, the following statements produce ranks of a vector by using several different methods of breaking ties:

```
x = {4 4 0 6};
rMean = ranktie(x); /* default is "Mean" */
rLow = ranktie(x, "Low");
rHigh = ranktie(x, "High");
rDense = ranktie(x, "Dense");
print rMean, rLow, rHigh, rDense;
```

Figure 23.259 Numerical Ranks of a Vector

rMean			
2.5	2.5	1	4
rLow			
2	2	1	4
rHigh			
3	3	1	4
rDense			
2	2	1	3

Although the RANKTIE function ranks only the elements of numerical matrices, you can rank the elements of a character matrix by using the [UNIQUE](#) function, as demonstrated by the following statements:

```
/* Create RANKTIE-like functionality for character matrices */
start ranktiec(x);
  s = unique(x);
  idx = j(nrow(x), ncol(x));
  ctr = 1;
  do i = 1 to ncol(s);
    t = loc(x = s[i]);
    nDups = ncol(t);
    idx[t] = ctr+(nDups-1)/2; /* =(ctr:ctr+nDups-1)[:] */
    ctr = ctr + nDups;
  end;
  return (idx);
finish;

/* call the RANKTIEC module */
x = {every good boy does fine and good and well every day};
rtc = ranktiec(x);
print rtc[colname=x];
```

Figure 23.260 Numerical Ranks of a Character Vector

rtc						
	EVERY	GOOD	BOY	DOES	FINE	AND
ROW1	6.5	9.5	3	5	8	1.5
rtc						
	GOOD	AND	WELL	EVERY	DAY	
ROW1	9.5	1.5	11	6.5	4	

RATES Function

RATES(*rates*, *oldfreq*, *newfreq*);

The RATES function computes a column vector of (per-period, such as per-year) interest rates converted from one base to another. The arguments to the RATES function are as follows:

<i>rates</i>	is an $n \times 1$ column vector of rates that correspond to the old base. Elements should be positive.
<i>oldfreq</i>	is a scalar that represents the old base. If positive, it represents discrete compounding as the reciprocal of the number of compoundings per period. If zero, it represents continuous compounding. If -1 , the rates represent discount factors. No other negative values are accepted.
<i>newfreq</i>	is a scalar that represents the new base. If positive, it represents discrete compounding as the reciprocal of the number of compoundings per period. If zero, it represents continuous compounding. If -1 , the rates represent discount factors. No other negative values are accepted.

Let $D(t)$ be the discount function, which is the present value of a unit amount to be received t periods from now. The discount function can be expressed in the following ways:

- with per-unit-time-period discount factors d_t :

$$D(t) = d_t^t$$

- with continuous compounding:

$$D(t) = e^{-r_t t}$$

- with discrete compounding:

$$D(t) = (1 + fr)^{-t/f}$$

where $0 < f < 1$ is the frequency, the reciprocal of the number of compoundings per unit time period. The RATES function converts between these three representations.

For example, the following example produces the output shown in [Figure 23.261](#):

```
rates = T(do(0.1, 0.3, 0.1));
oldfreq = 0;
newfreq = 0;
rates = rates(rates, oldfreq, newfreq);
print rates;
```

Figure 23.261 Interest Rates

rates	
	0.1
	0.2
	0.3

RATIO Function

RATIO(*ar*, *ma*, *terms* < , *dim* >);

The RATIO function divides matrix polynomials.

The arguments to the RATIO function are as follows:

- ar* is an $n \times (ns)$ matrix that represents a matrix polynomial generating function, $\Phi(B)$, in the variable B . The first $n \times n$ submatrix represents the constant term and must be nonsingular, the second $n \times n$ submatrix represents the first-order coefficients, and so on.
- ma* is an $n \times (mt)$ matrix that represents a matrix polynomial generating function, $\Theta(B)$, in the variable B . The first $n \times m$ submatrix represents the constant term, the second $n \times m$ submatrix represents the first-order term, and so on.
- terms* is a scalar that contains the number of terms to be computed, denoted by r in the following discussion. This value must be positive.
- dim* is a scalar that contains the value of m , a dimension of the matrix *ma*. The default value is 1.

The RATIO function multiplies a matrix of polynomials by the inverse of another matrix of polynomials. It is useful for expressing univariate and multivariate ARMA models in pure moving average or pure autoregressive forms.

The value returned is an $n \times (mr)$ matrix that contains the terms of $\Phi(B)^{-1}\Theta(B)$ considered as a matrix of rational functions in B that have been expanded as power series.

The RATIO function can be used to consolidate the matrix operators that are used in a multivariate time series model of the form

$$\Phi(B)\mathbf{Y}_t = \Theta(B)\epsilon_t$$

where $\Phi(B)$ and $\Theta(B)$ are matrix polynomial operators whose first matrix coefficients are identity matrices. The RATIO function can be used to compute a truncated form of $\Psi(B) = \Phi(B)^{-1}\Theta(B)$ for the equivalent infinite-order model

$$\mathbf{Y}_t = \Psi(B)\epsilon_t$$

The RATIO function can also be used for simple scalar polynomial division, giving a truncated form of $\theta(x)/\phi(x)$ for two scalar polynomials $\theta(x)$ and $\phi(x)$.

The cumulative sum of the elements of a column vector \mathbf{x} can be obtained by using the following statement:


```
ratio({ 1 -1}, x, ncol(x));
```

The following example defines polynomial coefficients that are used in a multivariate ARMA(1,1) model and computes the ratio of the polynomials:

```
ar = {1 0 -0.5 2,
      0 1 3 -0.8};
ma = {1 0 0.9 0.7,
      0 1 2 -0.4};
psi = ratio(ar, ma, 4, 2);
print psi;
```

Figure 23.262 The Ratio of Polynomials

psi							
1	0	1.4	-1.3	2.7	-1.45	11.35	-9.165
0	1	-1	0.4	-5	4.22	-12.1	7.726

RDODT and RUPDT Calls

```
CALL RDODT(def, rup, bup, sup, r, z <, b > <, y > <, ssq > );
```

```
CALL RUPDT(rup, bup, sup, r, z <, b > <, y > <, ssq > );
```

If $\mathbf{A} = \mathbf{QR}$ is the QR decomposition of the matrix \mathbf{A} , the RUPDT subroutine enables you to efficiently recompute the \mathbf{R} matrix when a new row is added to \mathbf{A} . This is called an update. Similarly, the RDODT subroutine enables you to efficiently recompute the \mathbf{R} matrix when an existing row is deleted from \mathbf{A} . This is called a downdate. You can also use the RDODT and RUPDT subroutines to downdate and update Cholesky decompositions.

The RDODT and RUPDT subroutines return the values:

- def* is only used for downdating, and it specifies whether the downdating of matrix \mathbf{R} by using the q rows in argument z has been successful. The result *def*=2 means that the downdating of \mathbf{R} by at least one row of \mathbf{Z} leads to a singular matrix and cannot be completed successfully (since the result of downdating is not unique). In that case, the results *rup*, *bup*, and *sup* contain missing values only. The result *def*=1 means that the residual sum of squares, *ssq*, could not be downdated successfully and the result *sup* contains missing values only. The result *def*=0 means that the downdating of \mathbf{R} by \mathbf{Z} was completed successfully.
- rup* is the $n \times n$ upper triangular matrix \mathbf{R} that has been updated or downdated by using the q rows in \mathbf{Z} .
- bup* is the $n \times p$ matrix \mathbf{B} of right-hand sides that has been updated or downdated by using the q rows in argument y . If the argument b is not specified, *bup* is not computed.
- sup* is a p vector of square roots of residual sum of squares that is updated or downdated by using the q rows of argument y . If *ssq* is not specified, *sup* is not computed.

The input arguments to the RDODT and RUPDT subroutines are as follows:

r	specifies an $n \times n$ upper triangular matrix \mathbf{R} to be updated or downdated by the q rows in \mathbf{Z} . Only the upper triangle of \mathbf{R} is used; the lower triangle can contain any information.
z	specifies a $q \times n$ matrix \mathbf{Z} used rowwise to update or downdate the matrix \mathbf{R} .
b	specifies an optional $n \times p$ matrix \mathbf{B} of right-hand sides that have to be updated or downdated simultaneously with \mathbf{R} . If b is specified, the argument y must also be specified.
y	specifies an optional $q \times p$ matrix \mathbf{Y} used rowwise to update or downdate the right-hand side matrix \mathbf{B} . If b is specified, the argument y must also be specified.
ssq	is an optional p vector that, if b is specified, specifies the square root of the error sum of squares that should be updated or downdated simultaneously with \mathbf{R} and \mathbf{B} .

The upper triangular matrix \mathbf{R} of the QR decomposition of an $m \times n$ matrix \mathbf{A} ,

$$\mathbf{A} = \mathbf{QR}, \text{ where } \mathbf{Q}'\mathbf{Q} = \mathbf{QQ}' = \mathbf{I}_m$$

is recomputed efficiently in two cases:

- *update*: An n vector z is added to matrix \mathbf{A} .
- *downdate*: An n vector z is deleted from matrix \mathbf{A} .

Computing the whole QR decomposition of matrix \mathbf{A} by Householder transformations requires $4mn^2 - 4n^3/3$ floating-point operations, whereas updating or downdating the QR decomposition (by Givens rotations) of one row vector z requires only $2n^2$ floating-point operations.

If the QR decomposition is used to solve the full-rank linear least squares problem

$$\min_x \|\mathbf{Ax} - b\|^2 = ssq$$

by solving the nonsingular upper triangular system

$$x = \mathbf{R}^{-1}\mathbf{Q}'b$$

then the RUPDT and RDODT subroutines can be used to update or downdate the p -transformed right-hand sides $\mathbf{Q}'\mathbf{B}$ and the residual sum-of-squares p vector ssq provided that for each n vector z added to or deleted from \mathbf{A} there is also a p vector y added to or deleted from the $m \times p$ right-hand-side matrix \mathbf{B} .

If the arguments z and y of the subroutines RUPDT and RDODT contain $q > 1$ row vectors for which \mathbf{R} (and $\mathbf{Q}'\mathbf{B}$, and eventually ssq) is to be updated or downdated, the process is performed stepwise by processing the rows z_k (and y_k), $k = 1, \dots, q$, in the order in which they are stored.

The QR decomposition of an $m \times n$ matrix \mathbf{A} , $m \geq n$, $\text{rank}(\mathbf{A}) = n$,

$$\mathbf{A} = \mathbf{QR}, \text{ where } \mathbf{Q}'\mathbf{Q} = \mathbf{QQ}' = \mathbf{I}_m$$

corresponds to the Cholesky factorization

$$\mathbf{C} = \mathbf{R}'\mathbf{R}, \text{ where } \mathbf{C} = \mathbf{A}'\mathbf{A}$$

of the positive definite $n \times n$ crossproduct matrix $\mathbf{C} = \mathbf{A}'\mathbf{A}$. In the case where $m \geq n$ and $\text{rank}(\mathbf{A}) = n$, the upper triangular matrix \mathbf{R} computed by the QR decomposition (with positive diagonal elements) is the same as the one computed by Cholesky factorization except for numerical error,

$$\mathbf{A}'\mathbf{A} = (\mathbf{QR})'(\mathbf{QR}) = \mathbf{R}'\mathbf{R}$$

Adding a row vector z to matrix \mathbf{A} corresponds to the rank-1 modification of the crossproduct matrix \mathbf{C}

$$\tilde{\mathbf{C}} = \mathbf{C} + z'z, \text{ where } \tilde{\mathbf{C}} = \tilde{\mathbf{A}}'\tilde{\mathbf{A}}$$

and the $(m + 1) \times n$ matrix $\tilde{\mathbf{A}}$ contains all rows of \mathbf{A} with the row z added.

Deleting a row vector z from matrix \mathbf{A} corresponds to the rank-1 modification

$$\mathbf{C}^* = \mathbf{C} - z'z, \text{ where } \mathbf{C}^* = \mathbf{A}^*\mathbf{A}^*$$

and the $(m - 1) \times n$ matrix \mathbf{A}^* contains all rows of \mathbf{A} with the row z deleted. Thus, you can also use the subroutines [RUPDT](#) and [RDODT](#) to update or downdate the Cholesky factor \mathbf{R} of a positive definite crossproduct matrix \mathbf{C} of \mathbf{A} .

The process of downdating an upper triangular matrix \mathbf{R} (and eventually a residual sum-of-squares vector *ssq*) is not always successful. First of all, the downdated matrix \mathbf{R} could be rank-deficient. Even if the downdated matrix \mathbf{R} is of full rank, the process of downdating can be ill-conditioned and does not work well if the downdated matrix is close (by rounding errors) to a rank-deficient one. In these cases, the downdated matrix \mathbf{R} is not unique and cannot be computed by subroutine [RDODT](#). If \mathbf{R} cannot be computed, *def* returns 2, and the results *rup*, *bup*, and *sup* return missing values.

The downdating of the residual sum-of-squares vector *ssq* can be a problem, too. In practice, the downdate formula

$$ssq_{\text{new}} = \sqrt{ssq_{\text{old}} - ssq_{\text{dod}}}$$

cannot always be computed because, due to rounding errors, the radicand can be negative. In this case, the result vector *sup* returns missing values, and *def* returns 1.

You can use various methods to compute the p columns x_k of the $n \times p$ matrix \mathbf{X} that minimize the p linear least squares problems with an $m \times n$ coefficient matrix \mathbf{A} , $m \geq n$, $\text{rank}(\mathbf{A}) = n$, and p right-hand-side vectors b_k (stored columnwise in the $m \times p$ matrix \mathbf{B}).

The methods in this section use the following simple example:

```
a = { 1 3 ,
      2 2 ,
      3 1 };
b = { 1, 1, 1 };
m = nrow(a);
n = ncol(a);
p = ncol(b);
```

- Cholesky decomposition of crossproduct matrix:

```
/* form and solve the normal equations */
aa = a` * a; ab = a` * b;
r = root(aa);
x = trisolv(2,r,ab);
x = trisolv(1,r,x);
print x;
```

- QR decomposition by Householder transformations:

```
call qr(qtb, r, piv, lindep, a, , b);
x = trisolv(1, r[,piv], qtb[1:n,]);
```

- Stepwise update by Givens rotations:

```
r = j(n,n,0); qtb = j(n,p,0); ssq = j(1,p,0);
do i = 1 to m;
  z = a[i,];
  y = b[i,];
  call rupdt(rup,bup,sup,r,z,qtb,y,ssq);
  r = rup;
  qtb = bup;
  ssq = sup;
end;
x = trisolv(1,r,qtb);
```

Or, equivalently:

```
r = j(n,n,0); qtb = j(n,p,0); ssq = j(1,p,0);
call rupdt(rup,bup,sup,r,a,qtb,b,ssq);
x = trisolv(1,rup,bup);
```

- Singular value decomposition:

```
call svd(u, d, v, a);
d = diag(1 / d);
x = v * d * u` * b;
```

For the preceding 3×2 example matrix **a**, each method obtains the unique LS estimator:

```
ss = ssq(a * x - b);
print ss x;
```

Figure 23.263 Least Squares Solution and Sum of Squared Residuals

ss	x
2.465E-31	0.25
	0.25

To compute the (transposed) matrix **Q**, you can use the following technique:

```
r = repeat(0,n,n);
y = i(m);
qt = repeat(0,n,m);
call rupdt(rup, qtup, sup, r, a, qt, y);
print qtup;
```

Figure 23.264 Transposed Matrix

qtup			
0.2672612	0.5345225	0.8017837	
-0.872872	-0.218218	0.4364358	

READ Statement

```
READ <range> <VAR operand> <WHERE(expression)> <INTO name <[ROWNAME=row-name
COLNAME=column-name]>> ;
```

The READ statement reads observations from the current SAS data set.

The arguments to the READ statement are as follows:

<i>range</i>	specifies a range of observations.
<i>operand</i>	selects a set of variables.
<i>expression</i>	is evaluated for being true or false.
<i>name</i>	is the name of the target matrix.
<i>row-name</i>	is a character matrix or quoted literal that contains descriptive row labels.
<i>column-name</i>	is a character matrix or quoted literal that contains descriptive column labels.

The clauses and options are explained in the following lists.

Use the READ statement to read variables or records from the current SAS data set into column matrices of the VAR clause or into the single matrix of the INTO clause. When the INTO clause is used, each variable in the VAR clause becomes a column of the target matrix, and all variables in the VAR clause must be of the same type. If you specify no VAR clause, the default variables for the INTO clause are all numeric variables. Read all character variables into a target matrix by using VAR _CHAR_.

You can use any of the following keywords to specify a *range* of observations:

ALL	all observations
CURRENT	the current observation
NEXT < <i>number</i> >	the next observation or the next <i>number</i> of observations
AFTER	all observations after the current one

POINT *value* observations specified by number, where *value* can be one of the following.

Value	Example
a single record number	point 5
a literal that contains several record numbers	point {2 5 10}
the name of a matrix that contains record numbers	point p
an expression in parentheses	point (p+1)

If the current data set has an index in use (see the [INDEX statement](#), the POINT option is invalid.

You can specify a set of variables to use with the VAR clause. The *operand* in the VAR clause can be one of the following:

- a literal that contains variable names
- the name of a matrix that contains variable names
- an expression in parentheses that yields variable names
- one of keywords described in the following list:

ALL	for all variables
CHAR	for all character variables
NUM	for all numeric variables.

The following examples demonstrate each possible way you can use the VAR clause.

```
var {x1 x5 x9};           /* a literal matrix of names      */
var x;                    /* a matrix that contains the names */
var ("x1":"x9");          /* an expression                  */
var _all_;                 /* a keyword                      */
```

The WHERE clause conditionally selects observations, within the *range* specification, according to conditions given in the clause. The general form of the WHERE clause is as follows:

WHERE (*variable comparison-op operand*) ;

The arguments to the WHERE clause are as follows:

<i>variable</i>	is a variable in the SAS data set.
<i>comparison-op</i>	is one of the following comparison operators:
<	less than
<=	less than or equal to
=	equal to

>	greater than
>=	greater than or equal to
^=	not equal to
?	contains a given string
^?	does not contain a given string
=:	begins with a given string
=*	sounds like or is spelled like a given string

operand is a literal value, a matrix name, or an expression in parentheses.

WHERE comparison arguments can be matrices. For the following operators, the WHERE clause succeeds if *all* the elements in the matrix satisfy the condition:

$\wedge = \wedge ? < \leq > \geq$

For the following operators, the WHERE clause succeeds if *any* of the elements in the matrix satisfy the condition:

$= ? =: =*$

Logical expressions can be specified within the WHERE clause by using the AND (&) and OR (|) operators. The general form is

clause & *clause* (for an AND clause)
clause | *clause* (for an OR clause)

where *clause* can be a comparison, a parenthesized clause, or a logical expression clause that is evaluated by using operator precedence.

NOTE: The expression on the left-hand side refers to values of the data set variables, and the expression on the right-hand side refers to matrix values.

You can specify ROWNAME= and COLNAME= matrices as part of the INTO clause. The COLNAME= matrix specifies the name of a new character matrix to be created. This COLNAME= matrix is created in addition to the target matrix of the INTO clause and contains variable names from the input data set corresponding to columns of the target matrix. The COLNAME= matrix has dimension $1 \times nvar$, where *nvar* is the number of variables contributing to the target matrix.

The ROWNAME= option specifies the name of a character variable in the input data set. The values of this variable are put in a character matrix with the same name as the variable. This matrix has the dimension $nobs \times 1$, where *nobs* is the number of observations in the range of the READ statement.

The *range*, VAR, WHERE, and INTO clauses are all optional and can be specified in any order.

Row and column names created via a READ statement are permanently associated with the INTO matrix. You do not need to use a [MATTRIB statement](#) to get this association.

For example, to read all observations from the data set variables NAME and AGE, use a READ statement with the VAR clause and the keyword ALL for the *range* operand. This creates two vectors with the same names as the data set variables. Here is the statement:

```
read all var{name age};
```

To read all variables for the 23rd observation only, use the following statement:

```
read point 23;
```

To read the data set variables NAME and ADDR for all observations with a STATE value of 'NJ', use the following statement:

```
read all var{name addr} where(state="NJ");
```

See [Chapter 7](#) for further information.

REMOVE Function

```
REMOVE(matrix, indices);
```

The REMOVE function discards elements from a matrix. The arguments to the REMOVE function are as follows:

matrix is a numeric or character matrix or literal.
indices specifies the indices of elements of *matrix* to remove.

The REMOVE function returns (as a row vector) a subset of the elements of the first argument. Elements that correspond to indices in the second argument are removed. The elements of the first argument are enumerated in row-major order, and the indices must be in the range 1 to np , where *matrix* is an $n \times p$ matrix. Nonintegral indices are truncated to their integer part. You can repeat the indices and give them in any order. If all elements are removed, the result is a null matrix (zero rows and zero columns).

The following statement removes the third element, which creates a row vector with three elements:

```
x = {5 6, 7 8};
a = remove(x, 3);      /* remove element 3 */
print a;
```

Figure 23.265 Result of Removing an Element

a		
5	6	8

The following statement causes all but the fourth element to be removed:

```
r = {3 2 3 1};
b = remove(x, r);      /* equivalent to removing elements 1:3 */
print b;
```


new-name is a character matrix or quoted literal that contains the new data set name.

The RENAME subroutine renames a SAS data set in the specified library. All of the arguments can directly be specified in quotes, although quotes are not required. If a one-level data set name is specified, the libname specified by the [RESET DEFLIB statement](#) is used. Examples of valid statements follow:

```
call rename ("a", "b");
call rename (a, b);
call rename (work, a, b);
```

REPEAT Function

REPEAT(*matrix*, *nrow*, *ncol*);

The REPEAT function creates a matrix of repeated values.

The arguments to the REPEAT function are as follows:

matrix is a numeric matrix or literal.
nrow gives the number of times *matrix* is repeated down rows.
ncol gives the number of times *matrix* is repeated across columns.

The REPEAT function creates a new matrix by repeating the values of the argument matrix *nrow***ncol* times, *ncol* times across the rows, and *nrow* times down the columns. The *matrix* argument can be numeric or character. For example, the following statements result in the matrix **Y**, repeating the **X** matrix twice down and three times across:

```
x={ 1 2 ,
    3 4} ;
y=repeat (x, 2, 3);
```

Y					
1	2	1	2	1	2
3	4	3	4	3	4
1	2	1	2	1	2
3	4	3	4	3	4

REPLACE Statement

REPLACE <range> <VAR operand> <WHERE(expression)> ;

The REPLACE statement replaces values of observations in a SAS data set.

The arguments to the REPLACE statement are as follows:

<i>range</i>	specifies a range of observations.
<i>operand</i>	selects a set of variables.
<i>expression</i>	is evaluated for being true or false.

The REPLACE statement replaces the values of observations in a SAS data set with current values of matrices with the same name. Use the *range*, VAR, and WHERE arguments to limit replacement to specific variables and observations. Replacement matrices should be the same type as the data set variables. The REPLACE statement uses matrix elements in row order replacing the value in the *i*th observation with the *i*th matrix element. If there are more observations in *range* than matrix elements, the REPLACE statement continues to use the last matrix element.

For example, the following statements cause all occurrences of 'ILL' to be replaced by 'IL' for the variable STATE:

```
state="IL";
replace all var{state} where (state="ILL");
```

You can use any of the following keywords to specify a *range* of observations:

ALL	all observations
CURRENT	the current observation
NEXT < <i>number</i> >	the next observation or the next <i>number</i> of observations
AFTER	all observations after the current one
POINT <i>value</i>	observations by number, where <i>value</i> can be one of the following:

Value	Example
a single record number	point 5
a literal that contains several record numbers	point {2 5 10}
the name of a matrix that contains record numbers	point p
an expression in parentheses	point (p+1)

If the current data set has an index in use (see the [INDEX statement](#), the POINT option is invalid.

You can specify a set of variables to use with the VAR clause. The *variables* argument can have the following values:

- a literal that contains variable names
- the name of a matrix that contains variable names
- an expression in parentheses that yields variable names

- one of the keywords described in the following list:

<u>ALL</u>	for all variables
<u>CHAR</u>	for all character variables
<u>NUM</u>	for all numeric variables

The following examples demonstrate each possible way you can use the VAR clause.

```
var {x1 x5 x9};           /* a literal matrix of names      */
var x;                    /* a matrix that contains the names */
var ("x1":"x9");          /* an expression                  */
var _all_;                 /* a keyword                       */
```

The WHERE clause conditionally selects observations, within the range specification, according to conditions given in the clause. The general form of the WHERE clause is

WHERE (*variable comparison-op operand*) ;

The arguments to the WHERE clause are as follows:

variable is a variable in the SAS data set.

comparison-op is any one of the following comparison operators:

<	less than
<=	less than or equal to
=	equal to
>	greater than
>=	greater than or equal to
^=	not equal to
?	contains a given string
^?	does not contain a given string
=:	begins with a given string
=*	sounds like or is spelled like a given string

operand is a literal value, a matrix name, or an expression in parentheses.

WHERE comparison arguments can be matrices. For the following operators, the WHERE clause succeeds if *all* the elements in the matrix satisfy the condition:

^= ^? < <= > >=

For the following operators, the WHERE clause succeeds if *any* of the elements in the matrix satisfy the condition:

= ? =: =*

Logical expressions can be specified within the WHERE clause by using the AND (&) and OR (|) operators. The general form is

clause & clause (for an AND clause)
clause | clause (for an OR clause)

where *clause* can be a comparison, a parenthesized clause, or a logical expression clause that is evaluated by using operator precedence.

NOTE: The expression on the left-hand side refers to values of the data set variables, and the expression on the right-hand side refers to matrix values.

The following statement replaces all variables in the current observation:

```
replace;
```

RESET Statement

RESET < options > ;

The RESET statement sets processing options. The options are described in the following list. Note that the prefix NO turns off the feature where indicated. For options that take operands, the operand should be a literal, a name of a matrix that contains the value, or an expression in parentheses. The [SHOW OPTIONS statement](#) displays the current settings of options.

AUTONAME

NOAUTONAME

specifies whether rows are automatically labeled ROW1, ROW2, and so on, and columns are labeled COL1, COL2, and so on, when a matrix is printed. Row-name and column-name attributes specified in the [PRINT statement](#) or associated via the [MATTRIB statement](#) override the default labels. The AUTONAME option causes the SPACES option to be reset to 4. The default is NOAUTONAME.

CENTER

NOCENTER

specifies whether output from the [PRINT statement](#) is centered on the page. The default is CENTER. This resets the global CENTER/NOCENTER option for the SAS session.

CLIP

NOCLIP

specifies whether SAS/IML graphs are automatically clipped outside the viewport; that is, any data falling outside the current viewport is not displayed. NOCLIP is the default.

DEFLIB=operand

specifies the default libname for SAS data sets when no other libname is given. This defaults to USER if a USER libname is set up, or WORK if not. The libname operand can be specified with or without quotes.

DETAILS**NODETAILS**

specifies whether additional information is printed from a variety of operations, such as when files are opened and closed. The default is NODETAILS.

FLOW**NOFLOW**

specifies whether operations are shown as executed. It is used for debugging only. The default is NOFLOW.

FUZZ <=number>**NOFUZZ**

specifies whether very small numbers are printed as zero rather than in scientific notation. If the absolute value of the number is less than the value specified in *number*, it is printed as 0. The *number* argument is optional, and the default value varies across hosts but is typically around 1E–12. The default is NOFUZZ.

FW=number

sets the field width for printing numeric values. The default field width is 9.

LINESIZE=n

specifies the linesize for printing. The default value is usually 78. This resets the global LINESIZE option for the SAS session.

LOG**NOLOG**

specifies whether output is routed to the log file rather than to the print file. On the log, the results are interleaved with the statements and messages. The NOLOG option routes output to the OUTPUT window in the SAS windowing environment and to the listing file in batch mode. The default is NOLOG.

NAME**NONAME**

specifies whether the matrix name or label is printed with the value for the [PRINT statement](#). The default is NAME.

PAGESIZE=*n*

specifies the pagesize for printing. The default value is inherited from the SAS environment. Changing the

PAGESIZE=

option also changes the global PAGESIZE option.

PRINT**NOPRINT**

specifies whether the final results from assignment statements are printed automatically. NOPRINT is the default.

PRINTADV=*n*

inserts blank lines into the log before printing out the value of a matrix. The default, PRINTADV=2, causes two blank lines to be inserted.

PRINTALL**NOPRINTALL**

specifies whether the intermediate and final results are printed automatically. The default is NOPRINTALL.

SPACES=*n*

specifies the number of spaces between adjacent matrices printed across the page. The default value is 1, except when AUTONAME is on. Then, the default value is 4.

STORAGE=< *libname.*>*memname*;

specifies the file to be the current library storage for **STORE** and **LOAD** statements. The default library storage is WORK.IMLSTOR. The *libname* argument is optional and defaults to Sasuser. It can be specified with or without quotes.

RESUME Statement

RESUME ;

The RESUME statement enables you to continue execution from the line in a module where the most recent **PAUSE statement** was executed. PROC IML issues an automatic pause when an error occurs inside a module. If a module was paused due to an error, the RESUME statement resumes execution immediately after the statement that caused the error. The **SHOW PAUSE statement** displays the current state of all paused modules.

RETURN Statement

RETURN <(*operand*)> ;

The RETURN statement causes a program to return to a previous calling point.

The RETURN statement with an *operand* is used in function modules that return a value. The *operand* can be a variable name or an expression. It is evaluated and the value is returned. The RETURN statement without an argument is used to return from a user-defined subroutine.

You can also use the RETURN statement in conjunction with a [LINK statement](#). If a LINK statement has been issued, the RETURN statement returns control to the statement that follows the LINK statement. See the description of the [LINK statement](#). Also, see [Chapter 6](#) for details.

If a RETURN statement is encountered outside of a module, execution is stopped as with a [STOP statement](#).

The following examples use the RETURN statement to exit from modules:

```
start sum1(a, b);
    sum = a+b;
    return(sum);
finish;
start sum2(s, a, b);
    s = a+b;
    return;
finish;

x = sum1(2, 3);
run sum2(y, 4, 5);
print x y;
```

Figure 23.267 Return from Module Calls

	x	y
	5	9

ROOT Function

ROOT(*matrix*);

The ROOT function performs the Cholesky decomposition of a symmetric and positive definite matrix, **A**. The Cholesky decomposition factors **A** into the product

$$\mathbf{A} = \mathbf{U}'\mathbf{U}$$

where **U** is upper triangular.

For example, the following statements compute the upper-triangular matrix, **u**, in the Cholesky decomposition of a matrix:


```

A = {25  0  5,
      0  4  6,
      5  6 59};
U = root(A);
print U;

```

Figure 23.268 Cholesky Decomposition

U		
5	0	1
0	2	3
0	0	7

If you need to solve a linear system and you already have a Cholesky decomposition of your matrix, then use the [TRISOLV function](#) as illustrated by the following statements:

```

b = {5, 2, 53};
/* Want to solve A * v = b.
   First solve U` z = b,
   then solve U v = z */
z = trisolv(2, U, b);
v = trisolv(1, U, z);
print v;

```

Figure 23.269 Solution to a Linear System

v		
0		
-1		
1		

The ROOT function performs most of its computations in the memory allocated for returning the Cholesky decomposition.

ROWCAT Function

ROWCAT(*matrix* < , *rows* > < , *columns* >);

The ROWCAT function concatenates rows of a character matrix without using blank compression. In particular, the function takes a character matrix or submatrix as its argument and creates a new matrix with one column whose elements are the concatenation of all row elements into a single string.

The arguments to the ROWCAT function are as follows:

matrix is a character matrix or quoted literal.

rows select the rows of *matrix*.
columns select the columns of *matrix*.

If the input matrix has n rows and m columns, the result will have n rows and 1 column. The element length of the result is m times the element length of the argument. The optional rows and columns arguments can be used to select which rows and columns are concatenated.

For example, the following statements produce the 2×1 matrix shown:

```
b = {"ABC" "D " "EF ",
     " GH" " I " " JK"};
a = rowcat(b);
```

```

A           2 rows      1 col      (character, size 9)

      ABCD EF
      GH I  JK
```

Quotes (") are needed only if you want to embed blanks or special characters or to maintain uppercase and lowercase distinctions.

The syntax

```
ROWCAT(matrix, rows, columns);
```

returns the same result as

```
ROWCAT(matrix[rows, columns]);
```

The syntax

```
ROWCAT(matrix, rows);
```

returns the same result as

```
ROWCAT(matrix[rows,]);
```

ROWCATC Function

```
ROWCATC(matrix <, rows > <, columns > );
```

The ROWCATC function concatenates rows of a character matrix by using blank compression.

The arguments the ROWCATC function are as follows:

matrix is a character matrix or quoted literal.
rows select the rows of *matrix*.
columns select the columns of *matrix*.

The ROWCATC function works the same way as the [ROWCAT function](#) except that blanks in element strings are moved to the end of the concatenation. For example, the following statements produce the matrix **A** as shown:

```
b={"ABC" "D " "EF ",
  " GH" " I " " JK"};
a=rowcatc(b);
```

```

A          2 rows      1 col      (character, size 9)

          ABCDEF
          GHIJK
```

Quotes (") are needed only if you want to embed blanks or special characters or to maintain uppercase and lowercase distinctions.

RUN Statement

RUN <name> <(arguments)> ;

The RUN statement executes a user-defined module or invokes PROC IML's built-in subroutines.

The arguments to the RUN statement are as follows:

name is the name of a user-defined module or a built-in subroutine.
arguments are arguments to the subroutine. Arguments can be both local and global.

The resolution order for the RUN statement is

1. A user-defined module
2. A built-in function or subroutine

This resolution order need only be considered if you have defined a module that has the same name as a built-in subroutine. If a RUN statement cannot be resolved at resolution time, a warning is produced. If the RUN statement is still unresolved when executed and a storage library is open at the time, an attempt is made to load a module from that storage. If no module is found, then the program is interrupted and an error message is generated. By default, the RUN statement tries to run the module named MAIN.

You will usually want to supply both a name and arguments, as follows:

```
run myf1(a,b,c);
```

See [Chapter 6](#) for further details.

RUPDT Call

CALL RUPDT(*rup*, *bup*, *sup*, *r*, *z* < , *b* > < , *y* > < , *ssq* >);

See the entry for the **RDODT** subroutine for details.

RZLIND Call

CALL RZLIND(*lindep*, *rup*, *bup*, *r* < , *sing* > < , *b* >);

The RZLIND subroutine computes rank-deficient linear least squares solutions, complete orthogonal factorizations, and Moore-Penrose inverses.

The RZLIND subroutine returns the following values:

<i>lindep</i>	is a scalar that contains the number of linear dependencies that are recognized in R (number of zeroed rows in <code>rup[n, n]</code>).
<i>rup</i>	is the updated $n \times n$ upper triangular matrix R that contains zero rows corresponding to zero recognized diagonal elements in the original R .
<i>bup</i>	is the $n \times p$ matrix B of right-hand sides that is updated simultaneously with R . If <i>b</i> is not specified, <i>bup</i> is not accessible.

The input arguments to the RZLIND subroutine are as follows:

<i>r</i>	specifies the $n \times n$ upper triangular matrix R . Only the upper triangle of <i>r</i> is used; the lower triangle can contain any information.
<i>sing</i>	is an optional scalar that specifies a relative singularity criterion for the diagonal elements of R . The diagonal element r_{ii} is considered zero if $r_{ii} \leq \text{sing} \ r_i\ $, where $\ r_i\ $ is the Euclidean norm of column r_i of R . If the value provided for <i>sing</i> is not positive, the default value $\text{sing} = 1000\epsilon$ is used, where ϵ is the relative machine precision.
<i>b</i>	specifies the optional $n \times p$ matrix B of right-hand sides that have to be updated or downdated simultaneously with R .

The singularity test used in the RZLIND subroutine is a relative test that uses the Euclidean norms of the columns r_i of **R**. The diagonal element r_{ii} is considered as nearly zero (and the *i*th row is zeroed out) if the following test is true:

$$r_{ii} \leq \text{sing} \|r_i\|, \text{ where } \|r_i\| = \sqrt{r_i' r_i}$$

Providing an argument $\text{sing} \leq 0$ is the same as omitting the argument *sing* in the RZLIND call. In this case, the default is $\text{sing} = 1000\epsilon$, where ϵ is the relative machine precision. If **R** is computed by the QR decomposition $\mathbf{A} = \mathbf{QR}$, then the Euclidean norm of column *i* of **R** is the same (except for rounding errors) as the Euclidean norm of column *i* of **A**.

Consider the following possible application of the RZLIND subroutine. Assume that you want to compute the upper triangular Cholesky factor \mathbf{R} of the $n \times n$ positive semidefinite matrix $\mathbf{A}'\mathbf{A}$,

$$\mathbf{A}'\mathbf{A} = \mathbf{R}'\mathbf{R} \text{ where } \mathbf{A} \in \mathcal{R}^{m \times n}, \text{ rank}(\mathbf{A}) = r, r \leq n \leq m$$

The Cholesky factor \mathbf{R} of a positive definite matrix $\mathbf{A}'\mathbf{A}$ is unique (with the exception of the sign of its rows). However, the Cholesky factor of a positive semidefinite (singular) matrix $\mathbf{A}'\mathbf{A}$ can have many different forms.

In the following example, \mathbf{A} is a 12×8 matrix with linearly dependent columns $a_1 = a_2 + a_3 + a_4$ and $a_1 = a_5 + a_6 + a_7$ with $r = 6$, $n = 8$, and $m = 12$.

```
a = {1 1 0 0 1 0 0,
      1 1 0 0 1 0 0,
      1 1 0 0 0 1 0,
      1 1 0 0 0 0 1,
      1 0 1 0 1 0 0,
      1 0 1 0 0 1 0,
      1 0 1 0 0 1 0,
      1 0 1 0 0 0 1,
      1 0 0 1 1 0 0,
      1 0 0 1 0 1 0,
      1 0 0 1 0 0 1,
      1 0 0 1 0 0 1};
a = a || uniform(j(12,1,1));
aa = a` * a;
m = nrow(a); n = ncol(a);
```

Applying the [ROOT function](#) to the coefficient matrix $\mathbf{A}'\mathbf{A}$ of the normal equations generates an upper triangular matrix \mathbf{R}_1 where linearly dependent rows are zeroed out. You can verify that $\mathbf{A}'\mathbf{A} = \mathbf{R}_1'\mathbf{R}_1$. Here is the code:

```
r1 = root(aa);
ss1 = ssq(aa - r1` * r1);
print ss1 r1 [format=best6.];
```

Applying the QR subroutine with column pivoting on the original matrix \mathbf{A} yields a different result, but you can also verify $\mathbf{A}'\mathbf{A} = \mathbf{R}_2'\mathbf{R}_2$ after pivoting the rows and columns of $\mathbf{A}'\mathbf{A}$. Here is the code:

```
ord = j(n,1,0);
call qr(q,r2,pivqr,lindqr,a,ord);
ss2 = ssq(aa[pivqr,pivqr] - r2` * r2);
print ss2 r2 [format=best6.];
```

Using the [RUPDT subroutine](#) for stepwise updating of \mathbf{R} by the m rows of \mathbf{A} finally results in an upper triangular matrix \mathbf{R}_3 with $n - r$ nearly zero diagonal elements. However, other elements in rows with nearly zero diagonal elements can have significant values. The following statements verify that $\mathbf{A}'\mathbf{A} = \mathbf{R}_3'\mathbf{R}_3$:

```

r3 = shape(0,n,n);
call rupdt(rup,bup,sup,r3,a);
r3 = rup;
ss3 = ssq(aa - r3` * r3);
print ss3 r3 [format=best6.];

```

The result \mathbf{R}_3 of the **RUPDT** subroutine can be transformed into the result \mathbf{R}_1 of the **ROOT** function by left applications of Givens rotations to zero out the remaining significant elements of rows with *small* diagonal elements. Applying the **RZLIND** subroutine on the upper triangular result \mathbf{R}_3 of the **RUPDT** subroutine generates a Cholesky factor \mathbf{R}_4 with zero rows corresponding to diagonal elements that are small, giving the same result as the **ROOT** function (except for the sign of rows) if its singularity criterion recognizes the same linear dependencies. Here is the code:

```

call rzlind(lind,r4,bup,r3);
ss4 = ssq(aa - r4` * r4);
print ss4 r4 [format=best6.];

```

Consider the rank-deficient linear least squares problem:

$$\min_x \|Ax - b\|^2 \text{ where } \mathbf{A} \in \mathcal{R}^{m \times n}, \text{ rank}(\mathbf{A}) = r, r \leq n \leq m$$

For $r = n$, the optimal solution, \hat{x} , is unique; however, for $r < n$, the rank-deficient linear least squares problem has many optimal solutions, each of which has the same least squares residual sum of squares:

$$ss = (\mathbf{A}\hat{x} - b)'(\mathbf{A}\hat{x} - b)$$

The solution of the full-rank problem, $r = n$, is illustrated in the **QR** call. The following list shows several solutions to the singular problem. The following example uses the 12×8 matrix from the preceding section and generates a new column vector b . The vector b and the matrix \mathbf{A} are shown in the output.

```

b = uniform(j(12,1,1));
ab = a` * b;
print b a [format=best6.];

```

Each entry in the following list solves the rank-deficient linear least squares problem. Note that while each method minimizes the residual sum of squares, not all of the given solutions are of minimum Euclidean length.

- Use the singular value decomposition of \mathbf{A} , given by $\mathbf{A} = \mathbf{UDV}'$. Take the reciprocals of significant singular values and set the small values of \mathbf{D} to zero.

```

call svd(u,d,v,a);
t = 1e-12 * d[1];
do i=1 to n;
    if d[i] < t then d[i] = 0.;
    else d[i] = 1. / d[i];
end;
x1 = v * diag(d) * u` * b;
len1 = x1` * x1;

```

```

ss1 = ssq(a * x1 - b);
x1 = x1`;
print ss1 len1, x1 [format=best6.];

```

The solution \hat{x}_1 obtained by singular value decomposition, $\hat{x}_1 = \mathbf{VD}^{-1}\mathbf{U}'b/4$, is of minimum Euclidean length.

- Use QR decomposition with column pivoting:

$$\mathbf{A}\mathbf{\Pi} = \mathbf{Q}\mathbf{R} = \begin{bmatrix} \mathbf{Y} & \mathbf{Z} \end{bmatrix} \begin{bmatrix} \mathbf{R}_1 & \mathbf{R}_2 \\ \mathbf{0} & \mathbf{0} \end{bmatrix} = \mathbf{Y} \begin{bmatrix} \mathbf{R}_1 & \mathbf{R}_2 \end{bmatrix}$$

Set the right part \mathbf{R}_2 to zero and invert the upper triangular matrix \mathbf{R}_1 to obtain a generalized inverse \mathbf{R}^- and an optimal solution \hat{x}_2 :

$$\mathbf{R}^- = \begin{bmatrix} \mathbf{R}_1^{-1} \\ \mathbf{0} \end{bmatrix} \hat{x}_2 = \mathbf{\Pi}\mathbf{R}^-\mathbf{Y}'b$$

```

ord = j(n,1,0);
call qr(qtb,r2,pivqr,lindqr,a,ord,b);
nr = n - lindqr;
r = r2[1:nr,1:nr];
x2 = shape(0,n,1);
x2[pivqr] = trisolv(1,r,qtb[1:nr]) // j(lindqr,1,0.);
len2 = x2` * x2;
ss2 = ssq(a * x2 - b);
x2 = x2`;
print ss2 len2, x2 [format=best6.];

```

Note that the residual sum of squares is minimal, but the solution \hat{x}_2 is not of minimum Euclidean length.

- Use the result \mathbf{R}_1 of the [ROOT function](#) on page 936 to obtain the vector *piv* which indicates the zero rows in the upper triangular matrix \mathbf{R}_1 :

```

r1 = root(aa);
nr = n - lind;
piv = shape(0,n,1);
j1 = 1; j2 = nr + 1;
do i=1 to n;
  if r1[i,i] ^= 0 then do;
    piv[j1] = i; j1 = j1 + 1;
  end;
  else do;
    piv[j2] = i; j2 = j2 + 1;
  end;
end;

```

Now compute \hat{x}_3 by solving the equation $\hat{x}_3 = \mathbf{R}^{-1}\mathbf{R}'\mathbf{A}'b$.

```

r = r1[piv[1:nr],piv[:nr]];
x = trisolv(2,r,ab[piv[1:nr]]);
x = trisolv(1,r,x);
x3 = shape(0,n,1);
x3[piv] = x // j(lind,1,0.);
len3 = x3` * x3;
ss3 = ssq(a * x3 - b);
x3 = x3`;
print ss3 len3, x3 [format=best6.];

```

Note that the residual sum of squares is minimal, but the solution \hat{x}_3 is not of minimum Euclidean length.

- Use the result \mathbf{R}_3 of the [RUPDT](#) call on page 940 and the vector *piv* (obtained in the previous solution), which indicates the zero rows of upper triangular matrices \mathbf{R}_1 and \mathbf{R}_3 . After zeroing out the rows of \mathbf{R}_3 belonging to small diagonal pivots, solve the system $\hat{x}_4 = \mathbf{R}^{-1}\mathbf{Y}'b$.

```

r3 = shape(0,n,n);
qtb = shape(0,n,1);
call rupdt(rup,bup,sup,r3,a,qtb,b);
r3 = rup; qtb = bup;
call rzlind(lind,r4,bup,r3,,qtb);
qtb = bup[piv[1:nr]];
x = trisolv(1,r4[piv[1:nr],piv[1:nr]],qtb);
x4 = shape(0,n,1);
x4[piv] = x // j(lind,1,0.);
len4 = x4` * x4;
ss4 = ssq(a * x4 - b);
x4 = x4`;
print ss4 len4, x4 [format=best6.];

```

Since the matrices \mathbf{R}_4 and \mathbf{R}_1 are the same (except for the signs of rows), the solution \hat{x}_4 is the same as \hat{x}_3 .

- Use the result \mathbf{R}_4 of the RZLIND subroutine in the previous solution, which is the result of the first step of *complete QR decomposition*, and perform the second step of complete QR decomposition. The rows of matrix \mathbf{R}_4 can be permuted to the upper trapezoidal form

$$\begin{bmatrix} \hat{\mathbf{R}} & \mathbf{T} \\ \mathbf{0} & \mathbf{0} \end{bmatrix}$$

where $\hat{\mathbf{R}}$ is nonsingular and upper triangular and \mathbf{T} is rectangular. Next, perform the second step of complete QR decomposition with the lower triangular matrix

$$\begin{bmatrix} \hat{\mathbf{R}}' \\ \mathbf{T}' \end{bmatrix} = \bar{\mathbf{Y}} \begin{bmatrix} \bar{\mathbf{R}} \\ \mathbf{0} \end{bmatrix}$$

which leads to the upper triangular matrix $\bar{\mathbf{R}}$.


```

r = r4[piv[1:nr],]`;
call qr(q,r5,piv2,lin2,r);
y = trisolv(2,r5,qtb);
x5 = q * (y // j(lind,1,0.));
len5 = x5` * x5;
ss5 = ssq(a * x5 - b);
x5 = x5`;
print ss5 len5, x5 [format=best6.];

```

The solution \hat{x}_5 obtained by complete QR decomposition has minimum Euclidean length.

- Perform both steps of complete QR decomposition. The first step performs the pivoted QR decomposition of \mathbf{A} ,

$$\mathbf{A}\Pi = \mathbf{Q}\mathbf{R} = \mathbf{Y} \begin{bmatrix} \mathbf{R} \\ \mathbf{0} \end{bmatrix} = \mathbf{Y} \begin{bmatrix} \hat{\mathbf{R}}\mathbf{T} \\ \mathbf{0} \end{bmatrix}$$

where $\hat{\mathbf{R}}$ is nonsingular and upper triangular and \mathbf{T} is rectangular. The second step performs a QR decomposition as described in the previous method. This results in

$$\mathbf{A}\Pi = \mathbf{Y} \begin{bmatrix} \bar{\mathbf{R}}' & \mathbf{0} \\ \mathbf{0} & \mathbf{0} \end{bmatrix} \bar{\mathbf{Y}}'$$

where $\bar{\mathbf{R}}'$ is lower triangular.

```

ord = j(n,1,0);
call qr(qtb,r2,pivqr,lindqr,a,ord,b);
nr = n - lindqr;
r = r2[1:nr,]`;
call qr(q,r5,piv2,lin2,r);
y = trisolv(2,r5,qtb[1:nr]);
x6 = shape(0,n,1);
x6[pivqr] = q * (y // j(lindqr,1,0.));
len6 = x6` * x6;
ss6 = ssq(a * x6 - b);
x6 = x6`;
print ss6 len6, x6 [format=best6.];

```

The solution \hat{x}_6 obtained by complete QR decomposition has minimum Euclidean length.

- Perform complete QR decomposition with the QR and LUPDT calls:

```

ord = j(n,1,0);
call qr(qtb,r2,pivqr,lindqr,a,ord,b);
nr = n - lindqr;
r = r2[1:nr,1:nr]`; z = r2[1:nr,nr+1:n]`;
call lupdt(lup,bup,sup,r,z);
rd = trisolv(3,lup,r2[1:nr,]);
rd = trisolv(4,lup,rd);
x7 = shape(0,n,1);
x7[pivqr] = rd` * qtb[1:nr,];

```

```
len7 = x7` * x7;
ss7 = ssq(a * x7 - b);
x7 = x7`;
print ss7 len7, x7 [format=best6.];
```

The solution \hat{x}_7 obtained by complete QR decomposition has minimum Euclidean length.

- Perform complete QR decomposition with the [RUPDT](#), [RZLIND](#), and [LUPDT](#) calls:

```
r3 = shape(0,n,n);
qtb = shape(0,n,1);
call rupdt(rup,bup,sup,r3,a,qtb,b);
r3 = rup; qtb = bup;
call rzlind(lind,r4,bup,r3,,qtb);
nr = n - lind; qtb = bup;
r = r4[piv[1:nr],piv[1:nr]]`;
z = r4[piv[1:nr],piv[nr+1:n]]`;
call lupdt(lup,bup,sup,r,z);
rd = trisolv(3,lup,r4[piv[1:nr],]);
rd = trisolv(4,lup,rd);
x8 = shape(0,n,1);
x8 = rd` * qtb[piv[1:nr],];
len8 = x8` * x8;
ss8 = ssq(a * x8 - b);
x8 = x8`;
print ss8 len8, x8 [format=best6.];
```

The solution \hat{x}_8 obtained by complete QR decomposition has minimum Euclidean length. The same result can be obtained with the [APPCORT](#) or [COMPORT](#) call.

You can use various orthogonal methods to compute the Moore-Penrose inverse \mathbf{A}^- of a rectangular matrix \mathbf{A} . The entries in the following list find the Moore-Penrose inverse of the matrix \mathbf{A} shown on page 942.

- Use the [GINV](#) operator. The [GINV](#) operator uses the singular decomposition $\mathbf{A} = \mathbf{UDV}'$. The result $\mathbf{A}^- = \mathbf{VD}^- \mathbf{U}'$ should be identical to the result given by the next solution.

```
ga = ginv(a);
t1 = a * ga; t2 = t1`;
t3 = ga * a; t4 = t3`;
ss1 = ssq(t1 - t2) + ssq(t3 - t4) +
      ssq(t1 * a - a) + ssq(t3 * ga - ga);
print ss1, ga [format=best6.];
```

- Use singular value decomposition. The singular decomposition $\mathbf{A} = \mathbf{UDV}'$ with $\mathbf{U}'\mathbf{U} = \mathbf{I}_m$, $\mathbf{D} = \text{diag}(d_i)$, and $\mathbf{V}'\mathbf{V} = \mathbf{V}\mathbf{V}' = \mathbf{I}_n$, can be used to compute $\mathbf{A}^- = \mathbf{VD}^\dagger \mathbf{U}'$, with $\mathbf{D}^\dagger = \text{diag}(d_i^\dagger)$ and

$$d_i^\dagger = \begin{cases} 0 & \text{where } d_i \leq \epsilon \\ 1/d_i & \text{otherwise} \end{cases}$$

The result A^- should be the same as that given by the [GINV](#) operator if the singularity criterion ϵ is selected correspondingly. Since you cannot specify the criterion ϵ for the [GINV](#) operator, the singular value decomposition approach can be important for applications where the [GINV](#) operator uses an unsuitable ϵ criterion. The slight discrepancy between the values of SS1 and SS2 is due to rounding that occurs in the statement that computes the matrix GA.

```
call svd(u,d,v,a);
do i=1 to n;
  if d[i] <= 1e-10 * d[1] then d[i] = 0.;
  else d[i] = 1. / d[i];
end;
ga = v * diag(d) * u`;
t1 = a * ga; t2 = t1`;
t3 = ga * a; t4 = t3`;
ss2 = ssq(t1 - t2) + ssq(t3 - t4) +
      ssq(t1 * a - a) + ssq(t3 * ga - ga);
print ss2;
```

- Use complete QR decomposition. The complete QR decomposition

$$A = Y \begin{bmatrix} \bar{R}' & 0 \\ 0 & 0 \end{bmatrix} \bar{Y}' \Pi'$$

where \bar{R}' is lower triangular, yields the Moore-Penrose inverse

$$A^- = \Pi \bar{Y} \begin{bmatrix} \bar{R}^{-'} & 0 \\ 0 & 0 \end{bmatrix} Y'$$

```
ord = j(n,1,0);
call qr(q1,r2,pivqr,lindqr,a,ord);
nr = n - lindqr;
q1 = q1[,1:nr]; r = r2[1:nr,]`;
call qr(q2,r5,piv2,lin2,r);
tt = trisolv(4,r5`,q1`);
ga = shape(0,n,m);
ga[pivqr,] = q2 * (tt // shape(0,n-nr,m));
t1 = a * ga; t2 = t1`;
t3 = ga * a; t4 = t3`;
ss3 = ssq(t1 - t2) + ssq(t3 - t4) +
      ssq(t1 * a - a) + ssq(t3 * ga - ga);
print ss3;
```

- Use complete QR decomposition with QR and [LUPDT](#):

```
ord = j(n,1,0);
call qr(q,r2,pivqr,lindqr,a,ord);
nr = n - lindqr;
r = r2[1:nr,1:nr]`; z = r2[1:nr,nr+1:n]`;
call lupdt(lup,bup,sup,r,z);
rd = trisolv(3,lup,r2[1:nr,]);
```

```

rd = trisolv(4,lup,rd);
ga = shape(0,n,m);
ga[pivqr,] = rd` * q[,1:nr]`;
t1 = a * ga; t2 = t1`;
t3 = ga * a; t4 = t3`;
ss4 = ssq(t1 - t2) + ssq(t3 - t4) +
      ssq(t1 * a - a) + ssq(t3 * ga - ga);
print ss4;

```

- Use complete QR decomposition with [RUPDT](#) and [LUPDT](#):

```

r3 = shape(0,n,n);
y = i(m); qtb = shape(0,n,m);
call rupdt(rup,bup,sup,r3,a,qtb,y);
r3 = rup; qtb = bup;
call rzlind(lind,r4,bup,r3,,qtb);
nr = n - lind; qtb = bup;
r = r4[piv[1:nr],piv[1:nr]]`;
z = r4[piv[1:nr],piv[nr+1:n]]`;
call lupdt(lup,bup,sup,r,z);
rd = trisolv(3,lup,r4[piv[1:nr],]);
rd = trisolv(4,lup,rd);
ga = shape(0,n,m);
ga = rd` * qtb[piv[1:nr],];
t1 = a * ga; t2 = t1`;
t3 = ga * a; t4 = t3`;
ss5 = ssq(t1 - t2) + ssq(t3 - t4) +
      ssq(t1 * a - a) + ssq(t3 * ga - ga);
print ss5;

```

SAVE Statement

SAVE ;

The SAVE statement saves data to a SAS data set.

The SAVE statement flushes any data residing in output buffers for all active output data sets and files to ensure that the data are written to disk. This is equivalent to closing and then reopening the files.

SEQ, SEQSCALE, and SEQSHIFT Calls

CALL SEQ(*prob*, *domain* <, **TSCALE**=*tscale* > <, **EPS**=*eps* > <, **DEN**=*den* >);

CALL SEQSCALE(*prob*, *gscale*, *domain*, *level* <, **IGUESS**=*iguess* > <, **TSCALE**=*tscale* > <, **EPS**=*eps* > <, **DEN**=*den* >);

```
CALL SEQSHIFT(prob, shift, domain, plevel < , IGUESS=iguess > < , TSCALE=tscale > < , EPS=eps >
               < , DEN=den > );
```

The SEQ, SEQSCALE, and SEQSHIFT subroutines perform discrete sequential tests.

The SEQSHIFT subroutine returns the following values:

<i>prob</i>	is an $(m + 1) \times n$ matrix. The $[i, j]$ entry in the array contains the probability at the $[i, j]$ entry of the argument <i>domain</i> . Also, the probability at infinity at every level j is returned in the last entry ($[m + 1, j]$) of column j . Upon a successful completion of any routine, this variable is always returned.
<i>gscale</i>	is a numeric variable that returns from the routine SEQSCALE and contains the scaling of the current geometry defined by <i>domain</i> that would yield a given significance level <i>level</i> .
<i>shift</i>	is a numeric variable that returns from the routine SEQSHIFT and contains the shift of current geometry defined by <i>domain</i> that would yield a given power level <i>plevel</i> .

The input arguments to the SEQSHIFT subroutine are as follows:

<i>domain</i>	specifies an $m \times n$ matrix that contains the boundary points separating the intervals of continuation/stopping of the sequential test. Each column k contains the boundary points at level k sorted in an ascending order. The values .M and .P represent $-\infty$ and $+\infty$, respectively. They must start on the first row, and any remaining entries must be filled with a missing value. Elements that follow the missing value in any column are ignored. The number of columns n is equal to the number of stages present in the sequential test. The row dimension m must be even, and it is equal to the maximum number of boundary points in a level. In fact, <i>domain</i> is the tabular form of the finite boundary points. Entries in <i>domain</i> with absolute values that exceed a standardized value of 8 at any level are internally reset to a standardized value of 8 or -8 , depending on the sign of the entry. This is reflected in the results returned for the probabilities and the densities.
<i>tscale</i>	specifies an optional $n - 1$ vector that describes the time intervals between two consecutive stages. In the absence of <i>tscale</i> , these time intervals are internally set to 1. The keyword for <i>tscale</i> is TSCALE.
<i>eps</i>	specifies an optional numeric parameter for controlling the absolute precision of the computation. In the absence of <i>eps</i> , the precision is internally set to $1\text{E}-7$. The keyword for <i>eps</i> is EPS.
<i>den</i>	specifies an optional character string to describe the name of an $m \times n$ matrix. The $[i, j]$ entry in the matrix returns the density of the distribution at the $[i, j]$ entry of the matrix specified by the <i>domain</i> argument. The keyword for <i>den</i> is DEN.
<i>iguess</i>	specifies an optional numeric parameter that contains an initial guess for the variable <i>gscale</i> in the SEQSCALE subroutine or for the variable <i>mean</i> in the SEQSHIFT subroutine. In general, very good estimates for these initial guesses can be provided by an iterative process, and these estimates become extremely valuable near convergence. The keyword for <i>iguess</i> is IGUESS.
<i>level</i>	specifies a numeric parameter in the SEQSCALE subroutine that contains the required significance level to be achieved through scaling the <i>domain</i> (see the description of SEQSCALE).
<i>plevel</i>	specifies a numeric parameter in the SEQSHIFT subroutine that provides the required power level to be achieved through shifting the <i>domain</i> (see the description of SEQSHIFT).

SEQ Call

To compute the probability from a sequential test, you must specify a matrix that contains the boundaries. With the optional additional information concerning the time intervals and the target accuracy, or their default values, the SEQ subroutine returns the matrix that contains the probability and optionally returns the density from a sequential test evaluated at each given point of the boundary. Let C_j denote the continuation set at each level j . C_j is defined to be the union at the j th level of all the intervals bounded from below by the points with even indices $0, 2, 4, \dots$ and from above by the points with odd indices $1, 3, \dots$

The SEQ subroutine computes, with $\mu = 0$, the densities

$$f_j(s, \mu) = \int_{C_{j-1}} \phi(s - y, \mu, t_{j-1}) f_{j-1}(y, \mu) dy, \text{ for } j = 2, 3, \dots$$

with

$$f_1(s, \mu) = \frac{1}{\sqrt{2\pi}} \exp \left[-\frac{(s - \mu)^2}{2} \right]$$

and

$$\phi(s, \mu, t) = \frac{1}{\sqrt{2\pi t}} \exp \left[-\frac{(s - \mu)^2}{2t} \right]$$

with the associated probability at any point a at level j to be

$$P_j(a, \mu) = \int_{C_{j-1}} \Phi(a - y, \mu, t_j) f_{j-1}(y, \mu) dy, \text{ for } j = 2, 3, \dots$$

with

$$\Phi(b, \mu, t) = \int_{-\infty}^b \phi(s, \mu, t) ds$$

The notation τ denotes the vector of time intervals t_1, \dots, t_{n-1} , and $P_j(g, \mu, \tau)$ denotes the probability of continuation at the j th level for a given domain g , a given mean μ , and a given time vector τ . The variance at the j th level can be computed from τ .

$$\begin{aligned} \sigma_1^2 &= 1 \\ \sigma_{j+1}^2 &= \sigma_j^2 + \tau_j, \text{ for } j = 1, 2, \dots \end{aligned}$$

It is important to understand the limitations that are imposed internally on the domain by the numerical method. Any element g_{ij} will always be limited within a symmetric interval with standardized values not to exceed 8. That is,

$$g_{ij} = \max[\min(g_{ij}, 8\sigma_j), -8\sigma_j]$$

SEQSCALE Call

Given a domain g , an optional time vector τ , and a probability level p_s , the SEQSCALE subroutine finds the amount of scaling s that would solve the problem

$$P_n(gs, 0) = p_s$$

The result for the amount of scaling s is returned as the second argument of the SEQSCALE subroutine, *scale*. Note that because of the complexity of the problem, the SEQSCALE subroutine will not attempt to scale a domain with multiple intervals of continuation.

For a significance level of α , set $p_s = 1 - \alpha$.

SEQSHIFT Call

Given a geometry g , an optional time vector τ , and a power level $1 - \beta$, the SEQSHIFT subroutine finds the mean μ that solves $\mu \geq 0$ such that $P_n(g, \mu) = \beta$.

Actually, a simple transformation of the variables in the sequential problem yields the following result:

$$P_j(g^\mu, 0) = P_j(g, \mu), \text{ for } j = 1, 2, \dots, n$$

where g^μ is given by $g_{ij}^\mu = g_{ij} - \mu j$.

Many options are available with the NLP family of optimization routines, which are described in Chapter 4, “Nonlinear Optimization Subroutines.”

Consider the following continuation intervals:

$$\begin{aligned} C_1 &= \{-6, 2\} \\ C_2 &= \{-6, 3\} \\ C_3 &= \{-6, 4, 5, 6\} \\ C_4 &= \{-6, 4\} \end{aligned}$$

The following statements compute the probability from the sequential test at each boundary point specified in the geometry.

```
/* function to insert in m the geometry column a at level k*/
start table(m,a,k);
  if ncol(m) = 0 & nrow(m) = 0 then m = j(nrow(a),k,.);
  if nrow(m) < nrow(a) then m = m// j(nrow(a)-nrow(m),ncol(m),.);
  if ncol(m) < k then m = m || j(nrow(m),k-ncol(m),.);
  m[1:nrow(a),k] = a;
finish;

call table(m,{-6,2},1);
call table(m,{-6,3},2);
call table(m,{-6,4,5,6},3);
call table(m,{-6,4},4);
call seq(prob,m) eps = 1.e-8 den="density";
print m;
print prob;
print density;
```

The following output displays the values returned for m , *prob* and *den*, respectively.

The probability at the level $k = 3$ at the point $x = 6$ is $prob[4, 3] = 0.96651$, while the density at the same point is $density[4, 3] = 0.0000524$.

Consider the continuation intervals

$$\begin{aligned} C_1 &= \{-20, 2\} \\ C_2 &= \{-20, 20\} \\ C_3 &= \{-3, 3\} \end{aligned}$$

Note that the continuation at level 2 can be effectively considered infinite, and it does not numerically affect the results of the computation at level 3. The following statements verify this by using the *tscale* parameter to compute this problem.

```
reset nocenter;
/* function to insert in m the geometry column a at level k */
start table(m,a,k);
  if ncol(m) = 0 & nrow(m) = 0 then m = j(nrow(a),k,.);
  if nrow(m) < nrow(a) then m = m // j(nrow(a)-nrow(m),ncol(m),.);
  if ncol(m) < k then m = m || j(nrow(m),k-ncol(m),.);
  m[1:nrow(a),k] = a;
finish;

call table(m,{-20,2},1);
call table(m,{-20,20},2);
call table(m,{-3,3},3);

/*****
/* TSCALE has the default value of 1 */
*****/
call seq(prob1,m) eps = 1.e-8 den="density";
print m[format=f5.] prob1[format=e12.5];

call table(mm,{-20,2},1);
call table(mm,{-3,3},2);
  /* You can show a 2-step separation between the levels */
  /* while dropping the intermediate level at 2 */
  /*
tscale = { 2 };
call seq(prob2,mm) eps = 1.e-8 den="density" TSCALE=tscale;
print mm[format=f5.] prob2[format=e12.5];
```

The output shows the values returned for the variables **m**, **prob1**, **mm** and **prob2**.

Some internal limitations are imposed on the geometry. Consider the three-level case with geometry *m* in the preceding statements. Since the *tscale* variable is not specified, it is set to its default value, (1, 1). The variance at the *j*th level is $\sigma_j^2 = j$ for $j = 1, 2, 3$. The first level has a lower boundary point of -20 , as represented by the value of $m[1, 1]$. Since the absolute standardized value is larger than 8, this point is replaced internally by the value -8 . Hence, the densities and the probabilities reported for the first level at this point are not for the given value -20 ; instead, they are for the internal value of -8 . For practical purposes, this limitation is not severe since the absolute error introduced is of the order of 10^{-16} .

The computations performed by the first call of the SEQ subroutine can be simplified since the second level is large enough to be considered infinite. The matrix MM contains the first and third columns of the matrix M. However, in order to specify the two-step separation between the levels, you must specify *tscale*=2.


```
end;
print summary[format=10.5];
```

Note that the variables *eps* and *tscale* have been internally set to their default values. The following values are returned for the matrix SUMMARY:

These values compare well with the values shown in Table 3 of Pocock (1982). Differences are of the order of 10^{-5} .

This example shows how to verify the results in Table 1 of Wang and Tsiatis (1987). For a given δ , the following program finds Γ that yields a symmetric continuation interval given by

$$-\Gamma_j^\delta \leq C_j \leq \Gamma_j^\delta$$

with a given significance level of α :

```
start func(delta,k) global(level);
  m      = (1:k)##delta;
  mm     = (-m/m);
  /*****/
  /* meet the significance level */
  /* by scaling */
  /*****/
  call seqscale(prob,scale,mm,level);
  return(scale);
finish;

/*****/
/* alpha levels of 0.05 and 0.01 */
/*****/

blevel      = {0.95 0.99};
do i = 1 to 2;
  level      = blevel[i];
  free summary;
  do delta   = 0 to .7 by .1;
    free row;
    do k=2 to 5;
      x      = func(delta,k);
      row    = row || x;
    end;
    summary  = summary //row;
  end;
  print summary[format=10.5];
end;
```

The value of SUMMARY for the 0.95 level is as follows.

The value for SUMMARY for the 0.99 level is as follows.

Note that since *eps* and *tscale* are not specified, they are internally set to their default values.

This example verifies the results in Table 2 of Pocock (1977). The following program finds Γ that yields a symmetric continuation interval given by

$$-\Gamma\sqrt{j} \leq C_j \leq \Gamma\sqrt{j}$$

for five groups. The overall significance level is α (the probability *palpha* = $1 - \alpha$), and the power is $1 - \beta$.

```
%let nl = 5;
start func(plevel) global(level, scale, mean, palpha, beta, tn, asn);
  m      = sqrt((1: &nl));
  mm     = -m //m;
  /*****
  /* meet the significance level */
  /* by scaling                    */
  *****/

  call seqscale(prob, scale, mm, level);
  palpha = (prob[2, ] - prob[1, ]) [&nl];
  mm     = mm * scale;

  /*****
  /* meet the power condition      */
  *****/

  call seqshift(prob, mean, mm, plevel);
  return(mean);
finish;

/*****
/* alpha = 0.95 */
*****/

level   = 9.50000E-01;
bplevel = { 0.5 .25 .1 0.05 0.01};
free summary;
do i = 1 to 5;
  summary = summary || func(bplevel[i]);
end;
print summary[format=10.5];
```

The value returned for SUMMARY are shown in the following table, and the entries agree with Table 2 of Pocock (1977).

SUMMARY

0.99359	1.31083	1.59229	1.75953	2.07153
---------	---------	---------	---------	---------

This example illustrates how to find the optimal boundary of the δ -class of Wang and Tsiatis (1987). The δ -class boundary has the form

$$-\Gamma j^\delta \leq C_j \leq \Gamma j^\delta$$

The δ -class boundary is optimal if it minimizes the average sample number while satisfying the required significance level α and the required power $1 - \beta$. You can use the following program to verify some of the results published in Tables 2 and 3 of Wang and Tsiatis (1987):

```
%let nl=5;
start func(delta) global(level,plevel,mean,
                        scale,alpha,beta,tn,asn);

    m      = ((1: &nl))##delta;
    mm     = (-m//m);

    /*****
    /* meet the significance level */
    *****/

    call seqscale(prob,scale,mm,level);
    alpha   = (prob[2,]-prob[1,]) [&nl];
    mm      = mm *scale;

    /*****
    /* meet the power condition */
    *****/

    call seqshift(prob,mean,mm,plevel);
    beta    = (prob[2,]-prob[1,]) [&nl];

    /*****
    /* compute the average sample number */
    *****/

    p      = prob[3,]-prob[2,]+prob[1,];
    tn     = 4*mean##2; /* number per group */
    asn    = tn * ( &nl - p *(%eval(&nl-1):0)`);
    return(asn);
finish;

/*****
/* set up the global variables needed by func */
*****/

level    = 0.95;
plevel   = 0.01;

/*****
/* set up the controlling options of the */
/* optimization routine */
*****/

opt      = {0 2 0 1 6};
tc       = repeat(.,1,12);
tc[1]    = 100;
tc[7]    = 1.e-4;
```

```

par      = { 1.e-13 . 1.e-10 . . .} || . || epsd;

/*****
/* provide the initial guess */
/* and let nlpdd do the work */
*****/

delta    = 0.5;
call nlpdd(rc,rx,"func",delta) opt=opt tc=tc par=par;

```

The following output displays the results.

```

                                Optimization Start
                                Parameter Estimates

                                Gradient
                                Objective
                                Function

N Parameter      Estimate      Value of Objective Function = 35.232023082

1 X1             -1.500000      -8.09752

                                Double Dogleg Optimization
Dual Broyden - Fletcher - Goldfarb - Shanno Update (DBFGS)
Without Parameter Scaling
Gradient Computed by Finite Differences
Number of Parameter Estimates 1

Parameter Estimates      2
Functions (Observations) 2

                                Optimization Start

Active Constraints      0 Criterion = 35.232
Max Abs Gradient Element 8.098 Radius = 1.000

Iter   Restart   Function   Active   Objective
      Calls     Constraints  Function

1       0         3         0       34.8914
2*      0         4         0       34.8774
3*      0         5         0       34.8774

Iter   difcrit   maxgrad   lambda   slope

1       0.3406    1.644    49.273   -0.830
2*      0.0140    0.0440     0    -0.0144
3*      0.00001   0.00013     0    -1E-5

                                Optimization Results

Iterations              3 Function Calls              6

```

Gradient Calls	5	Active Constraints	0
Criterion	34.877417	Max Grad Element	0.000126832
Slope	-0.0000100034	Radius	1

NOTE: FCONV convergence criterion satisfied.

Optimization Results
Parameter Estimates

N	Parameter	Estimate	Gradient
1	X1	0.586554	-0.0001268

Value of Objective Function = 34.877416815

The optimal function value of 34.88 agrees with the entry in Table 2 of Wang and Tsatis (1987) for five groups, $\alpha = 0.05$, and $1 - \beta = 0.99$. Note that the variables *eps* and *tsc* are internally set to their default values. For more information about the **NLPDD** subroutine, see the section “**NLPDD Call**” on page 826. For details about the *opt*, *tc*, and *par* arguments in the **NLPDD** call, see the section “**Options Vector**” on page 356, the section “**Termination Criteria**” on page 360, and the section “**Control Parameters Vector**” on page 367, respectively.

You can replicate other values in Table 2 of Wang and Tsatis (1987) by changing the values of the variables NL and PLEVEL. You can obtain values from Table 3 by changing the value of the variable LEVEL to 0.99 and specifying NL and PLEVEL accordingly.

This example illustrates how to find the boundaries that minimize ASN given the required significance level and the required power. It replicates some of the results published in Table 3 of Pocock (1982). The program computes the domain that

- minimizes the ASN
- yields a given significance level of 0.05
- yields a given power $1 - \beta$ under the alternative hypothesis

The last two nonlinear conditions on the optimization process can be incorporated as a penalty applied on the error in these nonlinear conditions. The following program does the computations for a power of 0.9.

```
%let nl=5;
start func(m) global(level,plevel,sigma,epss,
                    geometry,stgeom,gscscale,mean,alpha,beta,tn,asn);
  m      = abs(m);
  mm     = (-m // m)*sigma;
  /*****
  /* meet the significance level */
  *****/

  call seqscale(prob,gscscale,mm,level) iguess=gscscale eps=epss;
```

```

stgeom = gscale*m;
geometry= mm*gscale;

alpha = (prob[2,]-prob[1,]) [&nl];

/*****
/* meet the power condition */
*****/

call seqshift(prob,mean,geometry,plevel) iguess=mean eps=epss;
beta = (prob[2,]-prob[1,]) [&nl];
p = prob[3,] - prob[2,]+prob[1,];

/*****
/* compute the average sample number */
*****/

tn = 4*mean##2; /* number per group */
asn = tn * ( &nl - p * (%eval(&nl-1):0)`);
return(asn);
finish;

/*****
/* set up the global variables needed by func */
*****/
epss = 1.e-8;
epso = 1.e-5;
level = 9.50000E-01;
plevel = 0.05;
sigma = diag(sqrt(1:5));

/*****
/* set up the controlling options of the */
/* optimization routine */
*****/

opt = {0 2 0 1 6};
tc = repeat(.,1,12);
tc[1] = 100;
tc[7] = 1.e-4;
par = { 1.e-13 . 1.e-10 . . .} || . || epso;

/*****
/* provide the constraint matrix */
/* you need monotonically increasing */
/* significance levels */
*****/

con = { . . . . . . . ,
        . . . . . . . ,
        1 -1 . . . 1 0 ,
        . 1 -1 . . 1 0 ,
        . . 1 -1 . 1 0 ,

```

```

. . . 1 -1 1 0 };

/*****
/* provide the initial guess */
/* and let nlp do the work */
*****/

m      = { 1 1 1 1 1 };
call nlpdd(rc,rx,"func",m) opt=opt blc = con tc=tc par=par;
print stgeom;

```

Note that while *eps* has been set to $eps=10^{-8}$, *tscale* has been internally set to its default value. You can choose to run the program with and without the specification of the keyword IGUESS to see the effect on the execution time.

Note the following about the optimization process:

- Different levels of precision are imposed on different modules. In this example, *epss*, which is used as the precision for the sequential tests, is $1E-8$. The absolute and relative function criteria for the objective function are set to $par[7]=1E-5$ and $tc[7]=1E-4$, respectively. Since finite differences are used to compute the first and second derivatives, the sequential test should be more precise than the optimization routine. Otherwise, the finite difference estimation is worthless. Optimally, if the precision of the function evaluation is $O(\epsilon)$, the first- and second-order derivatives should be estimated with perturbations $O(\epsilon^{\frac{1}{2}})$ and $O(\epsilon^{\frac{1}{3}})$, respectively. For example, if all three precision levels are set to $1E-5$, the optimization process does not work properly.
- Line search techniques that do not depend on the computation of the derivative are preferable.
- The amount of printed information from the optimization routines is controlled by *opt[2]* and can be set to any value between 0 and 3. Larger numbers produce more output.

SEQSCALE Call

```
CALL SEQSCALE(prob, gscale, domain, level <, IGUESS=iguess> <, TSCALE=tscale> <,
              EPS=eps> <, DEN=den> );
```

The SEQSCALE subroutine computes estimates of scales associated with discrete sequential tests.

See the entry for the [SEQ](#) subroutine for details.

SEQSHIFT Call

```
CALL SEQSHIFT(prob, shift, domain, plevel <, IGUESS=iguess> <, TSCALE=tscale> <, EPS=eps>
              <, DEN=den> );
```


The SEQSHIFT subroutine computes estimates of means associated with discrete sequential tests.
See the entry for the [SEQ](#) subroutine for details.

SETDIF Function

SETDIF(*matrix1*, *matrix2*);

The SETDIF function returns as a row vector the sorted set (without duplicates) of all element values present in *matrix1* but not in *matrix2*. If the resulting set is empty, the SETDIF function returns a null matrix (with zero rows and zero columns).

The arguments to the SETDIF function are as follows:

- matrix1* is a reference matrix. Elements of *matrix1* not found in *matrix2* are returned in a vector. It can be either numeric or character.
- matrix2* is the comparison matrix. Elements of *matrix1* not found in *matrix2* are returned in a vector. It can be either numeric or character, depending on the type of *matrix1*.

The argument matrices and result can be either both character or both numeric. For character matrices, the element length of the result is the same as the element length of the *matrix1*. Shorter elements in the second argument are padded on the right with blanks for comparison purposes.

For example, the following statements produce the matrix **C**, as shown:

```
a = {1 2 4 5};  
b = {3 4};  
c = setdif(a,b);
```

C	1 row	3 cols	(numeric)
	1	2	5

SETIN Statement

SETIN *SAS-data-set* < **NOBS** *name* > < **POINT** *value* > ;

The SETIN data set makes a data set the current input data set.

The arguments to the SETIN statement are as follows:

- SAS-data-set* can be specified with a one-level name (for example, A) or a two-level name (for example, Sasuser.A). For more information about specifying SAS data sets, see the chapter on data sets in *SAS Language Reference: Concepts*.
- name* is the name of a variable to contain the number of observations in the data set.

value specifies the current observation.

The SETIN statement chooses the specified data set from among the data sets already opened for input by the [EDIT](#) or [USE](#) statement. This data set becomes the current input data set for subsequent data management statements. The NOBS option is not required. If specified, the NOBS option returns the number of observations in the data set in the scalar variable *name*. The POINT option makes the specified observation the current one. It positions the data set to a particular observation. The [SHOW DATASETS](#) command lists data sets already opened for input.

In the example that follows, if the data set WORK.A has 20 observations, the variable SIZE is set to 20. Also, the current observation is set to 10.

```
setin work.a nobs size point 10;
list;                          /* lists observation 10 */
```

SETOUT Statement

SETOUT *SAS-data-set* < **NOBS** *name* > < **POINT** *value* > ;

The SETOUT data set makes a data set the current output data set.

The arguments to the SETOUT statement are as follows:

<i>SAS-data-set</i>	can be specified with a one-level name (for example, A) or a two-level name (for example, Sasuser.A). For more information about specifying SAS data sets, see the chapter on SAS data sets in <i>SAS Language Reference: Concepts</i> .
<i>name</i>	is the name of a variable to contain the number of observations in the data set.
<i>value</i>	specifies the observation to be made the current observation.

The SETOUT statement chooses the specified data set from among those data sets already opened for output by the [EDIT](#) or [CREATE](#) statement. This data set becomes the current output data set for subsequent data management statements. If specified, the NOBS option returns the number of observations currently in the data set in the scalar variable *name*. The POINT option makes the specified observation the current one.

In the example that follows, the data set WORK.A is made the current output data set and the fifth observation is made the current observation. The number of observations in WORK.A is returned in the variable SIZE.

```
setout work.a nobs size point 5;
```

SHAPE Function

SHAPE(*matrix*, *nrow* < , *ncol* > < , *pad-value* >);

The SHAPE function reshapes and repeats values in a matrix. The arguments are as follows:

<i>matrix</i>	is a numeric or character matrix or literal.
<i>nrow</i>	specifies the number of rows for the new matrix.
<i>ncol</i>	specifies the number of columns for the new matrix.
<i>pad-value</i>	specifies a value to use for elements of the new matrix if the quantity $nrow \times ncol$ is greater than the number of elements in <i>matrix</i> .

The SHAPE function creates a new matrix from data in *matrix*. The values *nrow* and *ncol* specify the number of rows and columns, respectively, in the new matrix. The function can reshape both numeric and character matrices.

There are three ways of using the function:

- If only *nrow* is specified, the number of columns is determined as the number of elements in the object matrix divided by *nrow*. The number of elements must be exactly divisible; otherwise, a conformability error is diagnosed.
- If both *nrow* and *ncol* are specified, but not *pad-value*, the result is obtained moving along the rows until the desired number of elements is obtained. The operation cycles back to the beginning of the object matrix to get more elements, if needed.
- If *pad-value* is specified, the operation moves the elements of the object matrix first and then fills in any extra positions in the result with the *pad-value*.

If *nrow* or *ncol* is specified as 0, the number of rows or columns, respectively, becomes the number of values divided by *ncol* or *nrow*.

For example, the following statements create constant matrices of a given size:

```
r = shape(12, 3, 4);      /* 3 x 4 matrix with constant value 12 */
s = shape({99 31}, 3, 3); /* 3 x 3 matrix with alternating values */
print r, s;
```

Figure 23.270 Constant and Repeated Matrices

r			
12	12	12	12
12	12	12	12
12	12	12	12
s			
99	31	99	
31	99	31	
99	31	99	

Notice that the SHAPE function produces the result matrix by traversing the argument matrix in row-major order until the specified number of elements is reached. If necessary, the SHAPE function reuses elements.

You can also use the SHAPE function to reshape an existing matrix, as shown in the following statements:

```
t = shape(1:6, 2);
print t;
```

Figure 23.271 Reshaped Matrix

t		
1	2	3
4	5	6

SHAPECOL Function

```
SHAPECOL(matrix, nrow <, ncol > <, pad-value > );
```

The SHAPECOL function reshapes and repeats values in a matrix. It is similar to the [SHAPE function](#) except that the SHAPECOL function produces the result matrix by traversing the argument matrix in column-major order.

```
A = {1 2 3, 4 5 6};
c = shapecol(A, 3);
v = shapecol(A, 0, 1);
print c v;
```

Figure 23.272 Reshaped Matrices

c		v
1	5	1
4	3	4
2	6	2
		5
		3
		6

The vector **v** in the example is called the “vec of **A**” and is written **vec(A)**. Uses of the **vec** operator in matrix algebra are described in Harville (1997). One important property is the relationship between the **vec** operator and the [Kronecker product](#). If **A**, **B**, and **X** have the appropriate dimensions, then

$$\text{vec}(\mathbf{AXB}) = (\mathbf{B}' \otimes \mathbf{A})\text{vec}(\mathbf{X})$$

There is also a relationship between the SHAPECOL function and the [SHAPE function](#). If **A** is a matrix, then the following two computations are equivalent:

```
b = shapecol(A, m, n, padVal);
c = T(shape(A`, n, m, padVal));
```

See the [VECH function](#) for a similar function that is useful for computing with symmetric matrices.

SHOW Statement

SHOW *operands* ;

The SHOW statement prints system information. The following *operands* are available:

ALL	shows all the information included by OPTIONS, SPACE, DATASETS, FILES, and MODULES.
ALLNAMES	behaves like NAMES, but also shows names without values.
CONTENTS	shows the names and attributes of the variables in the current SAS data set.
DATASETS	shows all open SAS data sets.
FILES	shows all open files.
MEMORY	returns the size of the largest chunk of main memory available.
MODULES	shows all modules that exist in the current PROC IML environment. A module already referenced but not yet defined is listed as undefined.
<i>name</i>	shows attributes of the specified matrix. If the name of a matrix is one of the SHOW keywords, then both the information for the keyword and the matrix are shown.
NAMES	shows attributes of all matrices having values. Attributes include number of rows, number of columns, data type, and size.
OPTIONS	shows current settings of all PROC IML options (see the RESET statement).
PAUSE	shows the status of all paused modules that are pending resume.
SPACE	shows the workspace and symbol space size and their current usage.
STORAGE	shows the modules and matrices in the current PROC IML library storage.
WINDOWS	shows all active windows opened by WINDOW statements .

An example of a valid statement follows:

```
show all;
```

SOLVE Function

SOLVE(*A*, *B*);

The SOLVE function solves a system of linear equations.

The arguments to the SOLVE function are as follows:

- A* is an $n \times n$ nonsingular matrix.
- B* is an $n \times p$ matrix.

The SOLVE function solves the set of linear equations $\mathbf{AX} = \mathbf{B}$ for \mathbf{X} . The matrix \mathbf{A} must be square and nonsingular.

The expression $\mathbf{X} = \text{SOLVE}(\mathbf{A}, \mathbf{B})$ is mathematically equivalent to using the INV function in the expression $\mathbf{X} = \text{INV}(\mathbf{A}) * \mathbf{B}$. However, the SOLVE function is recommended over the INV function because it is more efficient and more accurate. An example follows:

```
x = solve(a,b);
```

The solution method used is discussed in Forsythe, Malcom, and Moler (1967).

The SOLVE function uses a criterion to determine whether the input matrix is singular. See the [INV function](#) for details.

If \mathbf{A} is an $n \times n$ matrix, the SOLVE function temporarily allocates an n^2 array in addition to the memory allocated for the return matrix.

SOLVELIN Call

```
CALL SOLVELIN(x, status, A, b, method);
```

The SOLVELIN subroutine uses direct decomposition to solve sparse symmetric linear systems.

The SOLVELIN subroutine returns the following values:

x is the solution to $Ax = b$.
status is the final status of the solution.

The input arguments to the SOLVELIN subroutine are as follows:

A is the sparse coefficient matrix in the equation $Ax = b$. You can use [SPARSE function](#) to convert a matrix from dense to sparse storage.
b is the right side of the equation $Ax = b$.
method is the name of the decomposition to be used.

The input matrix *A* represents the coefficient matrix in sparse format; it is an n by 3 matrix, where n is the number of nonzero elements. The first column contains the nonzero values, while the second and third columns contain the row and column locations for the nonzero elements, respectively. Since *A* is assumed to be symmetric, only the elements on and below the diagonal should be specified, and it is an error to specify elements above the diagonal.

The solution to the system is returned in *x*. Your program should also check the returned *status* to make sure that a solution was found.

status = 0 indicates success.

status = 1 indicates the matrix *A* is not positive-definite.

status = 2 indicates the system ran out of memory.

If the SOLVELIN subroutine is unable to solve your system, you can try the iterative method subroutine [ITSOLVER](#).

Two different factorization methods are available from the call, Cholesky and Symbolic LDL, specified as 'CHOL' or 'LDL' with the *method* parameter. Both these factorizations are applicable only to positive-definite symmetric systems; if your system is not positive-definite or not symmetric, you can use an [ITSOLVER](#) call.

The following example uses SOLVELIN to solve the system:

$$\begin{bmatrix} 3 & 1.1 & 0 & 0 \\ 1.1 & 4 & 1 & 3.2 \\ 0 & 1 & 10 & 0 \\ 0 & 3.2 & 0 & 3 \end{bmatrix} x = \begin{bmatrix} 1 \\ 1 \\ 1 \\ 1 \end{bmatrix}$$

```
/* value      row column */
A = { 3        1        1,
      1.1      2        1,
      4        2        2,
      1        3        2,
      3.2      4        2,
      10       3        3,
      3        4        4};

/* right hand side */
b = {1, 1, 1, 1};

call solvelin(x, status, A, b, 'LDL');
print status x;
```

The results are as follows:

STATUS	X
0	2.68
	-6.4
	0.74
	7.16

SORT Call

CALL SORT(*matrix* <, *by* <, *descend* >);

The SORT subroutine sorts a matrix by the values of one or more columns. The arguments to the SORT subroutine are as follows:

- matrix* is the input matrix. It is sorted in place by the call. If you want to preserve the original order of the data, make a copy of *matrix*.
- by* specifies the columns used to sort the matrix. The argument *by* is either a numeric matrix that contains column numbers, or a character matrix that contains the names of columns assigned to *matrix* by a [MATTRIB statement](#) or [READ statement](#). If *by* is not specified, then the first column is used.
- descend* specifies which columns, if any, should be sorted in descending order. Any *by* columns not specified as descending will be ascending. If *descend* = *by*, then all *by* columns will be descending; if *descend* is skipped or is a null matrix, then all *by* columns will be ascending.

The SORT subroutine is used to sort a matrix according to the values in the columns specified by the *by* and *descend* arguments. Because the sort is done in place, very little additional memory space is required. The SORT subroutine is not as fast as the [SORTNDX call](#) for matrices with a large number of rows. After a matrix has been sorted, the unique combinations of values in the *by* columns can be obtained from the [UNIQUEBY function](#).

For example, the following statements sort a matrix:

```
m = { 1 1 0,
      2 2 0,
      1 1 1,
      2 2 2};
call sort(m, {1 3}, 3); /* ascending by col 1; descending by col 3 */
print m;
```

Figure 23.273 Sorted Matrix

m		
1	1	1
1	1	0
2	2	2
2	2	0

SORT Statement

SORT <DATA=SAS-data-set> <OUT=SAS-data-set> **BY** <DESCENDING variables> ;

The SORT statement sorts a SAS data set. You can use the following clauses with the SORT statement:

- DATA=SAS-data-set** names the SAS data set to be sorted. It can be specified with a one-level name (for example, A) or a two-level name (for example, Sasuser.A). For more information about specifying SAS data sets, see the chapter on SAS data sets in *SAS Language Reference: Concepts*. Note that the DATA= portion of the specification is optional.
- OUT=SAS-data-set** specifies a name for the output data set. If this clause is omitted, the DATA= data set is sorted and the sorted version replaces the original data set.

BY <i>variables</i>	specifies the variables to be sorted. A BY clause <i>must</i> be used with the SORT statement.
DESCENDING	specifies the variables are to be sorted in descending order.

The SORT statement sorts the observations in a SAS data set by one or more variables, stores the resulting sorted observations in a new SAS data set, or replaces the original. In contrast with other data processing statements, it is *mandatory* that the data set to be sorted be closed prior to the execution of the SORT statement.

The SORT statement first arranges the observations in the order of the first variable in the BY clause; then it sorts the observations with a given value of the first variable by the second variable, and so forth. Every variable in the BY clause can be preceded by the keyword DESCENDING to denote that the variable that follows is to be sorted in descending order. Note that the SORT statement always retains the same relative positions of the observations with identical BY variable values.

For example, the following statement sorts the SAS data set CLASS by the variables AGE and HEIGHT, where AGE is sorted in descending order, and all observations with the same AGE value are sorted by HEIGHT in ascending order:

```
sort class out=sclass by descending age height;
```

The output data set SCLASS contains the sorted observations. When a data set is sorted in place (without the OUT= clause) any indexes associated with the data set become invalid and are automatically deleted.

Note that all the clauses of the SORT statement must be specified in the order given in the preceding list.

SORTNDX Call

CALL SORTNDX(*index*, *matrix* < , *by* > < , *descend* >);

The SORTNDX subroutine creates an index to reorder a matrix by specified columns.

The SORTNDX subroutine returns the following value:

index is a vector such that *index*[*i*] is the row index of the *i*th element of *matrix* when sorted according to *by* and *descend*. Consequently, *matrix*[*index*,] is the sorted matrix.

The arguments to the SORTNDX subroutine are as follows:

<i>matrix</i>	is the input matrix, which is not modified by the call.
<i>by</i>	specifies the columns used to sort the matrix. The argument <i>by</i> is either a numeric matrix that contains column numbers, or a character matrix that contains the names of columns assigned to <i>matrix</i> by a MATTRIB statement or READ statement . If <i>by</i> is not specified, then the first column is used.
<i>descend</i>	specifies which columns, if any, should be sorted in descending order. Any <i>by</i> columns not specified as descending will be ascending. If <i>descend</i> = <i>by</i> , then all <i>by</i> columns will be descending; if <i>descend</i> is skipped or is a null matrix, then all <i>by</i> columns will be ascending.

The SORTNDX subroutine can be used to process the rows of a matrix in a sorted order, without having to actually modify the matrix.

For example, the following statements return a vector that gives the order of the rows in a matrix:

```
m = { 1 1 0,
      2 0 0,
      1 3 1,
      2 2 2 };
call sortndx(ndx, m, {1 3}, 3);
print ndx;
```

Figure 23.274 Sort Index

ndx
3
1
4
2

The output is shown in [Figure 23.274](#). The SORTNDX subroutine returns the vector **ndx** that indicates how rows of **m** will appear if you sort **m** in ascending order by column 1 and in descending order by column 3. The values of the vector **ndx** indicate that row 3 of **m** will be the first row in the sorted matrix. Row 1 of **m** will become the second row. Row 4 will become the third row, and row 2 will become the last row.

The matrix can be physically sorted with the [SORT call](#)), as follows:

```
sorted = m[ndx,];
```

The SORTNDX subroutine can be used with the [UNIQUEBY function](#) to extract the unique combinations of values in the *by* columns.

SOUND Call

```
CALL SOUND(freq<, dur>);
```

The SOUND subroutine generates a tone with a frequency (in hertz) given by the *freq* parameter and a duration (in seconds) given by the *dur* parameter.

The arguments to the SOUND subroutine are as follows:

- freq* is a numeric matrix or literal that contains the frequency in hertz.
- dur* is a numeric matrix or literal that contains the duration in seconds. Note that the *dur* argument differs from that in the DATA step.

Matrices can be specified for frequency and duration to produce multiple tones, but if both arguments are nonscalar, then the number of elements must match. The duration argument is optional and defaults to 0.25 (one quarter second).

For example, the following statements produce tones from an ascending musical scale, all with a duration of 0.2 seconds:

```
notes = 400#(2##do(0, 1, 1/12));
call sound(notes, 0.2);
```

SPARSE Function

SPARSE(x <, $type$ >);

The SPARSE function converts an $n \times p$ matrix that contains many zeros into a matrix stored in a sparse format which suitable for use with the [ITSOLVER](#) call or the [SOLVEIN](#) call.

The arguments are as follows:

x	specifies an $n \times p$ numerical matrix. Typically, x contains many zeros and only k nonzeros, where k is much smaller than np .				
$type$	specifies whether the x matrix is symmetric. The following values are valid: <table border="0" data-bbox="406 924 1442 1081"> <tr> <td>"symmetric"</td><td>specifies that only the lower triangular nonzero values of the x matrix are used.</td></tr> <tr> <td>"unsymmetric"</td><td>specifies that all nonzero values of the x matrix are used. This is the default value.</td></tr> </table>	"symmetric"	specifies that only the lower triangular nonzero values of the x matrix are used.	"unsymmetric"	specifies that all nonzero values of the x matrix are used. This is the default value.
"symmetric"	specifies that only the lower triangular nonzero values of the x matrix are used.				
"unsymmetric"	specifies that all nonzero values of the x matrix are used. This is the default value.				

The $type$ argument is not case-sensitive. The first three characters are used to determine the value. For example, "SYM" and "symmetric" specify the same option.

The matrix returned by the SPARSE function is a $k \times 3$ matrix that contains the following values:

- The first column contains the nonzero values of the x matrix.
- The second column contains the row numbers for each value.
- The third column contains the column numbers for each value.

For example, the following statements compute a sparse representation of a dense matrix with many zeros:

```
x = {3    1.1  0    0    ,
      1.1  4    0    3.2,
      0    1   10    0    ,
      0    3.2  0    3    };
a = sparse(x, "sym");
print a[colname={"Value" "Row" "Col"}];
```

Figure 23.275 Sparse Data Representation

Value	a	
	Row	Col
3	1	1
1.1	2	1
4	2	2
1	3	2
10	3	3
3.2	4	2
3	4	4

SPLINE and SPLINEC Calls

CALL SPLINE(*fitted*, *data* < , *smooth* > < , *delta* > < , *nout* > < , *type* > < , *slope* >);

CALL SPLINEC(*fitted*, *coeff*, *endSlopes*, *data* < , *smooth* > < , *delta* > < , *nout* > < , *type* > < , *slope* >);

The SPLINE and SPLINEC subroutines fit cubic splines to data. The SPLINE subroutine is the same as SPLINEC but does not return the matrix of spline coefficients needed to call SPLINEV, nor does it return the slopes at the endpoints of the curve.

The SPLINEC subroutine returns the following values:

fitted is an $n \times 2$ matrix of fitted values.

coeff is an $n \times 5$ (or $n \times 9$) matrix of spline coefficients. The matrix contains the cubic polynomial coefficients for the spline for each interval. Column 1 is the left endpoint of the x -interval for the regular (nonparametric) spline or the left endpoint of the parameter for the parametric spline. Columns 2 – 5 are the constant, linear, quadratic, and cubic coefficients, respectively, for the x -component. If a parametric spline is used, then columns 6 – 9 are the constant, linear, quadratic, and cubic coefficients, respectively, for the y -component. The coefficients for each interval are with respect to the variable $x - x_i$ where x_i is the left endpoint of the interval and x is the point of interest. The matrix *coeff* can be processed to yield the integral or the derivative of the spline. This, in turn, can be used with the SPLINEV function to evaluate the resulting curves. The SPLINEC subroutine returns *coeff*.

endSlopes is a 1×2 matrix that contains the slopes of the two ends of the curve expressed as angles in degrees. The SPLINEC subroutine returns the *endSlopes* argument.

The input arguments to the SPLINEC subroutine are as follows:

data specifies a $n \times 2$ (or $n \times 3$) matrix of (x, y) points on which the spline is to be fit. The optional third column is used to specify a weight for each data point. If *smooth* > 0, the weight column is used in calculations. A weight ≤ 0 causes the data point to be ignored in calculations.

- smooth* is an optional scalar that specifies the degree of smoothing to be used. If *smooth* is omitted or set equal to 0, then a cubic interpolating spline is fit to the data. If *smooth* > 0, then a cubic spline is used. Larger values of *smooth* generate more smoothing.
- delta* is an optional scalar that specifies the resolution constant. If *delta* is specified, the fitted points are spaced by the amount *delta* on the scale of the first column of *data* if a regular spline is used or on the scale of the curve length if a parametric spline is used. If both *nout* and *delta* are specified, *nout* is used and *delta* is ignored.
- nout* is an optional scalar that specifies the number of fitted points to be computed. The default is *nout*=200. If *nout* is specified, then *nout* equally spaced points are returned. The *nout* argument overrides the *delta* argument.
- type* is an optional 1 × 1 (or 1 × 2) character matrix or quoted literal that contains the type of spline to be used. The first element of *type* should be one of the following:
- `periodic`, which requests periodic endpoints
 - `zero`, which sets second derivatives at endpoints to 0

The *type* argument controls the endpoint constraints unless the *slope* argument is specified. If `periodic` is specified, the response values at the beginning and end of column 2 of *data* must be the same unless the smoothing spline is being used. If the values are not the same, an error message is printed and no spline is fit. The default value is `zero`. The second element of *type* should be one of the following.

- `nonparametric`, which requests a nonparametric spline
- `parametric`, which requests a parametric spline

If `parametric` is specified, a parameter sequence $\{t_i\}$ is formed as follows: $t_1 = 0$ and

$$t_i = t_{i-1} + \sqrt{(x_i - x_{i-1})^2 + (y_i - y_{i-1})^2}$$

Splines are then fit to both the first and second columns of *data*. The resulting splined values are paired to form the output. Changing the relative scaling of the first two columns of *data* changes the output because the sequence $\{t_i\}$ assumes Euclidean distance.

Note that if the points are not arranged in strictly ascending order by the first columns of *data*, then a parametric method must be used. An error message results if the nonparametric spline is requested.

- slope* is an optional 1 × 2 matrix of endpoint slopes given as angles in degrees. If a parametric spline is used, the angle values are used modulo 360. If a nonparametric spline is used, the tangent of the angles is used to set the slopes (that is, the effective angles range from −90 to 90 degrees).

see Stoer and Bulirsch (1980), Reinsch (1967), and Pizer (1975) for descriptions of the methods used to fit the spline. For simplicity, the following explanation assumes that the *data* matrix does not contain a weighting column.

Nonparametric splines can be used to fit data for which you believe there is a functional relationship between the X and Y variables. The unique values of X (stored in the first column of *data*) form a partition $\{a = x_1 < x_2 < \dots < x_n = b\}$ of the interval $[a, b]$. You can use a spline to interpolate the data (produce a

curve that passes through each data point) provided that there is a single Y value for each X value. The spline is created by constructing cubic polynomials on each subinterval $[x_i, x_{i+1}]$ so that the value of the cubic polynomials and their first two derivatives coincide at each x_i .

An interpolating spline is not uniquely determined by the set of Y values. To achieve a unique interpolant, S , you must specify two constraints on the endpoints of the interval $[a, b]$. You can achieve uniqueness by specifying one of the following conditions:

- $S''(a) = 0, S''(b) = 0$. The second derivative at both endpoints is zero. This is the default condition, but can be explicitly set by using `type='zero'`.
- Periodic conditions. If your data are periodic so that x_1 can be identified with x_n , and if $y_1 = y_n$, then the interpolating spline already satisfies $S(a) = S(b)$. Setting `type='periodic'` further requires that $S'(a) = S'(b)$ and $S''(a) = S''(b)$.
- Fixed slopes at endpoints. Setting `slope={y'_1, y'_n}` requires that $S'(a) = y'_1$ and $S'(b) = y'_n$.

The following codeu give three examples of computing an interpolating spline for data. Note that the first and last Y values are the same, so you can ask for a periodic spline.

```
data = { 0 5, 1 3, 2 5, 3 4, 4 6, 5 7, 6 6, 7 5 };

/* Compute three spline interpolants of the data */
/* (1) a cubic spline with type=zero (the default) */
call spline(fitted,data);

/* (2) A periodic spline */
call spline(periodicFitted,data) type='periodic';

/* (3) A spline with specific slopes at endpoints */
call spline(slopeFitted,data) slope={45 30};
```

You can also use a spline to smooth data. In general, a smoothing spline will not pass through any data pair exactly. A very small value of the *smooth* smoothing parameter will approximate an interpolating polynomial for data in which each unique X value is assigned the mean of the Y values that correspond to that X value. As the *smooth* parameter gets very large, the spline will approximate a linear regression.

The following statements compute two smoothing splines for the same data as in the previous example. The spline coefficients are passed to the `SPLINEV` function which evaluates the smoothing spline at the original X values. Note that the smoothing spline does not pass through the original Y values. Note also that the smoothing parameter for the periodic spline is smaller, so the periodic spline has more “wiggles” than the corresponding spline with the larger smoothing parameter.

```
data = { 0 5, 1 3, 2 5, 3 4, 4 6, 5 7, 6 6, 7 5 };

/* Compute spline smoothers of the data. */
call splinec(fitted,coeff,endSlopes,data) smooth=1;

/* Evaluate the smoother at the original X positions */
smoothFit = splinev(coeff, data[,1]);
```

```

/* Compute periodic spline smoother of the data. */
call splinec(fitted,coeff,endslopesP,data)
      smooth=0.1 type="periodic";

/* Evaluate the smoother at the original X positions */
smoothPeriodicFit = splinev(coeff, data[,1]);

/* Compare the two fits. Verify that the periodic
   spline has identical slopes at the end points. */
print smoothFit smoothPeriodicFit, endslopesP;

```

SMOOTHFIT	SMOOTHPERIODICFIT
0 4.4761214	0 4.7536432
1 4.002489	1 3.5603915
2 4.2424509	2 4.3820561
3 4.8254655	3 4.47148
4 5.7817386	4 5.8811872
5 6.3661254	5 6.8331581
6 6.0606327	6 6.1180839
7 5.2449764	7 4.7536432

ENDSLOPESP
-58.37255 -58.37255

A parametric spline can be used to interpolate or smooth data for which there does not seem to be a functional relationship between the X and Y variables. A partition $\{t_i\}$ is formed as explained in the documentation for the *type* parameter. Splines are then used to fit the X and Y values independently.

The following program fits a parametric curve to data that is shaped like an “S.” The variable *fitted* is returned as a *numParam* × 2 matrix that contains the ordered pairs that correspond to the parametric spline. These ordered pairs correspond to *numParam* evenly spaced points in the domain of the parameter *t*.

The purpose of the SPLINEV function is to evaluate (*score*) an interpolating or smoothing spline at an arbitrary set of points. The following program shows how to construct the parameters that correspond to the original data by using the formula specified in the documentation for the *type* argument. These parameters are used to construct the evenly spaced parameters that correspond to the data in the *fitted* matrix.

```

data = {3 7, 2 7, 1 6, 1 5, 2 4, 3 3, 3 2, 2 1, 1 1};

/* Compute parametric spline interpolant */
numParam = 20;
call splinec(fitted,coeff,endslopes,data)
      nout=numParam type={"zero" "parametric"};

/* Form the parameters mapped onto the data */
/* Evaluating the splines at t would return data */
t = j(nrow(data),1,0); /* first parameter is zero */

```

```

do i = 2 to nrow(t);
  t[i] = t[i-1] + sqrt( (data[i,1]-data[i-1,1])##2 +
                      (data[i,2]-data[i-1,2])##2 );
end;

/* construct numParam evenly-spaced parameters
   between 0 and t[nrow(t)] */
params = do(0, t[nrow(t)], t[nrow(t)]/(numParam-1))`;

/* evaluate the parametric spline at these points */
xy = splinev(coeff, params);
print params fitted xy;

```

The output from this program is as follows:

PARAMS			FITTED			XY		
0	3	7	0	3	7	0	3	7
0.6897753	2.3002449	7.0492667	2.3002449	7.0492667	2.3002449	7.0492667	2.3002449	7.0492667
1.3795506	1.6566257	6.8416091	1.6566257	6.8416091	1.6566257	6.8416091	1.6566257	6.8416091
2.0693259	1.1581077	6.3289203	1.1581077	6.3289203	1.1581077	6.3289203	1.1581077	6.3289203
2.7591012	0.9203935	5.6475064	0.9203935	5.6475064	0.9203935	5.6475064	0.9203935	5.6475064
3.4488765	1.0128845	4.9690782	1.0128845	4.9690782	1.0128845	4.9690782	1.0128845	4.9690782
4.1386518	1.4207621	4.4372889	1.4207621	4.4372889	1.4207621	4.4372889	1.4207621	4.4372889
4.8284271	2	4	2	4	2	4	2	4
5.5182024	2.5792379	3.5627111	2.5792379	3.5627111	2.5792379	3.5627111	2.5792379	3.5627111
6.2079777	2.9871155	3.0309218	2.9871155	3.0309218	2.9871155	3.0309218	2.9871155	3.0309218
6.897753	3.0796065	2.3524936	3.0796065	2.3524936	3.0796065	2.3524936	3.0796065	2.3524936
7.5875283	2.8418923	1.6710797	2.8418923	1.6710797	2.8418923	1.6710797	2.8418923	1.6710797
8.2773036	2.3433743	1.1583909	2.3433743	1.1583909	2.3433743	1.1583909	2.3433743	1.1583909
8.9670789	1.6997551	0.9507333	1.6997551	0.9507333	1.6997551	0.9507333	1.6997551	0.9507333
9.6568542	1	1	1	1	1	1	1	1

Attempting to evaluate a spline outside of its domain of definition will result in a missing value. For example, the following statements define a spline on the interval $[0, 7]$. Attempting to evaluate the spline at points outside of this interval (-1 or 20) results in missing values.

```

data = { 0 5, 1 3, 2 5, 3 4, 4 6, 5 7, 6 6, 7 5 };
call splinec(fitted,coeff,endSlopes,data) slope={45 45};
v = splinev(coeff,{-1 1 2 3 3.5 4 20});
print v;

```

v	
-1	.
1	3
2	5
3	4
3.5	4.7073171
4	6
20	.

One use of splines is to estimate the integral of a function that is known only by its value at a discrete set of points. Many people are familiar with elementary methods of numerical integration such as the Left-Hand Rule, the Trapezoid Rule, and Simpson's Rule. In the Left-Hand Rule, the integral of discrete data is estimated by the exact integral of a piecewise constant function between the data. In the Trapezoid Rule, the integral is estimated by the exact integral of a piecewise linear function connecting the data. In Simpson's Rule, the integral is estimated as the exact integral of a piecewise quadratic function between the data points.

Since a cubic spline is a sequence of cubic polynomials, it is possible to compute the exact integral of the cubic spline and use this as an estimate for the integral of the discrete data. The next example takes a function defined by discrete data and finds the integral and the first moment of the function.

The implementation of the integrand function (`fcheck`) uses a useful trick to evaluate a spline at a single point. Note that if you pass in a scalar argument to the `SPLINEV` function, you get back a vector that represents the evaluation of the spline along evenly spaced points. To get around this, the following statements evaluate the spline at the vector `x // x` and then extract the entry in the first row, second column. This number is the value of the spline evaluated at `x`.

```
x = { 0, 2, 5, 7, 8, 10 };
y = x + 0.1*sin(x);
a = x || y;
call splinec(fit,coeff,endslopes,a);

start fcheck(x) global(coeff,pow);
  /* The first column of v contains the points of evaluation
     while the second column contains the evaluation. */
  v = x##pow # splinev(coeff,x //x) [1,2];
  return(v);
finish;

/* use QUAD to integrate */
start moment(po) global(coeff,pow);
  pow = po;
  call quad(z,"fcheck",coeff[,1]) eps = 1.e-10;
  v1 = sum(z);
  return(v1);
finish;

mass = moment(0); /* to compute the mass */
mass = mass //
  (moment(1)/mass) // /* to compute the mean */
  (moment(2)/mass) ; /* to compute the meansquare */
print mass;

/* Check the computation by using Gauss-Legendre integration: this
   is good for moments up to maxng. */

gauss = {
  -9.3246951420315205e-01
  -6.6120938646626448e-01
  -2.3861918608319743e-01
  2.3861918608319713e-01
  6.6120938646626459e-01
```

```

    9.3246951420315183e-01,
    1.713244923791701e-01
    3.607615730481388e-01
    4.679139345726905e-01
    4.679139345726904e-01
    3.607615730481389e-01
    1.713244923791707e-01  };
ngauss = ncol(gauss);
maxng   = 2*ngauss-4;

start moment1(pow) global (coeff, gauss, ngauss, maxng);
  if pow < maxng then do;
    nrow    = nrow(coeff);
    ncol    = ncol(coeff);
    left    = coeff[1:nrow-1,1];
    right   = coeff[2:nrow,1];
    mid     = 0.5*(left+right);
    interv  = 0.5*(right - left);
    /* scale the weights on each interval */
    wgts    = shape(interv*gauss[2,],1);
    /* scale the points on each interval */
    pts     = shape(interv*gauss[1,] + mid * repeat(1,1,ngauss),1) ;
    /* evaluate the function */
    eval    = splinev(coeff,pts)[,2]`;
    mat     = sum (wgts#pts##pow#eval);
  end;
  return(mat);
finish;

mass = moment1(0);          /* to compute the mass */
mass = mass // (moment1(1)/mass) // (moment1(2)/mass) ;
print mass; /* should agree with earlier result */

```

The program prints the following results:

```

      MASS
50.204224
  6.658133
49.953307

      MASS
50.204224
  6.658133
49.953307

```

SPLINEV Function

SPLINEV(*coeff* <, *delta* > <, *nout* >);

The SPLINEV function evaluates a cubic spline at a set of points. The function returns a two-column matrix that contains the points of evaluation in the first column and the corresponding fitted values of the spline in the second column.

The arguments to the SPLINEV function are as follows:

- | | |
|--------------|--|
| <i>coeff</i> | is an $n \times 5$ (or $n \times 9$) matrix of spline coefficients, as returned by the SPLINEC Call . The <i>coeff</i> argument should not contain missing values. |
| <i>delta</i> | is an optional vector that specifies evaluation points. If <i>delta</i> is a scalar, the spline is evaluated at equally spaced points <i>delta</i> apart. If <i>delta</i> is a vector arranged in ascending order, the spline is evaluated at each of these values. Evaluation at a point outside the support of the spline results in a missing value in the output. If you specify the <i>delta</i> argument, you cannot specify the <i>nout</i> argument. |
| <i>nout</i> | is an optional scalar that specifies the number of fitted points desired. The default is <i>nout</i> =200. If you specify the <i>nout</i> argument, you cannot specify the <i>delta</i> argument. |

See the section “[SPLINE and SPLINEC Calls](#)” on page 972 for details and examples.

SPOT Function

SPOT(*times*, *forward_rates*);

The SPOT function returns an $n \times 1$ vector of (per-period) spot rates, given vectors of forward rates and times. The function takes the following arguments:

- | | |
|---------------|--|
| times | is an $n \times 1$ column vector of times in consistent units. Elements should be nonnegative. |
| forward_rates | is an $n \times 1$ column vector of corresponding (per-period) forward rates. Elements should be positive. |

The SPOT function transforms the given spot rates as

$$s_1 = f_1$$

$$s_i = \left(\prod_{j=1}^{j=i} (1 + f_j)^{t_j - t_{j-1}} \right)^{\frac{1}{t_i}} - 1; \quad i = 2, \dots, n$$

where, by convention, $t_0 = 0$.

For example, the following statements produce the output shown in [Figure 23.276](#):

```
time = T(do(1, 5, 1));
forward = T(do(0.05, 0.09, 0.01));
```

```
spot = spot(time, forward);
print spot;
```

Figure 23.276 Spot Rates

spot
0.05
0.0549882
0.0599686
0.0649413
0.0699065

SQRSYM Function

SQRSYM(*matrix*);

where *matrix* is a symmetric numeric matrix.

The SQRSYM function takes a packed-symmetric matrix (such as generated by the [SYMSQR function](#)) and transforms it back into a dense square matrix. The elements of the argument are unpacked (rowwise) into the lower triangle of the result and reflected across the diagonal into the upper triangle.

For example, the following statements return a symmetric matrix:

```
v = T(1:6);
sqr = sqrsym(v);
print sqr;
```

Figure 23.277 Symmetric Matrix

sqr		
1	2	4
2	3	5
4	5	6

The SQRSYM function and the [SYMSQR function](#) are inverse operations on the set of symmetric matrices.

SQRT Function

SQRT(*matrix*);

The SQRT function returns the positive square roots of each element of the argument matrix. An example of a valid statement follows.

```

a = {1 2 3 4};
c = sqrt(a);
print c;

```

Figure 23.278 Square Roots

c			
1	1.4142136	1.7320508	2

SQRVECH Function

SQRVECH(*matrix*);

The SQRVECH function transforms a packed-symmetric matrix into a dense square matrix. The elements of the argument are unpacked (columnwise) into the lower triangle of the result and reflected across the diagonal into the upper triangle. The argument *matrix* should be a column-stacked, packed-symmetric matrix, such as generated by the [VECH](#) function.

For example, the following statements return a symmetric matrix:

```

v = T(1:6);
sqr = sqrvech(v);
print sqr;

```

Figure 23.279 Symmetric Matrix

sqr		
1	2	3
2	4	5
3	5	6

The SQRVECH function and the [VECH](#) function are inverse operations on the set of symmetric matrices.

SSQ Function

SSQ(*matrix1* <, *matrix2*, ..., *matrix15* >);

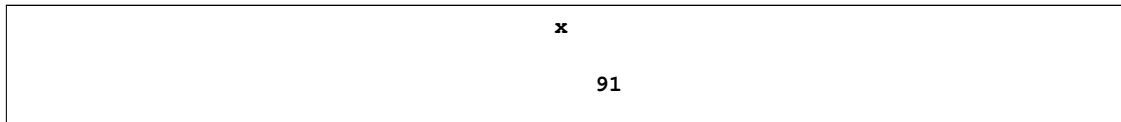
The SSQ function returns as a single numeric value the (uncorrected) sum of squares for all the elements of all arguments. You can specify as many as 15 numeric argument matrices.

The SSQ function checks for missing arguments and does not include them in the accumulation. If all arguments are missing, the result is 0.

An example of a valid statement follows:

```
a = {1 2 3, 4 5 6};
x = ssq(a);
print x;
```

Figure 23.280 Sums of Squares



START Statement

START < name > < (arguments) > < **GLOBAL**(arguments) > ;

language statements

FINISH < name > ;

The **START** statement defines the start of a module definition. Subsequent statements are not executed immediately, but are instead collected for later execution. The **FINISH statement** signals the end of a module definition.

The arguments to the **START** statement are as follows:

name is the name of a user-defined module.

arguments are names of variable arguments to the module. Arguments can be either input variables or output (returned) variables. Arguments listed in the **GLOBAL** clause are treated as global variables. Otherwise, the arguments are local.

language statements are statements making up the body of the module.

When no *name* argument is given in the **START** statement, the module name **MAIN** is used by default. If an error occurs during module compilation, the module is not defined. See [Chapter 6](#) for details.

The following example defines a module named **MYMOD** that has two local variables (**A** and **B**) and two global variables (**X** and **Y**). The module creates the variable **Y** from the arguments **A**, **B**, and **X**.

```
start mymod(a,b) global(x,y);
    y=a*x+b;
finish;

x = 1:4;
call mymod(2, 1);
print y;
```

Figure 23.281 Results of Calling a Module

y			
3	5	7	9

STD Function

STD(x);

The STD function computes a sample standard deviation of data. The sample standard deviation of a column vector is computed as the square root of the sample variance. See the [VAR function](#) for details.

When *x* is a matrix, the sample variance is computed for each column, as the following example shows:

```
x = {5 1 10,
      6 2 3,
      6 8 .,
      6 7 9,
      7 2 13};
```

```
std = std(x);
print std;
```

Figure 23.282 Standard Deviation of Columns

std		
0.7071068	3.2403703	4.1932485

The STD function returns a missing value for columns with fewer than two nonmissing observations.

STOP Statement

STOP ;

The STOP statement stops the program, and no further matrix statements are executed. However, PROC IML does not exit, and continues to execute if more statements are submitted. See also the descriptions of the [RETURN](#) and [ABORT](#) statements.

If execution was interrupted by a [PAUSE statement](#) or by a break, the STOP statement clears all the paused states and returns to immediate mode.

STORAGE Function

STORAGE();

The **STORAGE** function returns a matrix of the names of all of the matrices and modules in the current storage library. The result is a character vector with each matrix or module name occupying a row. Matrices are listed before modules. The **SHOW STORAGE** command separately lists all of the modules and matrices in storage.

For example, the following statements reset the current library storage to MYLIB and then print a list of the modules and matrices in storage:

```
reset storage="MYLIB";
```

Issue the following command to get the resulting matrix:

```
a = storage();  
print a;
```

STORE Statement

STORE <MODULE=(*module-list*)> <matrix-list> ;

The **STORE** statement stores matrices and modules in a storage library.

The arguments to the **STORE** statement are as follows.

module-list is a list of module names.

matrix-list is a list of matrix names.

The following statement stores the modules A, B, and C and the matrix X:

```
store module=(A B C) X;
```

The special operand **_ALL_** can be used to store all matrices or all modules. For example, the following statement stores all matrices and modules:

```
store _all_ module=_all_;
```

The storage library can be specified by using the **RESET STORAGE** statement and defaults to **WORK.IMLSTOR**. The **SHOW STORAGE** statement lists the current contents of the storage library. The following statement stores all matrices:

```
store;
```


See Chapter 17, “[Storage Features](#),” and also the descriptions of the [LOAD](#), [REMOVE](#), [RESET](#), and [SHOW](#) statements for related information.

SUBMIT Statement

SUBMIT <parameters> </options> ;

language statements

ENDSUBMIT ;

The SUBMIT statement enables you to submit SAS statements for processing from within a SAS/IML program. You can use the SUBMIT statement to call SAS procedures, DATA steps, and macros. All statements between the SUBMIT and the [ENDSUBMIT](#) statements are referred to as a *SUBMIT block*. The SUBMIT block is processed by the SAS language processor.

If you use the R option, the SUBMIT statement enables you to submit statements to the R language for processing.

The SUBMIT statement must appear on a line by itself. All SAS/IML matrices that are defined prior to the SUBMIT statement remain defined after the ENDSUBMIT statement.

parameters specifies one or more optional SAS/IML matrices whose values are substituted into the language statements in the SUBMIT block. To reference a parameter in the SUBMIT block, prefix the name of the parameter with an ampersand (&). If you do not specify the *parameters* argument, the SUBMIT block is sent without modification to the SAS (or R) language processor.

The following options are available in the SUBMIT statement after a slash (/).

OK=ok-matrix specifies the name of a matrix. The matrix is set to 1 if the SUBMIT block executes without error, and to 0 otherwise.

R specifies that statements in the SUBMIT block are processed by the R statistical software. You can use the R option to call functions in the R language, provided that the following statements are true:

1. the R statistical software is installed on the SAS workspace server.
2. The SAS system administrator at your site has enabled the RLANG SAS system option. (See “[The RLANG System Option](#)” on page 190.)

The following example calls a SAS procedure from a PROC IML program. The example passes in a parameter which is used by the FREQ procedure:

```
proc iml;
  VarName = "Sex";
  submit VarName;
  proc freq data=Sashelp.Class;
    table &VarName / out=OutFreq;
```

```
run;
endsubmit;
```

Prior to the SUBMIT statement, the program defines the **VarName** matrix. The matrix contains the name of a variable in the `Sashelp.Class` data set. The **VarName** matrix is listed in the SUBMIT statement, which means that the contents of the matrix is available for substitution into the SUBMIT block. The SUBMIT block references the contents of the matrix by preceding the matrix name by an ampersand (&). Consequently, the FREQ procedure carries out a one-way frequency analysis for the Sex variable. The output from PROC FREQ is shown in [Figure 23.283](#).

Figure 23.283 Result of Calling a SAS Procedure

The FREQ Procedure				
Sex	Frequency	Percent	Cumulative Frequency	Cumulative Percent
F	9	47.37	9	47.37
M	10	52.63	19	100.00

The preceding statements also create output data set, `OutFreq`. The following statements read the data into SAS/IML matrices:

```
use OutFreq;
read all var VarName into Levels;
read all var {Count};
close OutFreq;

print Count[rowname=Levels];
```

Notice that the **VarName** matrix is still defined, even after the FREQ procedure has finished execution. The statements read portions of the PROC FREQ output data set into two SAS/IML vectors. The output from the program is shown in [Figure 23.284](#).

Figure 23.284 Result of Calling a SAS Procedure

COUNT	
F	9
M	10

Chapter 10, “[Submitting SAS Statements](#),” provides details and further examples of submitting SAS statements. Chapter 11, “[Calling Functions in the R Language](#),” describes how to submit R statements and provides examples.

You cannot use the SUBMIT statement in code that is pushed to the input command queue with the EXECUTE, PUSH, or QUEUE subroutines.

SUBSTR Function

SUBSTR(*matrix*, *position* < , *length* >);

The SUBSTR function takes a character matrix as an argument (along with starting positions and lengths) and produces a character matrix with the same dimensions as the argument. Elements of the result matrix are substrings of the corresponding argument elements.

The arguments to the SUBSTR function are as follows:

matrix is a character matrix or quoted literal.
position is a numeric matrix or scalar that contains the starting position.
length is a numeric matrix or scalar that contains the length of the substring.

Each substring is constructed by using the starting *position* supplied. If a *length* is supplied, this length is the length of the substring. If no *length* is supplied, the remainder of the argument string is the substring.

The *position* and *length* arguments can be scalars or numeric matrices. If *position* or *length* is a matrix, its dimensions must be the same as the dimensions of the argument matrix or submatrix. If either one is a matrix, its values are applied to the substringing of the corresponding elements of the *matrix*. If *length* is supplied, the element length of the result is MAX(*length*); otherwise, the element length of the result is

$$\text{NLENG}(\text{matrix}) - \text{MIN}(\text{position}) + 1$$

The following statements return the output shown:

```
B = {abc def ghi, jkl mno pqr};
a = substr(b, 3, 2);
```

```

A          2 rows      3 cols      (character, size 2)

          C  F  I
          L  O  R
```

The element size of the result is 2; the elements are padded with blanks.

SUM Function

SUM(*matrix1* < , *matrix2*, . . . , *matrix15* >);

The SUM function returns as a single numeric value the sum of all the elements in all arguments. There can be as many as 15 argument matrices. The SUM function checks for missing values and does not include them in the accumulation. It returns 0 if all values are missing.

For example, consider the following statements:

```
a={2 1, 0 -1};
b=sum(a);
```

These statements return the following scalar:

B	1 row	1 col	(numeric)
		2	

SUMMARY Statement

SUMMARY <CLASS *operand*> <VAR *operand*> <WEIGHT *operand*> <STAT *operand*> <OPT *operand*> <WHERE(*expression*)> ;

The SUMMARY statement computes statistics for numeric variables for an entire data set or a subset of observations in the data set. The statistics can be stratified by the use of CLASS variables. The computed statistics are displayed in tabular form and optionally can be saved in matrices. Like most other data processing statements, the SUMMARY statement works on the current data set.

The following options are available with the SUMMARY statement:

CLASS *operand*

specifies the variables in the current input SAS data set to be used to group the summaries. The *operand* is a character matrix that contains the names of the variables, for example:

```
summary class { age sex} ;
```

Both numeric and character variables can be used as CLASS variables.

VAR *operand*

computes statistics for a set of numeric variables from the current input data set. The *operand* is a character matrix that contains the names of the variables. Also, the special keyword `_NUM_` can be used as a VAR operand to specify all numeric variables. If the VAR clause is missing, the SUMMARY statement produces only the number of observations in each class group.

WEIGHT *operand*

specifies a character value that contains the name of a numeric variable in the current data set whose values are to be used to weight each observation. Only one variable can be specified.

STAT *operand*

computes the statistics specified. The *operand* is a character matrix that contains the names of statistics. For example, to get the mean and standard deviation, specify the following:

```
summary stat{mean std};
```

The following list describes the keywords that can be specified as the STAT *operand*:

CSS	computes the corrected sum of squares.
MAX	computes the maximum value.
MEAN	computes the mean.
MIN	computes the minimum value.
N	computes the number of observations in the subgroup used in the computation of the various statistics for the corresponding analysis variable.
NMISS	computes the number of observations in the subgroup having missing values for the analysis variable.
STD	computes the standard deviation.
SUM	computes the sum.
SUMWGT	computes the sum of the WEIGHT variable values if WEIGHT is specified; otherwise, computes the number of observations used in the computation of statistics.
USS	computes the uncorrected sum of squares.
VAR	computes the variance.

When the STAT clause is omitted, the SUMMARY statement computes these statistics for each variable in the VAR clause:

- MAX
- MEAN
- MIN
- STD

Note that NOBS, the number of observations in each CLASS group, is always given.

OPT operand

sets the PRINT or NOPRINT and SAVE or NOSAVE options. The NOPRINT option suppresses the printing of the results from the SUMMARY statement. The SAVE option requests that the SUMMARY statement save the resultant statistics in matrices. The *operand* is a character matrix that contains one or more of the options.

When the SAVE option is set, the SUMMARY statement creates a CLASS vector for each CLASS variable, a statistic matrix for each analysis variable, and a column vector named `_NOBS_`. The CLASS vectors are named by the corresponding CLASS variable and have an equal number of rows. There are as many rows as there are subgroups defined by the interaction of all CLASS variables. The statistic matrices are named by the corresponding analysis variable. Each column of the statistic matrix corresponds to a statistic requested, and each row corresponds to the statistics of the subgroup defined by the CLASS variables. If no CLASS variable has been specified, each statistic matrix has one row, that contains the statistics of the entire population. The `_NOBS_` vector contains the number of observations for each subgroup.

The default is PRINT NOSAVE.

WHERE *expression*

conditionally selects observations, within the *range* specification, according to conditions given in *expression*. The general form of the WHERE clause is

WHERE (*variable comparison-op operand*) ;

The arguments to the WHERE clause are as follows:

variable is a variable in the SAS data set.

comparison-op is one of the following comparison operators:

<	less than
<=	less than or equal to
=	equal to
>	greater than
>=	greater than or equal to
^=	not equal to
?	contains a given string
^?	does not contain a given string
=:	begins with a given string
=*	sounds like or is spelled like a given string

operand is a literal value, a matrix name, or an expression in parentheses.

WHERE comparison arguments can be matrices. For the following operators, the WHERE clause succeeds if *all* the elements in the matrix satisfy the condition:

\neq $\neq?$ $<$ \leq $>$ \geq

For the following operators, the WHERE clause succeeds if *any* of the elements in the matrix satisfy the condition:

$=$ $?$ $=:$ $=*$

Logical expressions can be specified within the WHERE clause, by using the AND (&) and OR (|) operators. The general form is

clause & *clause* (for an AND clause)

clause | *clause* (for an OR clause)

where *clause* can be a comparison, a parenthesized clause, or a logical expression clause that is evaluated by using operator precedence. Notice that the expression on the left-hand side refers to values of the data set variables, and the expression on the right-hand side refers to matrix values.

See [Chapter 7](#) for an example that uses the SUMMARY statement.

SVD Call

CALL SVD(*u, q, v, a*);

The SVD subroutine computes the singular value decomposition for a numerical matrix. The input to the SVD subroutine is as follows:

a is the $m \times n$ input matrix that is factored as described in the following discussion.

The SVD subroutine returns the following output arguments:

u is an $m \times n$ orthonormal matrix

q is an $n \times 1$ vector that contains the singular values

v is an $n \times n$ orthonormal matrix

If $m \geq n$, the SVD subroutine factors a real $m \times n$ matrix **A** into the form

$$\mathbf{A} = \mathbf{U} \text{diag}(\mathbf{Q}) \mathbf{V}'$$

where

$$\mathbf{U}'\mathbf{U} = \mathbf{V}'\mathbf{V} = \mathbf{V}\mathbf{V}' = \mathbf{I}_n$$

and **Q** contains the singular values of **A**. The columns of **U** contains of the orthonormal eigenvectors of $\mathbf{A}\mathbf{A}'$, and **V** contains the orthonormal eigenvectors of $\mathbf{A}'\mathbf{A}$. **Q** contains the square roots of the eigenvalues of $\mathbf{A}'\mathbf{A}$ and $\mathbf{A}\mathbf{A}'$, except for some zeros.

If $m < n$, a corresponding decomposition is done where **U** and **V** switch roles:

$$\mathbf{A} = \mathbf{U} \text{diag}(\mathbf{Q}) \mathbf{V}'$$

where

$$\mathbf{U}'\mathbf{U} = \mathbf{U}\mathbf{U}' = \mathbf{V}'\mathbf{V} = \mathbf{I}_w$$

The singular values are sorted in descending order.

For information about the method used in the SVD subroutine, see Wilkinson and Reinsch (1971).

The following example is taken from Wilkinson and Reinsch (1971):

```
a = {22  10  2  3  7,
      14  7  10  0  8,
      -1 13 -1 -11 3,
      -3 -2 13 -2 4,
      9  8  1 -2 4,
      9  1 -7 5 -1,
      2 -6 6 5 1,
      4  5  0 -2 2};
call svd(u, q, v, a);
print u, q, v;
```

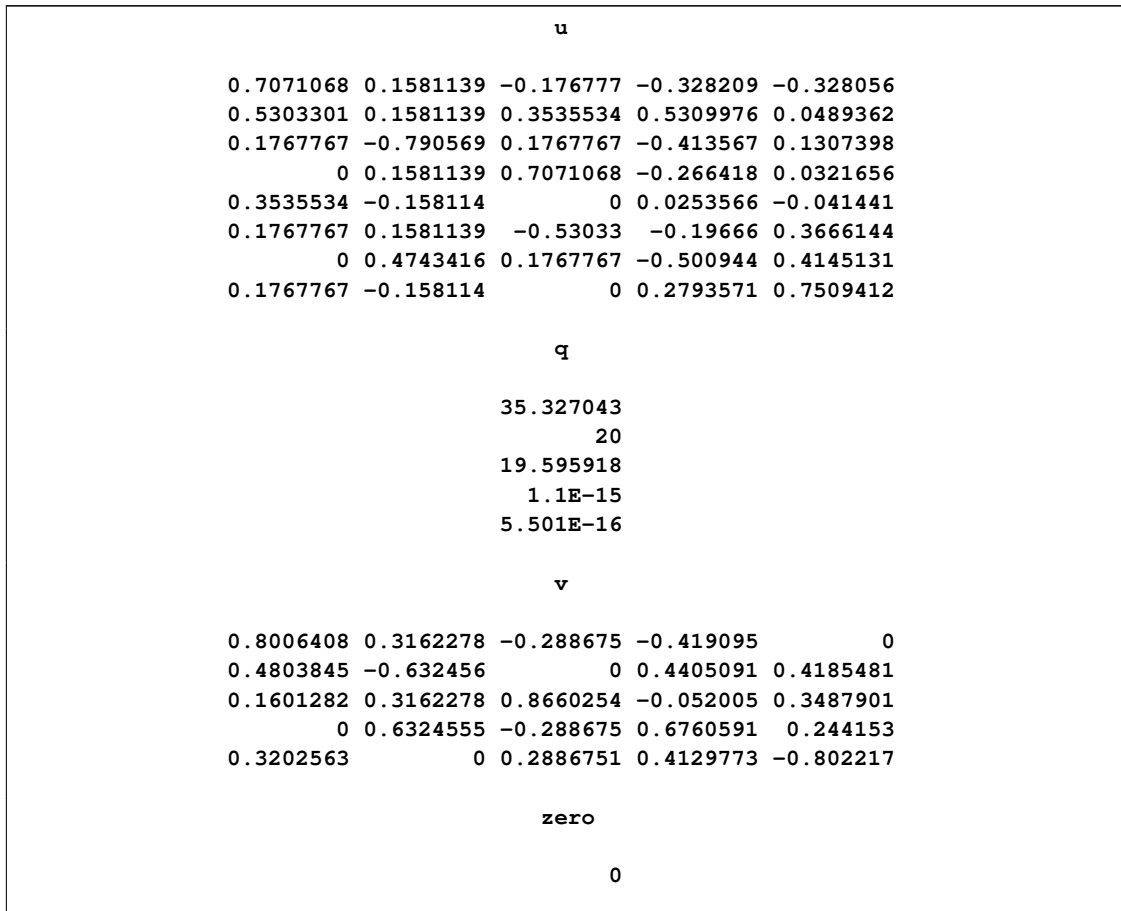
```

/* check correctness of factors */
zero = ssq(a - u*diag(q)*v`);
reset fuzz;          /* print small numbers as zero */
print zero;

```

The matrix is rank-3 with exact singular values $\sqrt{1248}$, 20, $\sqrt{384}$, 0, and 0. Because of the repeated singular values, the last two columns of the **U** matrix are not uniquely determined. A valid result is shown in Figure 23.285:

Figure 23.285 Singular Value Decomposition



The SVD routine performs most of its computations in the memory allocated for returning the singular value decomposition.

SWEEP Function

SWEEP(*matrix*, *index-vector*);

The SWEEP function sweeps *matrix* on the pivots indicated in *index-vector* to produce a new matrix.

The arguments the SWEEP function are as follows:

matrix is a numeric matrix or literal.

index-vector is a numeric vector that indicates the pivots.

The values of the index vector must be less than or equal to the number of rows or the number of columns in *matrix*, whichever is smaller.

For example, suppose that **A** is partitioned into

$$\begin{bmatrix} \mathbf{R} & \mathbf{S} \\ \mathbf{T} & \mathbf{U} \end{bmatrix}$$

such that **R** is $q \times q$ and **U** is $(m - q) \times (n - q)$. Let

$$\mathbf{I} = [1 \ 2 \ 3 \ \dots \ q]$$

Then, the statement

B=sweep(A, I) ;

becomes

$$\begin{bmatrix} \mathbf{R}^{-1} & \mathbf{R}^{-1}\mathbf{S} \\ -\mathbf{TR}^{-1} & \mathbf{U} - \mathbf{TR}^{-1}\mathbf{S} \end{bmatrix}$$

The index vector can be omitted. In this case, the function sweeps the matrix on all pivots on the main diagonal 1:MIN(*nrow*,*ncol*).

The SWEEP function has sequential and reversibility properties when the submatrix swept is positive definite:

- SWEEP(SWEEP(**A**,1),2)=SWEEP(**A**,{ 1 2 })
- SWEEP(SWEEP(**A**,**I**),**I**)=**A**

See Beaton (1964) for more information about these properties.

To use the SWEEP function for regression, suppose the matrix **A** contains

$$\begin{bmatrix} \mathbf{X}'\mathbf{X} & \mathbf{X}'\mathbf{Y} \\ \mathbf{Y}'\mathbf{X} & \mathbf{Y}'\mathbf{Y} \end{bmatrix}$$

where $\mathbf{X}'\mathbf{X}$ is $k \times k$.

Then **B** = SWEEP(**A**, 1 . . . *k*) contains

$$\begin{bmatrix} (\mathbf{X}'\mathbf{X})^{-1} & (\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\mathbf{Y} \\ -\mathbf{Y}'\mathbf{X}(\mathbf{X}'\mathbf{X})^{-1} & \mathbf{Y}'(\mathbf{I} - \mathbf{X}(\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}')\mathbf{Y} \end{bmatrix}$$

The partitions of **B** form the beta values, SSE, and a matrix proportional to the covariance of the beta values for the least squares estimates of **B** in the linear model

$$\mathbf{Y} = \mathbf{XB} + \epsilon$$

If any pivot becomes very close to zero (less than or equal to $1\text{E}-12$), the row and column for that pivot are zeroed. See Goodnight (1979) for more information.

An example that uses the SWEEP function for regression follows:

```
x = { 1  1  1,
      1  2  4,
      1  3  9,
      1  4 16,
      1  5 25,
      1  6 36,
      1  7 49,
      1  8 64 };

y = { 3.929,
      5.308,
      7.239,
      9.638,
      12.866,
      17.069,
      23.191,
      31.443 };

n = nrow(x);      /* number of observations */
k = ncol(x);      /* number of variables */
xy = x||y;        /* augment design matrix */
A = xy` * xy;     /* form cross products */
S = sweep( A, 1:k );

beta = S[1:k,4];  /* parameter estimates */
sse = S[4,4];     /* sum of squared errors */
mse = sse / (n-k); /* mean squared error */
cov = S[1:k, 1:k] # mse; /* covariance of estimates */
print cov, beta, sse;
```

COV

```
0.9323716 -0.436247 0.0427693
-0.436247 0.2423596 -0.025662
0.0427693 -0.025662 0.0028513
```

BETA

```
5.0693393
-1.109935
0.5396369
```

SSE

```
2.395083
```

The SWEEP function performs most of its computations in the memory allocated for the result matrix.

SYMSQR Function

SYMSQR(*matrix*);

The SYMSQR function takes a square numeric matrix (size $n \times n$) and compacts the elements from the lower triangle into a column vector ($n(n + 1)/2$ rows). The matrix is not checked for symmetry, but usually *matrix* is a symmetric matrix.

The following statement produces the output shown:

```
sym=symsqr({1 2, 3 4});
```

SYM	3 rows	1 col	(numeric)
		1	
		3	
		4	

Note that the 2 is lost since it is only present in the upper triangle.

T Function

T(*matrix*);

The T (transpose) function returns the transpose of its argument. It is equivalent to the transpose operator as written with a transpose postfix operator ('), but since some keyboards do not support the backquote character, this function is provided as an alternate.

For example, the following statements produce the matrix **Y**, as shown:

```
x={1 2, 3 4};
y=t(x);
```

Y	2 rows	2 cols	(numeric)
	1	3	
	2	4	

TABULATE Call

CALL TABULATE(*levels*, *freq*, *x* <, *method* >);

The TABULATE subroutine counts the number of elements in each of the unique categories of the *x* argument.

The output arguments are as follows:

- levels* contains the unique sorted elements of the *x* argument. See also the [UNIQUE function](#).
- freq* contains the number of elements of *x* that match each element of *levels*.

The input arguments are as follows:

- x* specifies a vector of values.
- method* specifies whether missing values are included in the analysis. The following values are valid:
 - "nomissing" specifies that missing values are excluded from the analysis. This is the default value for the option.
 - "missing" specifies that missing values are counted as a valid separate level.

The *method* argument is not case-sensitive. The first two characters are used to determine the value. For example, "MISS" and "missing" specify the same option.

The following statements demonstrate the TABULATE subroutine:

```
x = {C, A, B, A, C, A};
call tabulate(labels, freq, x);
print freq[colname=labels];

x = {C, A, B, " ", A, C, A, " "};
call tabulate(labels, freq, x, "Missing");
labels = "Missing" || remove(labels, 1);
print freq[colname=labels];
```

Figure 23.286 Frequencies of Levels

freq			
A	B	C	
3	1	2	
freq			
Missing	A	B	C
2	3	1	2

TOEPLITZ Function

TOEPLITZ(*a*);

The TOEPLITZ function generates a Toeplitz matrix from a vector, or a block Toeplitz matrix from a matrix. A block Toeplitz matrix has the property that all matrices on the diagonals are the same. The argument *a* is an $(np) \times p$ or $p \times (np)$ matrix; the value returned is the $(np) \times (np)$ result.

The TOEPLITZ function uses the first $p \times p$ submatrix, \mathbf{A}_1 , of the argument matrix as the blocks of the main diagonal. The second $p \times p$ submatrix, \mathbf{A}_2 , of the argument matrix forms one secondary diagonal, with the transpose \mathbf{A}_2' forming the other. The remaining diagonals are formed accordingly. If the first $p \times p$ submatrix of the argument matrix is symmetric, the result is also symmetric. If \mathbf{A} is $(np) \times p$, the first p columns of the returned matrix, \mathbf{R} , are the same as \mathbf{A} . If \mathbf{A} is $p \times (np)$, the first p rows of \mathbf{R} are the same as \mathbf{A} .

The TOEPLITZ function is especially useful in time series applications, where the covariance matrix of a set of variables with its lagged set of variables is often assumed to be a block Toeplitz matrix.

If

$$\mathbf{A} = [\mathbf{A}_1 | \mathbf{A}_2 | \mathbf{A}_3 | \cdots | \mathbf{A}_n]$$

and if \mathbf{R} is the matrix formed by the TOEPLITZ function, then

$$\mathbf{R} = \begin{bmatrix} \mathbf{A}_1 & | & \mathbf{A}_2 & | & \mathbf{A}_3 & | & \cdots & | & \mathbf{A}_n \\ \mathbf{A}_2' & | & \mathbf{A}_1 & | & \mathbf{A}_2 & | & \cdots & | & \mathbf{A}_{n-1} \\ \mathbf{A}_3' & | & \mathbf{A}_2' & | & \mathbf{A}_1 & | & \cdots & | & \mathbf{A}_{n-2} \\ \vdots & & & & & & & & \\ \mathbf{A}_n' & | & \mathbf{A}_{n-1}' & | & \mathbf{A}_{n-2}' & | & \cdots & | & \mathbf{A}_1 \end{bmatrix}$$

If

$$\mathbf{A} = \begin{bmatrix} \mathbf{A}_1 \\ \mathbf{A}_2 \\ \vdots \\ \mathbf{A}_n \end{bmatrix}$$

and if \mathbf{R} is the matrix formed by the TOEPLITZ function, then

$$\mathbf{R} = \begin{bmatrix} \mathbf{A}_1 & | & \mathbf{A}_2' & | & \mathbf{A}_3' & | & \cdots & | & \mathbf{A}_n' \\ \mathbf{A}_2 & | & \mathbf{A}_1 & | & \mathbf{A}_2' & | & \cdots & | & \mathbf{A}_{n-1}' \\ \vdots & & & & & & & & \\ \mathbf{A}_n & | & \mathbf{A}_{n-1} & | & \mathbf{A}_{n-2} & | & \cdots & | & \mathbf{A}_1 \end{bmatrix}$$

Three examples follow.

```
r=toeplitz(1:5);
```

R	5 rows	5 cols	(numeric)	
1	2	3	4	5
2	1	2	3	4
3	2	1	2	3
4	3	2	1	2
5	4	3	2	1

```
r=toeplitz({1 2 ,
            3 4 ,
            5 6 ,
            7 8});
```

R	4 rows	4 cols	(numeric)	
1	2	5	7	
3	4	6	8	
5	6	1	2	
7	8	3	4	

```
r=toeplitz({1 2 3 4 ,
            5 6 7 8});
```

R	4 rows	4 cols	(numeric)	
1	2	3	4	
5	6	7	8	
3	7	1	2	
4	8	5	6	

TPSPLINE Call

CALL TPSPLINE(*fitted*, *coeff*, *adiag*, *gcv*, *x*, *y* < , *lambda* >);

The TPSPLINE subroutine fits a thin-plate smoothing spline (TPSS) to data. The generalized cross validation (GCV) function is used to select the smoothing parameter.

The TPSPLINE subroutine returns the following values:

<i>fitted</i>	is an $n \times 1$ vector of fitted values of the TPSS fit evaluated at the design points x . The n is the number of observations. The final TPSS fit depends on the optional <i>lambda</i> .
<i>coeff</i>	is a vector of spline coefficients. The vector contains the coefficients for basis functions in the null space and the representer of evaluation functions at unique design points. (see Wahba (1990) for more detail on reproducing kernel Hilbert space and representer of evaluation functions.) The length of <i>coeff</i> vector depends on the number of unique design points and the number of variables in the spline model. In general, let <i>nuobs</i> and k be the number of unique rows and the number of columns of x respectively. The length of <i>coeff</i> equals to $k + \text{nuobs} + 1$. The <i>coeff</i> vector can be used as an input of TPSPLNEV to evaluate the resulting TPSS fit at new data points.

adiag is an $n \times 1$ vector of diagonal elements of the “hat” matrix. See the “Details” section.

gcv If *lambda* is not specified, then *gcv* is the minimum value of the GCV function. If *lambda* is specified, then *gcv* is a vector (or scalar if *lambda* is a scalar) of GCV values evaluated at the *lambda* points. It provides you with both the ability to study the GCV curves by plotting *gcv* against *lambda* and the chance to identify a possible local minimum.

The input arguments to the TPSPLINE subroutine are as follows:

x is an $n \times k$ matrix of design points on which the TPSS is to be fit. The k is the number of variables in the spline model. The columns of *x* need to be linearly independent and contain no constant column.

y is the $n \times 1$ vector of observations.

lambda is a optional $q \times 1$ vector that contains λ values in $\log_{10}(n\lambda)$ scale. This option gives you the power to control how you want the TPSPLINE subroutine to function. If *lambda* is not specified (or *lambda* is specified and $q > 1$) the GCV function is used to choose the “best” λ and the returning *fitted* values are based on the λ that minimizes the GCV function. If *lambda* is specified and $q = 1$, no minimization of the GCV function is involved and the *fitted*, *coeff* and *adiag* values are all based on the TPSS fit that uses this particular *lambda*. This gives you the freedom to choose the λ that you deem appropriate.

Aside from the values returned, the TPSPLINE subroutine also prints other useful information such as the number of unique observations, the dimensions of the null space, the number of parameters in the model, a GCV estimate of λ , the smoothing penalty, the residual sum of square, the trace of $(I - A(\lambda))$, an estimate of σ^2 , and the sum of squares for replication.

No missing values are accepted within the input arguments. Also, you should use caution if you want to specify small *lambda* values. Since the true $\lambda = (10^{\log_{10} \text{lambda}})/n$, a very small value for *lambda* can cause λ to be smaller than the magnitude of machine error and usually the returned *gcv* values from such a λ cannot be trusted. Finally, when using TPSPLINE be aware that TPSS is a computationally intensive method. Therefore a large data set (that is, a large number of unique design points) will take a lot of computer memory and time.

For convenience, the TPSS method is illustrated with a two-dimensional independent variable $\mathbf{X} = (x^1, x^2)$. More details can be found in Wahba (1990), or in Bates et al. (1987).

Assume that the data are from the model

$$y_i = f(x_i) + \epsilon_i,$$

where $(x_i, y_i), i = 1, \dots, n$ are the observations. The function f is unknown and you assume that it is reasonably smooth. The error terms $\epsilon_i, i = 1, \dots, n$ are independent zero-mean random variables.

You measure the smoothness of f by the integral over the entire plane of the square of the partial derivatives of f of total order 2, that is

$$J_2(f) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \left[\frac{\partial^2 f}{\partial x_1^2} \right]^2 + 2 \left[\frac{\partial^2 f}{\partial x_1 \partial x_2} \right]^2 + \left[\frac{\partial^2 f}{\partial x_2^2} \right]^2 dx_1 dx_2$$

Using this as a smoothness penalty, the thin-plate smoothing spline estimate f_λ of f is the minimizer of

$$S_\lambda(f) = \frac{1}{n} \sum_{i=1}^n (y_i - f(x_i))^2 + \lambda J_2(f).$$

Duchon (1976) derived that the minimizer f_λ can be represented as

$$f_\lambda(x) = \sum_{i=1}^3 \beta_i \phi_i(x) + \sum_{i=1}^n \delta_i E_2(x - x_i),$$

where $(\phi_1(x), \phi_2(x), \phi_3(x)) = (1, x^1, x^2)$ and $E_2(s) = \frac{1}{2^3\pi} \|s\|^2 \ln(\|s\|)$.

Let matrix \mathbf{K} have entries $(\mathbf{K})_{ij} = E_2(x_i - x_j)$ and matrix \mathbf{T} have entries $(\mathbf{T})_{ij} = \phi_j(x_i)$. Then the minimization problem can be rewritten as finding coefficients β and δ to minimize

$$S_\lambda(\beta, \delta) = \frac{1}{n} \|y - \mathbf{T}\beta - \mathbf{K}\delta\|^2 + \lambda \delta^T \mathbf{K}\delta$$

The final TPSS fits can be viewed as a type of generalized ridge regression estimator. The λ is called the smoothing parameter, which controls the balance between the goodness of fit and the smoothness of the final estimate. The smoothing parameter can be chosen by minimizing the generalized cross validation function (GCV). If you write

$$\hat{y} = \mathbf{A}(\lambda)y$$

and call the $\mathbf{A}(\lambda)$ as the “*hat*” matrix, the GCV function $V(\lambda)$ is defined as

$$V(\lambda) = \frac{(1/n) \|(\mathbf{I} - \mathbf{A}(\lambda))y\|^2}{[(1/n) \text{tr}(\mathbf{I} - \mathbf{A}(\lambda))]^2}$$

The returned values from this function call provide the \hat{y} as *fitted*, the (β, δ) as *coeff*, and $\text{diag}(\mathbf{A}(\lambda))$ as *adiag*.

To evaluate the TPSS fit $f_\lambda(x)$ at new data points, you can use the `TPSPLNEV` call.

Suppose \mathbf{X}^{new} , a $m \times k$ matrix, contains the m new data points at which you want to evaluate f_λ . Let $(\mathbf{T}_{ij}^{\text{new}}) = \phi_j(x_i^{\text{new}})$ and $(\mathbf{K}_{ij}^{\text{new}}) = E_2(x_i^{\text{new}} - x_j)$ be the ij th elements of \mathbf{T}^{new} and \mathbf{K}^{new} respectively. The prediction at new data points \mathbf{X}^{new} is

$$y_{\text{pred}} = \mathbf{T}^{\text{new}}\beta + \mathbf{K}^{\text{new}}\delta$$

Therefore, the y_{pred} can be easily evaluated by using the coefficient (β, δ) obtained from the `TPSPLINE` call.

An example is given in the documentation for the [TPSPLNEV call](#).

TPSPLNEV Call

CALL TPSPLNEV(pred, xpred, x, coeff);

The `TPSPLNEV` subroutine evaluates the thin-plate smoothing spline (TPSS) at new data points. It is used after the [TPSPLINE subroutine](#) fits a thin-plate spline model to data.

The `TPSPLNEV` subroutine returns the following value:

pred is an $m \times 1$ vector of the predicated values of the TPSS fit evaluated at m new data points.

The input arguments to the TPSPLNEV subroutine are as follows:

xpred is an $m \times k$ matrix of data points at which the f_λ is evaluated, where m is the number of new data points and k is the number of variables in the spline model.

x is an $n \times k$ matrix of design points that is used as an input of [TPSPLINE call](#).

coeff is the coefficient vector returned from the [TPSPLINE call](#).

See the previous section on the [TPSPLINE call](#) for details about the TPSPLNEV subroutine.

As an example, consider the following data set, which consists of two independent variables. The plot of the raw data can be found in the first panel of [Figure 23.287](#).

```
x={ -1.0 -1.0,   -1.0 -1.0,   -0.5 -1.0,   -0.5 -1.0,
      0.0 -1.0,    0.0 -1.0,    0.5 -1.0,    0.5 -1.0,
      1.0 -1.0,    1.0 -1.0,   -1.0 -0.5,   -1.0 -0.5,
     -0.5 -0.5,   -0.5 -0.5,    0.0 -0.5,    0.0 -0.5,
      0.5 -0.5,    0.5 -0.5,    1.0 -0.5,    1.0 -0.5,
     -1.0  0.0,   -1.0  0.0,   -0.5  0.0,   -0.5  0.0,
      0.0  0.0,    0.0  0.0,    0.5  0.0,    0.5  0.0,
      1.0  0.0,    1.0  0.0,   -1.0  0.5,   -1.0  0.5,
     -0.5  0.5,   -0.5  0.5,    0.0  0.5,    0.0  0.5,
      0.5  0.5,    0.5  0.5,    1.0  0.5,    1.0  0.5,
     -1.0  1.0,   -1.0  1.0,   -0.5  1.0,   -0.5  1.0,
      0.0  1.0,    0.0  1.0,    0.5  1.0,    0.5  1.0,
      1.0  1.0,    1.0  1.0 };
```

```
y = {15.54, 15.76, 18.67, 18.50, 19.66, 19.80, 18.60, 18.52,
      15.87, 16.04, 10.92, 11.14, 14.81, 14.83, 16.56, 16.44,
      14.91, 15.06, 10.92, 10.94,  9.61,  9.65, 14.03, 14.03,
      15.77, 16.00, 14.00, 14.03,  9.56,  9.58, 11.21, 11.09,
      14.84, 14.99, 16.55, 16.51, 14.98, 14.72, 11.15, 11.17,
      15.83, 15.96, 18.64, 18.56, 19.54, 19.81, 18.57, 18.61,
      15.87, 15.90 };
```

Now generate a sequence of λ from -3.8 to -3.3 so that you can study the GCV function within this range. Use the following statement:

```
lambda = T( do(-3.8, -3.3, 0.1) );
```

Use the following statement to do the thin-plate smoothing spline fit and returning the fitted values on those design points.

```
call tpspline(fit, coef, adia, gcv, x, y, lambda);
```

The output from this subroutine follows.

SUMMARY OF TPSPLINE CALL

Number of observations	50
Number of unique design points	25
Dimension of polynomial Space	3
Number of Parameters	28
GCV Estimate of Lambda	0.00000668
Smoothing Penalty	2558.14323
Residual Sum of Squares	0.24611
Trace of (I-A)	25.40680
Sigma^2 estimate	0.00969
Sum of Squares for Replication	0.24223

After this `TPSPLINE` call, you obtained the fitted value. The fitted surface is plotted in the second panel of Figure 23.287. Also in Figure 23.287, panel 4, you plot the GCV function values against *lambda*. From panel 2, you see that because of the sparse design points, the fitted surface is a little bit rough. In order to study the TPSS fit $f_\lambda(x)$ more closely, you can use the following statements to generate a more dense grid on $[-1, 1] \times [-1, 1]$.

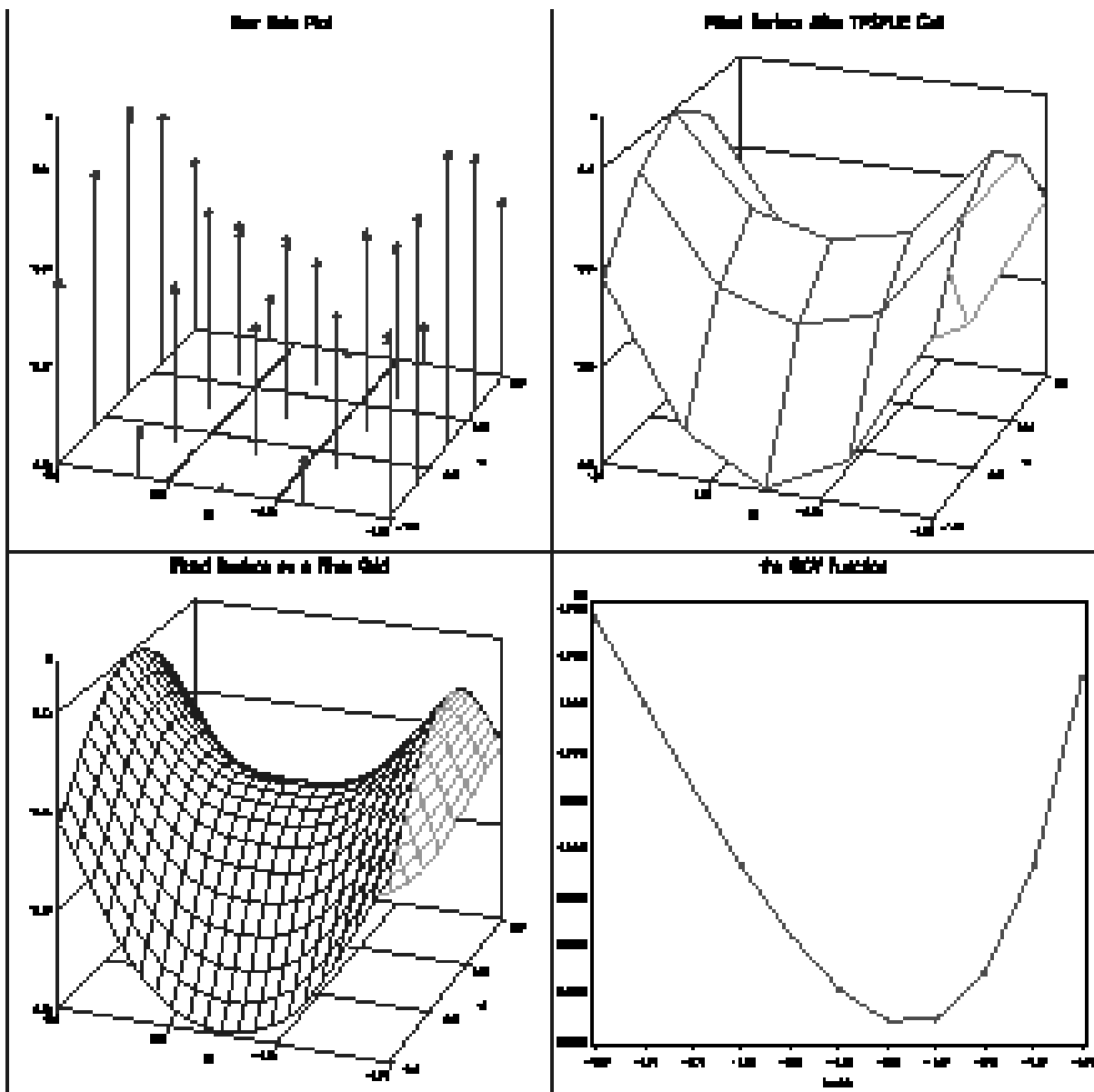
```
xGrid = T( do(-1, 1, 0.1) );
yGrid = T( do(-1, 1, 0.1) );
do i = 1 to nrow(xGrid);
    x1 = x1 // repeat(xGrid[i], nrow(yGrid));
    x2 = x2 // yGrid;
end;
xpred = x1 || x2;
```

Now you can use the function `TPSPLNEV` to evaluate $f_\lambda(x)$ on this dense grid. Here is the statement:

```
call tpsplnev(pred, xpred, x, coef);
```

The final fitted surface is plotted in Figure 23.287, panel 3.

Figure 23.287 Plots of Fitted Surface



TRACE Function

TRACE(*matrix*);

The TRACE function produces a single numeric value that is the sum of the diagonal elements of *matrix*. For example, the following statement produces the output shown:

```
a = trace({5 2, 1 3});
```

A	1 row	1 col	(numeric)
---	-------	-------	-----------

TRISOLV Function

TRISOLV(*form*, *R*, *b* <, *piv* >);

The TRISOLV function efficiently solves linear systems that involve a triangular matrix.

The TRISOLV function returns the $n \times p$ matrix **X** that contains p solutions of the p linear systems specified by *form*, *R*, and *b*.

The arguments to the TRISOLV function are as follows:

<i>form</i>	specifies which of the following form of a triangular linear system is to be solved:
<i>form</i> =1	solve $\mathbf{R}x = b$, R upper triangular
<i>form</i> =2	solve $\mathbf{R}'x = b$, R upper triangular
<i>form</i> =3	solve $\mathbf{R}'x = b$, R lower triangular
<i>form</i> =4	solve $\mathbf{R}x = b$, R lower triangular
<i>R</i>	specifies the $n \times n$ nonsingular upper (<i>form</i> =1,2) or lower (<i>form</i> =3,4) triangular coefficient matrix R . Only the upper or lower triangle of argument matrix <i>R</i> is used; the other triangle can contain any information.
<i>b</i>	specifies the $n \times p$ matrix, B , of p right-hand sides $b_k, k = 1 \dots p$.
<i>piv</i>	specifies an optional n vector that relates the order of the columns of matrix R to the order of the columns of an original coefficient matrix A for which matrix R has been computed as a factor. For example, the vector <i>piv</i> can be the result of the QR decomposition of a matrix A whose columns were permuted in the order $\mathbf{A}_{piv[1]}, \dots, \mathbf{A}_{piv[n]}$.

For *form*=1 and *form*=3, the solution is obtained by backward elimination. For *form*=2 and *form*=4, the solution is obtained by forward substitution.

If TRISOLV recognizes the upper or lower triangular matrix **R** as a singular matrix (that is, one that contains at least one zero diagonal element), it exits with an error message.

Consider the following example:

```

R = { 1  0  0  0,
      3  2  0  0,
      1 -3  5  0,
      2  7  9 -1 };

b = {1, 1, 4, -6 };
x = trisolv(4, R, b);
print x;
```

Figure 23.288 Solution of a Triangular System

x	
	1
	-1
	0
	1

Also see the example in the [QR call](#) section.

TSBAYSEA Call

CALL TSBAYSEA(*trend, season, series, adjust, abic, data* <, *order*> <, *sorder*> <, *rigid*> <, *npred*> <, *opt*> <, *cntl*> <, *print*>);

The TSBAYSEA subroutine performs Bayesian seasonal adjustment modeling.

The input arguments to the TSBAYSEA subroutine are as follows:

- | | |
|---------------|---|
| <i>data</i> | specifies a $T \times 1$ (or $1 \times T$) data vector. |
| <i>order</i> | specifies the order of trend differencing. The default is <i>order</i> =2. |
| <i>sorder</i> | specifies the order of seasonal differencing. The default is <i>sorder</i> =1. |
| <i>rigid</i> | specifies the rigidity of the seasonal pattern. The default is <i>rigid</i> =1. |
| <i>npred</i> | specifies the length of the forecast beyond the available observations. The default is <i>npred</i> =0. |
| <i>opt</i> | specifies the options vector. |
-
- | | |
|----------------|--|
| <i>opt</i> [1] | specifies the number of seasonal periods (<i>speriod</i>). By default, <i>opt</i> [1]=12. |
| <i>opt</i> [2] | specifies the year when the series starts (<i>year</i>). If <i>opt</i> [2]=0, there will be no trading day adjustment. By default, <i>opt</i> [2]=0. |
| <i>opt</i> [3] | specifies the month when the series starts (<i>month</i>). If <i>opt</i> [2]=0, this option is ignored. By default, <i>opt</i> [3]=1. |
| <i>opt</i> [4] | specifies the upper limit value for outlier determination (<i>rlim</i>). Outliers are considered as missing values. If this value is less than or equal to 0, TSBAYSEA assumes that the input data does not contain outliers. The default is <i>rlim</i> =0. See the section “ Missing Values ” on page 300. |
| <i>opt</i> [5] | refers to the number of time periods processed at one time (<i>span</i>). The default is <i>opt</i> [5]=4. |
| <i>opt</i> [6] | specifies the number of time periods to be shifted (<i>shift</i>). By default, <i>opt</i> [6]=1. |
| <i>opt</i> [7] | controls the transformation of the original series (<i>logt</i>). If <i>opt</i> [7]=1, log transformation is requested. No transformation (<i>opt</i> [7]=0) is the default. |

- cntl* specifies control values for the TSBAYSEA subroutine. These values are automatically set. Be careful if you change these values.
- cntl*[1] controls the adaptivity of the trading day adjustment component (*wtrd*). The default is *cntl*[1]=1.0.
 - cntl*[2] controls the sum of seasonal components within a period (*zersum*). The larger the value of *cntl*[2], the closer to zero this sum is. By default, *cntl*[2]=1.0.
 - cntl*[3] controls the leap year effect (*delta*). The default is *cntl*[3]=7.0.
 - cntl*[4] specifies the prior variance of the initial trend (*alpha*). The default is *cntl*[4]=0.01.
 - cntl*[5] specifies the prior variance of the initial seasonal component (*beta*). The default is *cntl*[5]=0.01.
 - cntl*[6] specifies the prior variance of the initial sum of seasonal components (*gamma*). The default is *cntl*[6]=0.01.
- print* requests the power spectrum and the estimated and forecast values of time series components. If *print*=2, the spectra of irregular, differenced trend and seasonal series are printed, together with estimates and forecast values. If *print*=1, only the estimates and forecast values of time series components are printed.
- If *print*=0, printed output is suppressed. The default is *print*=0.

The TSBAYSEA subroutine returns the following values:

- trend* refers to the estimate and forecast of the trend component.
- season* refers to the estimate and forecast of the seasonal component.
- series* refers to the smoothed and forecast values of the time series.
- adjust* refers to the seasonally adjusted series.
- abic* refers to the value of ABIC from the final estimates.

The TSBAYSEA subroutine performs Bayesian seasonal adjustments. The smoothness of the trend and seasonal components is controlled by the prior distribution. The Akaike Bayesian information criterion (ABIC) is defined to compare with alternative models. The basic TSBAYSEA procedure processes the block of data in which the length is SPAN*SPERIOD, while the first block of data consists of length (2*SPAN-1)*SPERIOD. The block of data is shifted successively by SHIFT*SPERIOD.

The TSBAYSEA subroutine decomposes the series y_t into the following form:

$$y_t = T_t + S_t + \epsilon_t$$

where T_t is a trend component, S_t denotes a seasonal component, and ϵ_t is an irregular component. To estimate the seasonal and trend components, some constraints are imposed such that the sum of squares of $\nabla^k T_t$, $\nabla_L^l S_t$, and $\sum_{i=0}^{L-1} S_{t-i}$ is small, where ∇ and ∇_L are difference operators. Then the solution can be obtained by minimizing

$$\sum_{t=1}^N \left\{ (y_t - T_t - S_t)^2 + d^2 \left[s^2 (\nabla^k T_t)^2 + (\nabla_L^l S_t)^2 + z^2 (S_t + \dots + S_{t-L+1})^2 \right] \right\}$$

where d measures the smoothness of the trend and seasonality, s measures the smoothness of the trend, and z is a smoothness constant for the sum of the seasonal variability. The value of d is estimated while the constants, s and z , are chosen *a priori*. The value of s is equal to $\frac{1}{RIGID}$, and the constant z is determined as $ZERSUM * RIGID / SPERIOD^{1/2}$. The larger the constant RIGID, the more rigid the seasonal pattern is. See the section “Bayesian Constrained Least Squares” on page 296 for more information.

To analyze the monthly data with rigidity 0.5, you can specify either of the following two statements:

```
call tsbaysea(trend,season,series,adj,abic) data=z order=2
      sorder=1 rigid=0.5 npred=10 print=2;
```

```
call tsbaysea(trend,season,series,adj,abic,z,2,1,0.5,10,,2);
```

The TREND, SEASON, and SERIES components contain 10-period-ahead forecast values in addition to the smoothed estimates. The detailed result is also printed since the PRINT=2 option is specified.

TSDECOMP Call

```
CALL TSDECOMP(comp, est, aic, data, <, xdata> <, order> <, sorder> <, nar> <, npred> <, init>
               <, opt> <, icmp> <, print> );
```

The TSDECOMP subroutine analyzes nonstationary time series by using smoothness priors modeling.

The input arguments to the TSDECOMP subroutine are as follows:

data specifies a $T \times 1$ (or $1 \times T$) data vector.

xdata specifies a $T \times K$ explanatory data matrix.

order specifies the order of trend differencing (0, 1, 2, or 3). The default is 2.

sorder specifies the order of seasonal differencing (0, 1, or 2). The default is 1.

nar specifies the order of the AR process. The default is 0.

npred specifies the length of the forecast beyond the available observations. The default is 0.

init specifies the initial values of parameters. The initial values are specified as variances for trend difference equation, AR process, seasonal difference equation, regression equation, and partial AR coefficients. The corresponding default variance values are 0.005, 0.8, $1E-5$, and $1E-5$. The default partial AR coefficient values are determined as

$$\psi_i = 0.88 \times (-0.6)^{i-1} i = 1, 2, \dots, nar$$

opt specifies the options vector.

opt[1] specifies the mean deletion option. The mean of the original series is subtracted from the series if *opt[1]*=−1. By default, the original series is processed (*opt[1]*=0). When regressors are specified, only the *opt[1]*=0 option is accepted.

opt[2] specifies the trading day adjustment. The default is *opt[2]*=0.

- opt[3]* specifies the year (≥ 1900) when the series starts. If *opt[3]*=0, there is no trading day adjustment. By default, *opt[3]*=0.
- opt[4]* specifies the number of seasons within a period (*speriod*). By default, *opt[4]*=12.
- opt[5]* controls the transformation of the original series. If *opt[5]*=1, log transformation is requested. By default, there is no transformation (*opt[5]*=0).
- opt[6]* specifies the maximum number of iterations allowed. The default is *opt[6]* = 200.
- opt[7]* specifies the update technique for the quasi-Newton optimization technique. If *opt[7]*=1 is specified, the dual Broyden, Fletcher, Goldfarb, and Shanno (BFGS) update method is used. If *opt[7]*=2 is specified, the dual Davidon, Fletcher, and Powell (DFP) update method is used. The default is *opt[7]*=1.
- opt[8]* specifies the line search technique for the quasi-Newton optimization method. The default is *opt[8]* = 2.
- 1 specifies a line search method that requires the same number of objective function and gradient calls for cubic interpolation and extrapolation.
 - 2 specifies a line search method that requires more objective function calls than gradient calls for cubic interpolation and extrapolation.
 - 3 specifies a line search method that requires the same number of objective function and gradient calls for cubic interpolation and extrapolation.
 - 4 specifies a line search method that requires the same number of objective function and gradient calls for cubic interpolation and stepwise extrapolation.
 - 5 specifies a line search method that is a modified version of *opt[8]*=4.
 - 6 specifies the golden section line search method that uses only function values for linear approximation.
 - 7 specifies the bisection line search method that uses only function values for linear approximation.
 - 8 specifies the Armijo line search method that uses only function values for linear approximation.
- opt[9]* specifies the upper bound of the variance estimates. If you specify *opt[9]*=*value*, the variances are estimated with the constraint that $\sigma \leq \text{value}$. When you specify the *opt[9]*=0 option, the upper bound is not imposed. The default is *opt[9]*=0.
- opt[10]* specifies the length of data used in backward filtering for the Kalman filter initialization. The default value of *opt[10]* is 100 if the number of observations is greater than 100; otherwise, the default value is the number of observations.

icmp specifies which component is computed.

- 1 requests the estimate and forecast of trend component.
- 2 requests the estimate and forecast of seasonal component.
- 3 requests the estimate and forecast of AR component.
- 4 requests the trading day adjustment component.
- 5 requests the regression component.

6 requests the time-varying regression coefficients.

You can compute multiple components by specifying a vector. For example, you can specify *icomp*={1 2 3 5}.

print specifies the print option. By default, printed output is suppressed (*print*=0). If you specify *print*=1, the subroutine prints the final estimates. The iteration history is printed if you specify *print*=2.

The TSDECOMP subroutine returns the following values:

comp refers to the estimate and forecast of the trend component.

est refers to the parameter estimates including coefficients of the AR process.

aic refers to the AIC statistic obtained from the final estimates.

The TSDECOMP subroutine analyzes nonstationary time series by using smoothness priors modeling (see the section “[Smoothness Priors Modeling](#)” on page 284 for more details). The likelihood function is maximized with respect to hyperparameters. The Kalman filter algorithm is used for filtering, smoothing, and forecasting. The TSDECOMP subroutine decomposes the time series y_t as follows:

$$y_t = T_t + S_t + TD_t + u_t + R_t + \epsilon_t$$

where T_t represents the trend component, S_t denotes the seasonal component, TD_t represents the trading day adjustment component, u_t denotes the autoregressive process component, R_t denotes regression effect components, and ϵ_t represents the irregular term with zero mean and constant variance.

The trend components are constrained as follows:

$$\nabla^k T_t = w_{1t}, w_{1t} \sim N(0, \tau_1^2)$$

When you specify the ORDER=0 option, the trend component is not estimated. The maximum order of differencing is 3 ($k = 0, \dots, 3$).

The seasonal components are denoted as a stochastically perturbed equation:

$$\left(1 + \sum_{i=1}^{L-1} \mathbf{B}^i\right)^l S_t = w_{2t}, w_{2t} \sim N(0, \tau_2^2)$$

When you specify SORDER=0, the seasonal component is not estimated. The maximum value of l is 2 ($l = 0, 1$, or 2).

The stationary autoregressive (AR) process is denoted as a stochastically perturbed equation:

$$u_t = \sum_{i=1}^p \alpha_i u_{t-i} + w_{3t}, w_{3t} \sim N(0, \tau_3^2)$$

where p is the order of AR process. When NAR=0 is specified, the AR process component is not estimated.

The time-varying regression coefficients are estimated if you include exogenous variables:

$$R_t = \mathbf{X}_t \beta_t$$

where \mathbf{X}_t contains m regressors except the constant term and $\beta'_t = (\beta_{1t}, \dots, \beta_{mt})$. The time-varying coefficients β_t follow the random walk process:

$$\beta_{jt} = \beta_{jt-1} + v_{jt}, v_{jt} \sim N(0, \sigma_j^2)$$

where β_{jt} is an element of the coefficient vector β_t .

The trading day adjustment component TD_t is deterministically restricted. See the section “[State Space and Kalman Filter Method](#)” on page 298, for more information.

You can estimate the time-varying coefficient model as follows:

```
call tsdecomp COMP=beta ORDER=0 SORDER=0 NAR=0
          DATA=y XDATA=x ICMP=6;
```

The output matrix BETA contains time-varying regression coefficients.

TSMLOCAR Call

```
CALL TSMLOCAR(arcoef, ev, nar, aic, start, finish, data <, maxlag> <, opt> <, missing> <, print>
);
```

The TSMLOCAR subroutine analyzes nonstationary or locally stationary time series by using the minimum AIC procedure.

The input arguments to the TSMLOCAR subroutine are as follows:

- | | |
|----------------|---|
| <i>data</i> | specifies a $T \times 1$ (or $1 \times T$) data vector. |
| <i>maxlag</i> | specifies the maximum lag of the AR process. This value should be less than half the length of locally stationary spans. The default is <i>maxlag</i> =10. |
| <i>opt</i> | specifies an options vector. |
| <i>opt</i> [1] | specifies the mean deletion option. The mean of the original data is deleted if <i>opt</i> [1]=−1. An intercept coefficient is estimated if <i>opt</i> [1]=1. If <i>opt</i> [1]=0, the original input data are processed assuming that the mean value of the input series is 0. The default is <i>opt</i> [1]=0. |
| <i>opt</i> [2] | specifies the span length to be used when breaking up the time series into separate blocks. By default, <i>opt</i> [2] = 0, which forces all of the time series values into a single span. |
| <i>opt</i> [3] | specifies the minimum AIC option. If <i>opt</i> [3]=0, the <i>maximum lag</i> AR process is estimated. If <i>opt</i> [3]=1, the minimum AIC procedure is performed. The default is <i>opt</i> [3]=1. |
| <i>missing</i> | specifies the missing value option. By default, only the first contiguous observations with no missing values are used (<i>missing</i> =0). The <i>missing</i> =1 option ignores observations with missing values. If you specify the <i>missing</i> =2 option, the missing values are replaced with the sample mean. <i>print</i> specifies the print option. By default, printed output is suppressed (<i>print</i> =0). The <i>print</i> =1 option prints the AR estimation result, while the <i>print</i> =2 option plots the power spectral density in addition to the AR estimates. |

The TSMLOCAR subroutine returns the following values:

<i>arcoef</i>	refers to an $\text{nar} \times 1$ AR coefficient vector of the final model if the intercept estimate is not included. If <i>opt</i> [1]=1, the first element of the <i>arcoef</i> vector is an intercept estimate.
<i>ev</i>	refers to the error variance.
<i>nar</i>	is the selected AR order of the final model. If <i>opt</i> [3]=0, <i>nar</i> = <i>maxlag</i> .
<i>aic</i>	refers to the minimum AIC value of the final model.
<i>start</i>	refers to the starting position of the input series, which corresponds to the first observation of the final model.
<i>finish</i>	refers to the ending position of the input series, which corresponds to the last observation of the final model.

The TSMLOCAR subroutine analyzes nonstationary (or locally stationary) time series by using the minimum AIC procedure. The data of length T is divided into J locally stationary subseries, which consist of $\frac{T}{J}$ observations. See the section “Nonstationary Time Series” on page 287 for details.

TSMLOMAR Call

CALL TSMLOMAR(*arcoef*, *ev*, *nar*, *aic*, *start*, *finish*, *data* < , *maxlag* > < , *opt* > < , *missing* > < , *print* >);

The TSMLOMAR subroutine analyzes nonstationary or locally stationary multivariate time series by using the minimum AIC procedure.

The input arguments to the TSMLOMAR subroutine are as follows:

<i>data</i>	specifies a $T \times M$ data matrix, where T is the number of observations and M is the number of variables to be analyzed.						
<i>maxlag</i>	specifies the maximum lag of the vector AR (VAR) process. This value should be less than $\frac{1}{2M}$ of the length of locally stationary spans. The default is <i>maxlag</i> =10.						
<i>opt</i>	specifies an options vector. <table border="0" style="margin-left: 20px;"> <tr> <td><i>opt</i>[1]</td><td>specifies the mean deletion option. The mean of the original data is deleted if <i>opt</i>[1]=−1. An intercept coefficient is estimated if <i>opt</i>[1]=1. If <i>opt</i>[1]=0, the original input data are processed assuming that the mean values of input series are zeros. The default is <i>opt</i>[1]=0.</td></tr> <tr> <td><i>opt</i>[2]</td><td>specifies the span length to be used when breaking up the time series into separate blocks. By default, <i>opt</i>[2] = 0, which forces all of the time series values into a single span.</td></tr> <tr> <td><i>opt</i>[3]</td><td>specifies the minimum AIC option. If <i>opt</i>[3]=0, the <i>maximum lag</i> VAR process is estimated. If <i>opt</i>[3]=1, a minimum AIC procedure is used. The default is <i>opt</i>[3]=1.</td></tr> </table>	<i>opt</i> [1]	specifies the mean deletion option. The mean of the original data is deleted if <i>opt</i> [1]=−1. An intercept coefficient is estimated if <i>opt</i> [1]=1. If <i>opt</i> [1]=0, the original input data are processed assuming that the mean values of input series are zeros. The default is <i>opt</i> [1]=0.	<i>opt</i> [2]	specifies the span length to be used when breaking up the time series into separate blocks. By default, <i>opt</i> [2] = 0, which forces all of the time series values into a single span.	<i>opt</i> [3]	specifies the minimum AIC option. If <i>opt</i> [3]=0, the <i>maximum lag</i> VAR process is estimated. If <i>opt</i> [3]=1, a minimum AIC procedure is used. The default is <i>opt</i> [3]=1.
<i>opt</i> [1]	specifies the mean deletion option. The mean of the original data is deleted if <i>opt</i> [1]=−1. An intercept coefficient is estimated if <i>opt</i> [1]=1. If <i>opt</i> [1]=0, the original input data are processed assuming that the mean values of input series are zeros. The default is <i>opt</i> [1]=0.						
<i>opt</i> [2]	specifies the span length to be used when breaking up the time series into separate blocks. By default, <i>opt</i> [2] = 0, which forces all of the time series values into a single span.						
<i>opt</i> [3]	specifies the minimum AIC option. If <i>opt</i> [3]=0, the <i>maximum lag</i> VAR process is estimated. If <i>opt</i> [3]=1, a minimum AIC procedure is used. The default is <i>opt</i> [3]=1.						
<i>missing</i>	specifies the missing value option. By default, only the first contiguous observations with no missing values are used (<i>missing</i> =0). The <i>missing</i> =1 option ignores observations with missing						

values. If you specify the *missing=2* option, the missing values are replaced with the sample mean.

print specifies the print option. By default, printed output is suppressed (*print=0*). The *print=1* option prints the AR estimates, minimum AIC, minimum AIC order, and innovation variance matrix.

The TSMLOMAR subroutine returns the following values.

arcoef refers to an $M \times (M * nar)$ VAR coefficient vector of the final model if the intercept vector is not included. If *opt[1]=1*, the first column of the *arcoef* matrix is an intercept estimate vector.

ev refers to the error variance matrix.

nar is the selected VAR order of the final model. If *opt[3]=0*, *nar=maxlag*.

aic refers to the minimum AIC value of the final model.

start refers to the starting position of the input series *data*, which corresponds to the first observation of the final model.

finish refers to the ending position of the input series *data*, which corresponds to the last observation of the final model.

The TSMLOMAR subroutine analyzes nonstationary (or locally stationary) multivariate time series by using the minimum AIC procedure. The data of length T is divided into J locally stationary subseries. See “Nonstationary Time Series” in the section “[Nonstationary Time Series](#)” on page 287 for details.

TSMULMAR Call

CALL TSMULMAR(*arcoef*, *ev*, *nar*, *aic*, *data* < , *maxlag* > < , *opt* > < , *missing* > < , *print* >);

The TSMULMAR subroutine estimates VAR processes by using the minimum AIC procedure.

The input arguments to the TSMULMAR subroutine are as follows:

data specifies a $T \times M$ data matrix, where T is the number of observations and M is the number of variables to be analyzed.

maxlag specifies the maximum lag of the VAR process. This value should be less than $\frac{1}{2M}$ of the length of input data. The default is *maxlag*=10.

opt specifies an options vector.

opt[1] specifies the mean deletion option. The mean of the original data is deleted if *opt[1]=-1*. An $M \times 1$ intercept vector is estimated if *opt[1]=1*. If *opt[1]=0*, the original input data are processed assuming that the mean value of the input data is 0. The default is *opt[1]=0*.

opt[2] specifies the minimum AIC option. If *opt[2]=0*, the *maximum lag* AR process is estimated. If *opt[2]=1*, the minimum AIC procedure is used, while the *opt[2]=2* option specifies the VAR order selection method based on the AIC. The default is *opt[2]=1*.

opt[3] specifies instantaneous response modeling if *opt[3]=1*. The default is *opt[3]=0*. See the section “[Multivariate Time Series Analysis](#)” on page 291 for more information.

- missing* specifies the missing value option. By default, only the first contiguous observations with no missing values are used (*missing*=0). The *missing*=1 option ignores observations with missing values. If you specify the *missing*=2 option, the missing values are replaced with the sample mean.
- print* specifies the print option. By default, printed output is suppressed (*print*=0). The *print*=1 option prints the final estimation result, while the *print*=2 option prints intermediate and final results.

The TSMULMAR subroutine returns the following values:

- arcoef* refers to an $M \times (M * nar)$ AR coefficient matrix if the intercept is not included. If *opt*[1]=1, the first column of the *arcoef* matrix is an intercept vector estimate.
- ev* refers to the error variance matrix.
- nar* is the selected VAR order of the minimum AIC procedure. If *opt*[2]=0, *nar*=*maxlag*.
- aic* refers to the minimum AIC value.

The TSMULMAR subroutine estimates the VAR process by using the minimum AIC method. The widely used VAR order selection method is added to the original TIMSAC program, which considers only the possibilities of zero coefficients at the beginning and end of the model. The TSMULMAR subroutine can also estimate the instantaneous response model. See the section “[Multivariate Time Series Analysis](#)” on page 291 for details.

TSPEARS Call

CALL TSPEARS(*arcoef*, *ev*, *nar*, *aic*, *data* < , *maxlag* < , *opt* < , *missing* < , *print* >);

The TSPEARS subroutine analyzes periodic AR models with the minimum AIC procedure.

The input arguments to the TSPEARS subroutine are as follows:

- data* specifies a $T \times 1$ (or $1 \times T$) data matrix.
- maxlag* specifies the maximum lag of the periodic AR process. This value should be less than $\frac{1}{2T}$ of the input series. The default is *maxlag*=10.
- opt* specifies an options vector.
- opt*[1] specifies the mean deletion option. The mean of the original data is deleted if *opt*[1]=-1. An intercept coefficient is estimated if *opt*[1]=1. If *opt*[1]=0, the original input data are processed assuming that the mean values of input series are zeros. The default is *opt*[1]=0.
- opt*[2] specifies the number of instants per period. By default, *opt*[2]=1.
- opt*[3] specifies the minimum AIC option. If *opt*[3]=0, the *maximum lag* AR process is estimated. If *opt*[3]=1, the minimum AIC procedure is used. The default is *opt*[3]=1.
- missing* specifies the missing value option. By default, only the first contiguous observations with no missing values are used (*missing*=0). The *missing*=1 option ignores observations with missing

values. If you specify the *missing=2* option, the missing values are replaced with the sample mean.

print specifies the print option. By default, printed output is suppressed (*print=0*). The *print=1* option prints the periodic AR estimates and intermediate process.

The TSPEARS subroutine returns the following values:

arcoef refers to a periodic AR coefficient matrix of the periodic AR model. If *opt[1]=1*, the first column of the *arcoef* matrix is an intercept estimate vector.

ev refers to the error variance.

nar refers to the selected AR order vector of the periodic AR model.

aic refers to the minimum AIC values of the periodic AR model.

The TSPEARS subroutine analyzes the periodic AR model by using the minimum AIC procedure. The data of length T are divided into d periods. There are J instants in one period. See the section “[Multivariate Time Series Analysis](#)” on page 291 for details.

TSPRED Call

```
CALL TSPRED(forecast, impulse, mse, data, coef, nar, nma < , ev > < , npred > < , start > < , constant >
);
```

The TSPRED subroutine provides predicted values of univariate and multivariate ARMA processes when the ARMA coefficients are input.

The input arguments to the TSPRED subroutine are as follows:

data specifies a $T \times M$ data matrix if the intercept is not included, where T denotes the length of the time series and M is the number of variables to be analyzed. If the univariate time series is analyzed, the input data should be a column vector.

coef refers to the $M(P + Q) \times M$ ARMA coefficient matrix, where P is an AR order and Q is an MA order. If the intercept term is included (*constant=1*), the first row of the coefficient matrix is considered as the intercept term and the coefficient matrix is an $M(P + Q + 1) \times M$ matrix. If there are missing values in the *coef* matrix, these are converted to zero.

nar specifies the order of the AR process. If the subset AR process is requested, *nar* should be a row or column vector. The default is *nar=0*.

nma specifies the order of the MA process. If the subset MA process is requested, *nma* should be a vector. The default is *nma=0*.

ev specifies the error variance matrix. If the *ev* matrix is not provided, the prediction error covariance will not be computed.

npred specifies the maximum length of multistep forecasting. The default is *npred=0*.

start specifies the position where the multistep forecast starts. The default is *start=T*.

constant specifies the intercept option. No intercept estimate is included if *constant*=0; otherwise, the intercept estimate is included in the first row of the coefficient matrix. If *constant*=-1, the coefficient matrix is estimated by using mean deleted series. By default, *constant*=0.

The TSPRED subroutine returns the following values:

forecast refers to predicted values.

impulse refers to the impulse response function.

mse refers to the mean square error of *s*-step-ahead forecast. A scalar missing value is returned if the error variance (*ev*) is not provided.

TSROOT Call

CALL TSROOT(matout, matin, nar, nma, <, qcoef> <, print>);

The TSROOT subroutine computes AR and MA coefficients from the characteristic roots of the model or computes the characteristic roots of the model from the AR and MA coefficients.

The input arguments to the TSROOT subroutine are as follows:

matin refers to the $(nar + nma) \times 2$ characteristic root matrix if the polynomial (ARMA) coefficients are requested (*qcoef*=1), where the first column of the *matin* matrix contains the real part of the root and the second column of the *matin* matrix contains the imaginary part of the root. When the characteristic roots are requested (*qcoef*=0), the first *nar* rows are complex AR coefficients and the last *nma* rows are complex MA coefficients. The default is *qcoef*=0.

nar specifies the order of the AR process. If you specify the subset AR model, the input *nar* should be a row or column vector.

nma specifies the order of the MA process. If you specify the subset MA model, the input *nma* should be a row or column vector.

qcoef requests the ARMA coefficients when the characteristic roots are provided (*qcoef*=1). By default, the characteristic roots of the polynomial are computed (*qcoef*=0).

print specifies the print option if *print*=1. By default, printed output is suppressed (*print*=0).

The TSROOT subroutine returns the following values

matout refers to the characteristic root matrix if *qcoef*=0; otherwise, the *matout* matrix contains the AR and MA coefficients.

TSTVCAR Call

CALL TSTVCAR(arcoef, variance, est, aic, data <, nar> <, init> <, opt> <, outlier> <, print>);

The TSTVCAR subroutine analyzes time series that are nonstationary in the covariance function.

The input arguments to the TSTVCAR subroutine are as follows:

<i>data</i>	specifies a $T \times 1$ (or $1 \times T$) data vector.
<i>nar</i>	specifies the order of the AR process. The default is <i>nar</i> =8.
<i>init</i>	specifies the initial values of the parameter estimates. The default is (1E-4, 0.3, 1E-5, 0).
<i>opt</i>	specifies an options vector.
<i>opt</i> [1]	specifies the mean deletion option. The mean of the original series is subtracted from the series if <i>opt</i> [1]=-1. By default, the original series is processed (<i>opt</i> [1]=0).
<i>opt</i> [2]	specifies the filtering period (<i>nfilter</i>). The number of state vectors is determined by $\frac{T}{nfilter}$. The default is <i>opt</i> [2]=10.
<i>opt</i> [3]	specifies the numerical differentiation method. If <i>opt</i> [3]=1, the one-sided (forward) differencing method is used. The two-sided (or central) differencing method is used if <i>opt</i> [3]=2. The default is <i>opt</i> [3]=1.
<i>outlier</i>	specifies the vector of outlier observations. The value should be less than or equal to the maximum number of observations. The default is <i>outlier</i> =0.
<i>print</i>	specifies the print option. By default, printed output is suppressed (<i>print</i> =0). The <i>print</i> =1 option prints the final estimates. The iteration history is printed if <i>print</i> =2.

The TSTVCAR subroutine returns the following values:

<i>arcoef</i>	refers to the time-varying AR coefficients.
<i>variance</i>	refers to the time-varying error variances. See the section “ Smoothness Priors Modeling ” on page 284 for details.
<i>est</i>	refers to the parameter estimates.
<i>aic</i>	refers to the value of AIC from the final estimates.

Nonstationary time series modeling usually deals with nonstationarity in the mean. The TSTVCAR subroutine analyzes the model that is nonstationary in the covariance. Smoothness priors are imposed on each time-varying AR coefficient and frequency response function. See the section “[Nonstationary Time Series](#)” on page 287 for details.

TSUNIMAR Call

CALL TSUNIMAR(*arcoef*, *ev*, *nar*, *aic*, *data* <, *maxlag* > <, *opt* > <, *missing* > <, *print* >);

The TSUNIMAR subroutine determines the order of an AR process with the minimum AIC procedure and estimates the AR coefficients.

The input arguments to the TSUNIMAR subroutine are as follows:

<i>data</i>	specifies a $T \times 1$ (or $1 \times T$) data vector, where T is the number of observations.
-------------	---

- maxlag* specifies the maximum lag of the AR process. This value should be less than half the number of observations. The default is *maxlag*=10.
- opt* specifies an options vector.
- opt*[1] specifies the mean deletion option. The mean of the original data is deleted if *opt*[1]=-1. An intercept term is estimated if *opt*[1]=1. If *opt*[1]=0, the original input data are processed assuming that the mean value of the input data is 0. The default is *opt*[1]=0.
- opt*[2] specifies the minimum AIC option. If *opt*[2]=0, the *maximum lag* AR process is estimated. The minimum AIC option, *opt*[2]=1, is the default.
- missing* specifies the missing value option. By default, only the first contiguous observations with no missing values are used (*missing*=0). The *missing*=1 option ignores observations with missing values. If you specify the *missing*=2 option, the missing values are replaced with the sample mean.
- print* specifies the print option. By default, printed output is suppressed (*print*=0). The *print*=1 option prints the final estimation result, while the *print*=2 option prints intermediate and final results.

The TSUNIMAR subroutine returns the following values.

- arcoef* refers to an $\text{nar} \times 1$ AR coefficient vector if the intercept is not included. If *opt*[1]=1, the first element of the *arcoef* vector is an intercept estimate.
- ev* refers to the error variance.
- nar* refers to the selected AR order by minimum AIC procedure. If *opt*[2]=0, then *nar* = *maximum lag*.
- aic* refers to the minimum AIC value.

The TSUNIMAR subroutine determines the order of the AR process by using the minimum AIC procedure and estimates the AR coefficients. All AR coefficient estimates up to maximum lag are printed if you specify the print option. See the section “[Least Squares and Householder Transformation](#)” on page 295 for more information.

TYPE Function

TYPE(*matrix*);

The TYPE function returns a single character value that represents the type of a matrix. The value is ‘N’ if the type of the matrix is numeric; it is ‘C’ if the type of the matrix is character; it is ‘U’ if the matrix does not have a value.

The following statements determine the type for three different matrices:

```
cMat = {"Rick" "Nancy"};
t1 = type(cMat);
nMat = {3.14159 2.71828};
t2 = type(nMat);
```

```
free uMat;
t3 = type(uMat);
print t1 t2 t3;
```

Figure 23.289 The Types of Matrices

t1	t2	t3
C	N	U

UNIFORM Function

UNIFORM(seed);

The UNIFORM function generates pseudorandom numbers from the uniform distribution on $[0, 1]$. The *seed* argument is a numeric matrix or literal. The elements of the *seed* argument can be any integer value up to $2^{31} - 1$.

The UNIFORM function returns one or more pseudorandom numbers with a uniform distribution over the interval 0 to 1. The UNIFORM function returns a matrix with the same dimensions as the argument. The first argument on the first call is used for the seed, or if that argument is 0, the system clock is used for the seed. The function is equivalent to the DATA step function RANUNI.

The following statements produce the output shown in [Figure 23.204](#):

```
seed = 123456;
c = j(10, 1, seed);      /* generate 10 number from the same seed */
b = uniform(c);
print b;
```

Figure 23.290 Random Values Generated from a Uniform Distribution

b
0.73902
0.2724794
0.7095326
0.3191636
0.367853
0.104491
0.0368003
0.5333324
0.3712995
0.0401944

For generating millions of pseudorandom numbers, use the [RANDGEN](#) subroutine.

UNION Function

UNION(*matrix1* <, *matrix2*, ..., *matrix15*>);

The UNION function returns as a row vector the sorted set (without duplicates) which is the union of the element values present in its arguments. There can be up to 15 arguments, which can be either all character or all numeric. For character arguments, the element length of the result is the longest element length of the arguments. Shorter character elements are padded on the right with blanks.

This function is identical to the [UNIQUE function](#).

The following statements produce the output shown:

```
a={1 2 4 5};
b={3 4};
c=union(a,b);
```

C	1 row	5 cols	(numeric)
1	2	3	4 5

The UNION function can be used to sort elements of a matrix when there are no duplicates by calling UNION with a single argument.

UNIQUE Function

UNIQUE(*matrix1* <, *matrix2*, ..., *matrix15*>);

The UNIQUE function returns as a row vector the sorted set (without duplicates) of all the element values present in its arguments. The arguments can be either all numeric or all character, and there can be up to 15 arguments specified. This function is identical to the [UNION function](#), the description of which includes an example.

UNIQUEBY Function

UNIQUEBY(*matrix* <, *by* <, *index* >);

The UNIQUEBY function returns the locations of the unique BY-group combinations for a sorted or indexed matrix. The arguments to the UNIQUEBY function are as follows:

matrix is the input matrix, which must be sorted or indexed according to the *by* columns.

- by* is either a numeric matrix of column numbers, or a character matrix that contains the names of columns that correspond to column labels assigned to *matrix* by a **MATTRIB statement** or **READ statement**. If *by* is not specified, then the first column is used.
- index* is a vector such that *index*[*i*] is the row index of the *i*th element of *matrix* when sorted according to *by*. Consequently, *matrix*[*index*,] is the sorted matrix. *index* can be computed for a matrix and a given set of *by* columns with the **SORTNDX call**. If the matrix is known to be sorted according to the *by* columns already, then *index* should be 1:nrow(*matrix*). In this case, you can also omit the *index* argument.

The **UNIQUEBY** function returns a column vector whose *i*th row gives the row in *index* whose value is the row in *matrix* of the *i*th unique combination of values in the *by* columns.

For example, the following statements use the **SORTNDX** subroutine to create a sort index for a matrix. The **UNIQUEBY** function is then used to determine the unique combinations of the columns of the matrix:

```
m = { 1 0,
      2 0,
      2 2,
      2 0,
      1 0,
      2 0,
      1 1 };
cols = 1:2;
call sortndx(ndx, m, cols);

sorted = m[ndx,];
unique_rows = uniqueby(m, cols, ndx);
unique_vals = m[ndx[unique_rows], cols];
print sorted, unique_rows unique_vals;
```

Figure 23.291 Unique Values of the Sort Variables

sorted		
1	0	
1	0	
1	1	
2	0	
2	0	
2	0	
2	2	
unique_rows unique_vals		
1	1	0
3	1	1
4	2	0
7	2	2

In addition, the following statements gives the number of unique values and the number of elements in each BY-group:

```

n = nrow(unique_rows);
size = j(n,1);
do i = 1 to n-1;
    size[i] = unique_rows[i+1] - unique_rows[i];
end;
size[n] = nrow(m) - unique_rows[n] + 1;
print n, size;

```

Figure 23.292 Number of BY Groups and Number of Elements in Each Group

n
4
size
2
1
3
1

If *matrix* is already sorted according to the *by* columns (see the [SORT call](#)), then UNIQUEBY can be called with 1:nrow(*matrix*) for the *index* argument, or the last argument can be omitted as shown in the following statement:

```

unique_loc = uniqueby(sorted, cols);
print unique_loc;

```

Figure 23.293 Position of Unique Rows for a Sorted Matrix

unique_loc
1
3
4
7

USE Statement

USE *SAS-data-set* < **VAR** *operand* > < **WHERE**(*expression*) > < **NOBS** *name* > ;

The USE statement opens a SAS data set for reading.

The arguments to the USE statement are as follows:

SAS-data-set can be specified with a one-level name (for example, A) or a two-level name (for example, Sasuser.A). For more information about specifying SAS data sets, see the chapter on SAS data sets in *SAS Language Reference: Concepts*.

<i>operand</i>	selects a set of variables.
<i>expression</i>	is evaluated for being true or false.
<i>name</i>	is the name of a variable to contain the number of observations.

If the data set has not already been opened, the USE statement opens the data set for read access. The USE statement also makes the data set the current input data set so that subsequent statements act on it. The USE statement optionally can define selection criteria that are used to control access.

The VAR clause specifies a set of variables to use, where *operand* can be any of the following:

- a literal that contains variable names
- the name of a matrix that contains variable names
- an expression in parentheses that yields variable names
- one of the following keywords:

<u>ALL</u>	for all variables
<u>CHAR</u>	for all character variables
<u>NUM</u>	for all numeric variables

The following examples demonstrate each possible way you can use the VAR clause:

```
var {x1 x5 x9};          /* a literal matrix of names      */
var x;                   /* a matrix that contains the names */
var ("x1": "x9");        /* an expression                    */
var _all_;               /* a keyword                        */
```

The WHERE clause conditionally selects observations, within the *range* specification, according to conditions given in the clause. The general form of the WHERE clause is as follows:

WHERE (*variable comparison-op operand*) ;

The arguments to the WHERE clause are as follows:

<i>variable</i>	is a variable in the SAS data set.
<i>comparison-op</i>	is one of the following comparison operators:
<	less than
<=	less than or equal to
=	equal to
>	greater than
>=	greater than or equal to
^=	not equal to
?	contains a given string

$\wedge ?$ does not contain a given string
 $=:$ begins with a given string
 $=*$ sounds like or is spelled like a given string

operand is a literal value, a matrix name, or an expression in parentheses.

WHERE comparison arguments can be matrices. For the following operators, the WHERE clause succeeds if *all* the elements in the matrix satisfy the condition:

$\wedge = \wedge ? < <= > >=$

For the following operators, the WHERE clause succeeds if *any* of the elements in the matrix satisfy the condition:

$= ? =: =*$

Logical expressions can be specified within the WHERE clause by using the AND (&) and OR (|) operators. The general form is

clause & *clause* (for an AND clause)
clause | *clause* (for an OR clause)

where *clause* can be a comparison, a parenthesized clause, or a logical expression clause that is evaluated by using operator precedence.

NOTE: The expression on the left-hand side refers to values of the data set variables, and the expression on the right-hand side refers to matrix values.

The VAR and WHERE clauses are optional, and you can specify them in any order. If a data set is already open, all the options that the data set was first opened with are still in effect. To override any old options, the new USE statement must explicitly specify the new options. Examples of valid statements follow.

```

use class;
use class var{name sex age};
use class var{name sex age} where(age>10);
  
```

VALSET Call

CALL VALSET(*matrix-name*, *new-value*);

The VALSET subroutine performs indirect assignment. The subroutine takes the name of a matrix and assigns a new value to that matrix.

The arguments to the VALSET subroutine are as follows:

matrix-name is a character matrix or literal that specifies the name of a matrix.
new-value is a value to which the matrix is set.

For example, the following statements assign the string “A” to the value of the **B** matrix. The VALSET subroutine assigns the value 99 to the matrix **A**.

```

B = "A";
call valset(B, 99);
print A;

```

The previous value of the indirect result is freed. The following statement sets **B** to 99, but the value of **A** is unaffected by this statement:

```
b=99;
```

VALUE Function

VALUE(*matrix-name*);

The VALUE function assigns values by indirect reference. The function takes the name of a matrix and returns the value of that matrix.

For example, the following statements find that the value of the argument **B** is **A**, then look up **A** and copy the value 1 2 3 to **C**:

```

a={1 2 3};
b="A";
c=value(b);

```

Here is the resulting output:

C	1 row	3 cols	(numeric)
	1	2	3

VAR Function

VAR(*x*);

The VAR function computes a sample variance of data. The arguments are as follows:

x specifies an $n \times p$ numerical matrix. The VAR function computes the variance of the p columns of this matrix.

The VAR function computes the sample variance of a column vector x as $\sum_{i=1}^n (x_i - \bar{x})^2 / (n - 1)$ where n is the number of nonmissing values of x and any missing values have been excluded. When x is a matrix, the sample variance is computed for each column, as the following example shows:


```
x = {5 1 10,
      6 2 3,
      6 8 5,
      6 7 9,
      7 2 13};
var = var(x);
print var;
```

Figure 23.294 Variance of Columns

var		
0.5	10.5	16

The following statement computes the standard deviation of each column:

```
sd = sqrt(var(x));
```

The VAR function returns a missing value for columns with fewer than two nonmissing observations.

VARMACOV Call

CALL VARMACOV(cov, phi, theta, sigma <, p> <, q> <, lag>);

The VARMACOV subroutine computes the theoretical cross-covariance matrices for a stationary VARMA(p, q) model.

The input arguments to the VARMACOV subroutine are as follows:

- phi* specifies a $km_p \times k$ matrix, Φ , that contains the autoregressive coefficient matrices, where m_p is the number of elements in the subset of the AR order and $k \geq 2$ is the number of variables. All the roots of $|\Phi(B)| = 0$ should be greater than one in absolute value, where $\Phi(B)$ is the finite order matrix polynomial in the backshift operator B , such that $B^j \mathbf{y}_t = \mathbf{y}_{t-j}$. You must specify either *phi* or *theta*.
- theta* specifies a $km_q \times k$ matrix that contains the moving average coefficient matrices, where m_q is the number of the elements in the subset of the MA order. You must specify either *phi* or *theta*.
- sigma* specifies a $k \times k$ symmetric positive-definite covariance matrix of the innovation series. If *sigma* is not specified, then an identity matrix is used.
- p* specifies the subset of the AR order. The quantity m_p is defined as

$$m_p = \text{nrow}(\text{phi}) / \text{ncol}(\text{phi})$$

where $\text{nrow}(\text{phi})$ is the number of rows of the matrix *phi* and $\text{ncol}(\text{phi})$ is the number of columns of the matrix *phi*.

If you do not specify *p*, the default subset is $p = \{1, 2, \dots, m_p\}$.

For example, consider a 4-dimensional vector time series, and ϕ is a 4×4 matrix. If you specify $p=1$ (the default, since $m_p = 4/4 = 1$), the VARMA(1) subroutine computes the theoretical cross-covariance matrices of VAR(1) as $\mathbf{y}_t = \Phi \mathbf{y}_{t-1} + \epsilon_t$.

If you specify $p=2$, the VARMA(2) subroutine computes the cross-covariance matrices of VAR(2) as $\mathbf{y}_t = \Phi \mathbf{y}_{t-2} + \epsilon_t$.

Let $\phi = [\Phi'_1, \Phi'_2]'$ be an 8×4 matrix. If you specify $p = \{1, 3\}$, the VARMA(3) subroutine computes the cross-covariance matrices of VAR(3) as $\mathbf{y}_t = \Phi_1 \mathbf{y}_{t-1} + \Phi_2 \mathbf{y}_{t-3} + \epsilon_t$. If you do not specify p , the VARMA(2) subroutine computes the cross-covariance matrices of VAR(2) as $\mathbf{y}_t = \Phi_1 \mathbf{y}_{t-1} + \Phi_2 \mathbf{y}_{t-2} + \epsilon_t$.

q specifies the subset of the MA order. The quantity m_q is defined as

$$m_q = \text{nrow}(\text{theta}) / \text{ncol}(\text{theta})$$

where $\text{nrow}(\text{theta})$ is the number of rows of matrix theta and $\text{ncol}(\text{theta})$ is the number of columns of matrix theta .

If you do not specify q , the default subset is $q = \{1, 2, \dots, m_q\}$.

The usage of q is the same as that of p .

lag specifies the length of lags, which must be a positive number. If $\text{lag} = h$, the VARMA(3) subroutine computes the cross-covariance matrices from lag zero to lag h . By default, $\text{lag} = 12$.

The VARMA(3) subroutine returns the following value:

cov is a $k(\text{lag} + 1) \times k$ matrix that contains the theoretical cross-covariance matrices of the VARMA(p, q) model.

Consider the following bivariate ($k = 2$) VARMA(1,1) model:

$$\mathbf{y}_t = \Phi \mathbf{y}_{t-1} + \epsilon_t - \Theta \epsilon_{t-1}$$

$$\Phi = \begin{bmatrix} 1.2 & -0.5 \\ 0.6 & 0.3 \end{bmatrix} \quad \Theta = \begin{bmatrix} -0.6 & 0.3 \\ 0.3 & 0.6 \end{bmatrix} \quad \Sigma = \begin{bmatrix} 1.0 & 0.5 \\ 0.5 & 1.25 \end{bmatrix}$$

To compute the cross-covariance matrices of this model, you can use the following statements:

```
phi = { 1.2 -0.5, 0.6 0.3 };
theta= {-0.6 0.3, 0.3 0.6 };
sigma= { 1.0 0.5, 0.5 1.25};
call varmacov(cov, phi, theta, sigma) lag=5;
```

VARMALIK Call

CALL VARMALIK(*lnl, series, phi, theta, sigma* <, *p*> <, *q*> <, *opt*>);

The VARMALIK subroutine computes the log-likelihood function for a VARMA(p, q) model.

The input arguments to the VARMALIK subroutine are as follows:

<i>series</i>	specifies an $n \times k$ matrix that contains the vector time series (assuming mean zero), where n is the number of observations and $k \geq 2$ is the number of variables.
<i>phi</i>	specifies a $km_p \times k$ matrix that contains the autoregressive coefficient matrices, where m_p is the number of the elements in the subset of the AR order. You must specify either <i>phi</i> or <i>theta</i> .
<i>theta</i>	specifies a $km_q \times k$ matrix that contains the moving average coefficient matrices, where m_q is the number of the elements in the subset of the MA order. You must specify either <i>phi</i> or <i>theta</i> .
<i>sigma</i>	specifies a $k \times k$ covariance matrix of the innovation series. If you do not specify <i>sigma</i> , an identity matrix is used.
<i>p</i>	specifies the subset of the AR order. See the VARMA COV subroutine.
<i>q</i>	specifies the subset of the MA order. See the VARMA COV subroutine.
<i>opt</i>	specifies the method of computing the log-likelihood function: <ul style="list-style-type: none"> <i>opt=0</i> requests the multivariate innovations algorithm. This algorithm requires that the time series is stationary and does not contain missing observations. <i>opt=1</i> requests the conditional log-likelihood function. This algorithm requires that the number of the observations in the time series must be greater than $p+q$ and that the series does not contain missing observations. <i>opt=2</i> requests the Kalman filtering algorithm. This is the default and is used if the required conditions in <i>opt=0</i> and <i>opt=1</i> are not satisfied.

The VARMALIK subroutine returns the following value:

<i>lnl</i>	is a 3×1 matrix that contains the log-likelihood function, the sum of log determinant of the innovation variance, and the weighted sum of squares of residuals. The log-likelihood function is computed as $-0.5 \times$ (the sum of last two terms).
------------	--

The options *opt=0* and *opt=2* are equivalent for stationary time series without missing values. Setting *opt=0* is useful for a small number of the observations and a high order of p and q ; *opt=1* is useful for a high order of P and q ; *opt=2* is useful for a low order of p and q , or for missing values in the observations.

Consider the following bivariate ($k = 2$) VARMA(1,1) model:

$$\mathbf{y}_t = \Phi \mathbf{y}_{t-1} + \epsilon_t - \Theta \epsilon_{t-1}$$

$$\Phi = \begin{bmatrix} 1.2 & -0.5 \\ 0.6 & 0.3 \end{bmatrix} \quad \Theta = \begin{bmatrix} -0.6 & 0.3 \\ 0.3 & 0.6 \end{bmatrix} \quad \Sigma = \begin{bmatrix} 1.0 & 0.5 \\ 0.5 & 1.25 \end{bmatrix}$$

To compute the log-likelihood function of this model, you can use the following statements:

```

phi  = { 1.2 -0.5, 0.6 0.3 };
theta= {-0.6 0.3, 0.3 0.6 };
sigma= { 1.0 0.5, 0.5 1.25};
call varmasim(yt, phi, theta) sigma=sigma;
call varmalik(lnl, yt, phi, theta, sigma);

```

VARMASIM Call

CALL VARMASIM(*series*, *phi*, *theta*, *mu*, *sigma*, *n* < , *p* > < , *q* > < , *initial* > < , *seed* >);

The VARMASIM subroutine generates a VARMA(*p*,*q*) time series.

The input arguments to the VARMASIM subroutine are as follows:

- phi* specifies a $km_p \times k$ matrix that contains the autoregressive coefficient matrices, where m_p is the number of the elements in the subset of the AR order and $k \geq 2$ is the number of variables. You must specify either *phi* or *theta*.
- theta* specifies a $km_q \times k$ matrix that contains the moving average coefficient matrices, where m_q is the number of the elements in the subset of the MA order. You must specify either *phi* or *theta*.
- mu* specifies a $k \times 1$ (or $1 \times k$) mean vector of the series. If *mu* is not specified, a zero vector is used.
- sigma* specifies a $k \times k$ covariance matrix of the innovation series. If *sigma* is not specified, an identity matrix is used.
- n* specifies the length of the series. If *n* is not specified, $n = 100$ is used.
- p* specifies the subset of the AR order. See the VARMA COV subroutine.
- q* specifies the subset of the MA order. See the VARMA COV subroutine.
- initial* specifies the initial values of random variables. If *initial* = a_0 , then y_{-p+1}, \dots, y_0 and $\epsilon_{-q+1}, \dots, \epsilon_0$ all take the same value a_0 . If the *initial* option is not specified, the initial values are estimated for the stationary vector time series; the initial values are assumed as zero for the nonstationary vector time series.
- seed* is a scalar that contains the random number seed. At the first execution of the subroutine, the seed variable is used as follows:
 - If *seed* > 0, the input seed is used for generating the series.
 - If *seed* = 0, the system clock is used to generate the seed.
 - If *seed* < 0, the value $(-1) \times (\text{seed})$ is used for generating the series.
 - If the seed is not supplied, the system clock is used to generate the seed.
 On subsequent calls of the subroutine in the DO loop like environment the seed variable is used as follows: If *seed* > 0, the seed remains unchanged. In other cases, after each execution of the subroutine, the current seed is updated internally.

The VARMASIM subroutine returns the following value:

- series* is an $n \times k$ matrix that contains the generated VARMA(*p*,*q*) time series. When either the *initial* option is specified or zero initial values are used, these initial values are not included in *series*.

Consider the following bivariate ($k = 2$) stationary VARMA(1,1) time series:

$$y_t - \mu = \Phi(y_{t-1} - \mu) + \epsilon_t - \Theta\epsilon_{t-1}$$

$$\Phi = \begin{bmatrix} 1.2 & -0.5 \\ 0.6 & 0.3 \end{bmatrix} \quad \Theta = \begin{bmatrix} -0.6 & 0.3 \\ 0.3 & 0.6 \end{bmatrix} \quad \mu = \begin{bmatrix} 10 \\ 20 \end{bmatrix} \quad \Sigma = \begin{bmatrix} 1.0 & 0.5 \\ 0.5 & 1.25 \end{bmatrix}$$

To generate this series, you can use the following statements:

```
phi = { 1.2 -0.5, 0.6 0.3 };
theta= {-0.6 0.3, 0.3 0.6 };
mu = { 10, 20 };
sigma= { 1.0 0.5, 0.5 1.25};
call varmasim(yt, phi, theta, mu, sigma, 100);
```

Consider a bivariate ($k = 2$) nonstationary VARMA(1,1) time series with the same μ , Σ , and Θ in the previous example and the following AR coefficient:

$$\Phi = \begin{bmatrix} 1.0 & 0 \\ 0 & 0.3 \end{bmatrix}$$

To generate this series, you can use the following statements:

```
phi = { 1.0 0.0, 0.0 0.3 };
call varmasim(yt, phi, theta, mu, sigma, 100) initial=3;
```

VECDIAG Function

VECDIAG(*matrix*);

The VECDIAG function creates a column vector whose elements are the elements on the main diagonal of *matrix*. For example, the following statements produce the column vector shown in [Figure 23.295](#):

```
a = {2 1, 0 -1};
d = vecdiag(a);
print d;
```

Figure 23.295 Diagonal of a Matrix

d
2
-1

VECH Function

VECH(*matrix*);

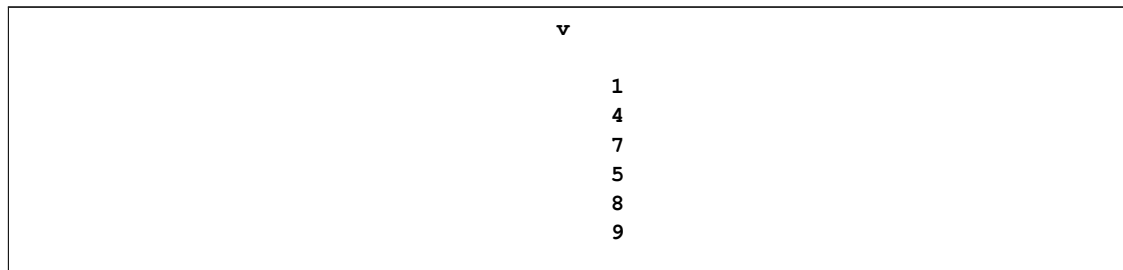
The VECH function creates a column vector whose elements are the stacked columns of the lower triangular elements of *matrix*. Often, the argument is a symmetric matrix, in which case the VECH function has the effect of discarding the “duplicate” elements that are above the matrix diagonal.

Uses of the VECH function in matrix algebra are described in Harville (1997). “Vech” is an abbreviation for “vector-half.”

The following statements produce the column vector shown in Figure 23.296:

```
a = {1 2 3, 4 5 6, 7 8 9};
v = vech(a);
print v;
```

Figure 23.296 Stacked Columns of Lower Triangular Matrix



The **SQRVECH** function and the **VECH** function are inverse operations on the set of symmetric matrices.

VNORMAL Call

CALL VNORMAL(series, mu, sigma, n <, seed>);

The VNORMAL subroutine generates a multivariate normal random series.

The input arguments to the VNORMAL subroutine are as follows:

- mu* specifies a $k \times 1$ (or $1 \times k$) mean vector, where $k \geq 2$ is the number of variables. You must specify either *mu* or *sigma*. If *mu* is not specified, a zero vector is used.
- sigma* specifies a $k \times k$ symmetric positive-definite covariance matrix. By default, *sigma* is an identity matrix with dimension k . You must specify either *mu* or *sigma*. If *sigma* is not specified, an identity matrix is used.
- n* specifies the length of the series. If *n* is not specified, $n = 100$ is used.
- seed* is a scalar that contains the random number seed. At the first execution of the subroutine, the seed variable is used as follows:

If *seed* > 0, the input seed is used for generating the series.

If *seed* = 0, the system clock is used to generate the seed.

If *seed* < 0, the value $(-1) \times (\text{seed})$ is used for generating the series.

If the seed is not supplied, the system clock is used to generate the seed.

On subsequent calls of the subroutine in the DO loop like environment the seed variable is used as follows: If *seed* > 0, the seed remains unchanged. In other cases, after each execution of the subroutine, the current seed is updated internally.

The VNORMAL subroutine returns the following value:

series is an $n \times k$ matrix that contains the generated normal random series.

Consider a bivariate ($k = 2$) normal random series with mean μ and covariance matrix Σ , where

$$\mu = \begin{bmatrix} 10 \\ 20 \end{bmatrix} \text{ and } \Sigma = \begin{bmatrix} 1.0 & 0.5 \\ 0.5 & 1.25 \end{bmatrix}$$

To generate this series, you can use the following statements:

```
mu    = { 10, 20 };
sigma= { 1.0  0.5, 0.5 1.25};
call vnormal(et, mu, sigma, 100);
```

VTSROOT Call

CALL VTSROOT(*root*, *phi*, *theta* <, *p*> <, *q*>);

The VTSROOT subroutine computes the characteristic roots of the model from AR and MA characteristic functions.

The input arguments to the VTSROOT subroutine are as follows:

- phi* specifies a $k m_p \times k$ matrix that contains the autoregressive coefficient matrices, where m_p is the number of the elements in the subset of the AR order and $k \geq 2$ is the number of variables. You must specify either *phi* or *theta*.
- theta* specifies a $k m_q \times k$ matrix that contains the moving average coefficient matrices, where m_q is the number of the elements in the subset of the MA order. You must specify either *phi* or *theta*.
- p* specifies the subset of the AR order. See the VARMA COV subroutine.
- q* specifies the subset of the MA order. See the VARMA COV subroutine.

The VTSROOT subroutine returns the following value:

root is a $k(p_{max} + q_{max}) \times 5$ matrix, where p_{max} is the maximum order of the AR characteristic function and q_{max} is the maximum order of the MA characteristic function. The first $k p_{max}$ rows refer to the results of the AR characteristic function; the last $k q_{max}$ rows refer to the results of the MA characteristic function.

The first column contains the real parts, x , of eigenvalues of companion matrix associated with the AR(p_{max}) or MA(q_{max}) characteristic function; the second column contains the imaginary parts, y , of the eigenvalues; the third column contains the moduli of the eigenvalues, $\sqrt{x^2 + y^2}$; the fourth column contains the arguments ($\arctan(y/x)$) of the eigenvalues, measured in radians from the positive real axis. The fifth column contains the arguments expressed in degrees rather than radians.

Consider the roots of the characteristic functions, $\Phi(B) = I - \Phi B$ and $\Theta(B) = I - \Theta B$, where I is an identity matrix with dimension 2 and

$$\Phi = \begin{bmatrix} 1.2 & -0.5 \\ 0.6 & 0.3 \end{bmatrix} \quad \Theta = \begin{bmatrix} -0.6 & 0.3 \\ 0.3 & 0.6 \end{bmatrix}$$

To compute these roots, you can use the following statements:

```
phi  = { 1.2 -0.5, 0.6 0.3 };
theta= {-0.6 0.3, 0.3 0.6 };
call vtsroot(root, phi, theta);
```

WAVFT Call

CALL WAVFT(*decomp, data, opt* <, *levels*>);

The fast wavelet transform (WAVFT) subroutine computes a specified discrete wavelet transform of the input data by using the algorithm of Mallat (1989). This transform decomposes the input data into sets of detail and scaling coefficients defined at a number of scales or “levels.”

The input data are used as scaling coefficients at the top level in the decomposition. The fast wavelet transform then recursively computes a set of detail and a set of scaling coefficients at the next lower level by respectively applying “low pass” and “high pass” conjugate mirror filters to the scaling coefficients at the current level. The number of coefficients in each of these new sets is approximately half the number of scaling coefficients at the level above them. Depending on the filters being used, a number of additional scaling coefficients, known as boundary coefficients, can be involved. These boundary coefficients are obtained by using a specified method to extend the sequence of interior scaling coefficients

Details of the discrete wavelet transform and the fast wavelet transformation algorithm are available in many references, including Mallat (1989), Daubechies (1992), and Ogden (1997).

The input arguments to the WAVFT subroutine are as follows:

data specifies the data to transform. These data must be in either a row or column vector.

opt refers to an options vector with the following components:

opt[1] specifies the boundary handling used in computing the wavelet transform. At each level of the wavelet decomposition, necessary boundary scaling coefficients are obtained by extending the interior scaling coefficients at that level as follows:

- 0 specifies extension by zero.
- 1 specifies periodic extension.
- 2 specifies polynomial extension.
- 3 specifies extension by reflection.
- 4 specifies extension by anti-symmetric reflection.

opt[2] specifies the polynomial degree that is used for polynomial extension. (The value of *opt*[2] is ignored if *opt*[1] ≠ 2.)

- 0 specifies constant extension.
 - 1 specifies linear extension.
 - 2 specifies quadratic extension.
- opt[3]* specifies the wavelet family.
- 1 specifies the Daubechies Extremal phase family (Daubechies 1992).
 - 2 specifies the Daubechies Least Asymmetric family (also known as the Symmlet family) (Daubechies 1992).
- opt[4]* specifies the wavelet family member. Valid values are
- 1 through 10, if *opt[3]*=1
 - 4 through 10, if *opt[3]*=2

Some examples of wavelet specifications are

- opt*={1 . 1 1}; specifies the first member (more commonly known as the Haar system) of the Daubechies extremal phase family with periodic boundary handling.
- opt*={2 1 2 5}; specifies the fifth member of the Symmlet family with linear extension boundary handling.

levels is an optional scalar argument that specifies the number of levels from the top level to be computed in the decomposition. If you do not specify this argument, then the decomposition terminates at level 0. Usually, you do not need to specify this optional argument. You use this option to avoid unneeded computations in situations where you are interested in only the higher level detail and scaling coefficients.

The WAVFT subroutine returns

decomp a row vector that encapsulates the specified wavelet transform. The information that is encoded in this vector includes:

- the options specified for computing the transform
- the number of detail coefficients at each level of the decomposition
- all detail coefficients
- the scaling coefficients at the bottom level of the decomposition
- boundary scaling coefficients at all levels of the decomposition

NOTE: *decomp* is a private representation of the specified wavelet transform and is not intended to be interpreted in its raw form. Rather, you should use this vector as an input argument to the [WAVIFT](#), [WAVPRINT](#), [WAVGET](#), and [WAVTHRSH](#) subroutines

The following program shows an example that uses wavelet calls to estimate and reconstruct a piecewise constant function:

```

/* define a piecewise constant step function */
start blocky(t);
  /* positions (p) and magnitudes (h) of jumps */
  p = {0.1 0.13 0.15 0.23 0.25 0.4 0.44 0.65 0.76 0.78 0.81};
  h = {4 -5 3 -4 5 -4.2 2.1 4.3 -3.1 2.1 -4.2};

  y=j(1, ncol(t), 0);
  do i=1 to ncol(p);
    diff=( (t-p[i])>=0 );
    y=y+h[i]*diff;
  end;
  return (y);
finish blocky;

n=2##8;
x=1:n;
x=(x-1)/n;
y=blocky(x);

opt = { 2, /* polynomial extension at boundary */
        1, /* using linear polynomial */
        1, /* Daubechies Extremal phase */
        3 /* family member 3 */
      };

call wavft(decomp, y, opt);
call wavprint(decomp,1); /* print summary information */

/* perform permanent thresholding */
threshOpt = { 2, /* soft thresholding */
              2, /* global threshold */
              ., /* ignored */
              -1 /* apply to all levels */
            };
call wavthrsh(decomp, threshOpt );

/* request detail coefficients at level 4 */
call wavget(detail4,decomp,2,4);

/* reconstruct function by using wavelets */
call wavift(estimate,decomp);

errorSS=ssq(y-estimate);
print errorSS;

```

Decomposition Summary

Decomposition Name	DECOMP
Wavelet Family	Daubechies Extremal Phase
Family Member	3
Boundary Treatment	Recursive Linear Extension
Number of Data Points	256
Start Level	0

ERRORSS

1.746E-25

WAVGET Call

CALL WAVGET(*result*, *decomp*, *request* < , *options* >);

The WAVGET subroutine is used to return information that is encoded in a wavelet decomposition.

The required input arguments are

decomp specifies a wavelet decomposition that has been computed by using a call to the [WAVFT](#) subroutine.

request specifies a scalar that indicates what information is to be returned.

You can specify different optional arguments depending on the value of *request*:

request=1 requests the number of points in the input data vector.

result returns as a scalar that contains this number.

request=2 requests the detail coefficients at a specified level. Valid syntax is

CALL WAVGET(*result*, *decomp*, 2, *level* < , *opt* >);

The arguments are as follows:

level is the level at which the detail coefficients are requested.

opt is an optional vector which specifies the thresholding to be applied to the returned detail coefficients. See the [WAVIFT](#) subroutine for details. If you omit this argument, no thresholding is applied.

result returns as a column vector that contains the specified detail coefficients.

request=3 requests the scaling coefficients at a specified level. Valid syntax is

CALL WAVGET(*result*, *decomp*, 3, *level* < , *opt* >);

The arguments are as follows:

level is the level at which the scaling coefficients are requested.

opt is an optional vector that specifies the thresholding to be applied. See the [WAVIFT](#) subroutine for a description of this vector. The scaling coefficients at the requested level are obtained by using the inverse wavelet transform, after applying the specified thresholding. If you omit this argument, no thresholding is applied.

result returns as a column vector that contains the specified scaling coefficients.

request=4 requests the thresholding status of the detail coefficients in *decomp*.

result returns as a scalar whose value is

0,	if the detail coefficients have not been thresholded
1,	otherwise

request=5 requests the wavelet options vector that you specified in the [WAVFT](#) subroutine to compute *decomp*.

result returns as a column vector with 4 elements that contains the specified options vector. See the [WAVFT](#) subroutine for the interpretation of the vector entries.

request=6 requests the index of the top level in *decomp*.

result returns as a scalar that contains this number.

request=7 requests the index of the lowest level in *decomp*.

result returns as a scalar that contains this number.

request=8 requests a vector evaluating the father wavelet used in *decomp*, at an equally spaced grid spanning the support of the father wavelet. The number of points in the grid is specified as a power of 2 times the support width of the father wavelet. For wavelets in the Daubechies extremal phase and least asymmetric families, the support width of the father wavelet is $2m - 1$, where m is the family member. Valid syntax is

CALL WAVGET(*result*, *decomp*, 8 < , *power* >);

The optional argument has the following meaning:

power is the exponent of 2 that determines the number of grid points used. *power* defaults to 8 if you do not specify this argument.

result returns as a column vector that contains the specified evaluation of the father wavelet.

An example is available in the documentation for the [WAVFT](#) subroutine.

WAVIFT Call

CALL WAVIFT(*result*, *decomp* < , *opt* > < , *level* >);

The Inverse Fast Wavelet Transform (WAVIFT) subroutine computes the inverse wavelet transform of a wavelet decomposition computed by using the [WAVFT](#) subroutine. Details of this algorithm are available in many references, including Mallat (1989), Daubechies (1992), and Ogden (1997).

The inverse transform yields an exact reconstruction of the original input data, provided that no smoothing is specified. Alternatively, a smooth reconstruction of the input data can be obtained by thresholding the detail coefficients in the decomposition prior to applying the inverse transformation. Thresholding, also known as shrinkage, replaces the detail coefficient $d_j^{(i)}$ at level i by $\delta_{T_i}(d_j^{(i)})$, where the $\delta_T(x)$ is a shrinkage function

and T_i is the threshold value used at level i . The wavelet subroutines support hard and soft shrinkage functions (Donoho and Johnstone 1994) and the nonnegative garrote shrinkage function (Breiman 1995). These functions are defined as follows:

$$\begin{aligned}\delta_T^{\text{hard}}(x) &= \begin{cases} 0 & |x| \leq T \\ x & |x| > T \end{cases} \\ \delta_T^{\text{soft}}(x) &= \begin{cases} 0 & |x| \leq T \\ x - T & x > T \\ x + T & x < -T \end{cases} \\ \delta_T^{\text{garrote}}(x) &= \begin{cases} 0 & |x| \leq T \\ x - T^2/x & |x| > T \end{cases}\end{aligned}$$

You can specify several methods for choosing the threshold values. Methods in which the threshold T_i varies with the level i are called adaptive. Methods where the same threshold is used at all levels are called global.

The input arguments to the WAVIFT subroutine are as follows:

decomp specifies a wavelet decomposition that has been computed by using a call to the [WAVFT](#) subroutine.

opt refers to an options vector that specifies the thresholding algorithm. If this optional argument is not specified, then no thresholding is applied.

The options vector has the following components:

opt[1] specifies the thresholding policy.

- 0 specifies that no thresholding be done. If *opt[1]*=0 then all other entries in the options vector are ignored.
- 1 specifies hard thresholding.
- 2 specifies soft thresholding.
- 3 specifies garrote thresholding.

opt[2] specifies the method for selecting the threshold.

- 0 specifies a global user-supplied threshold.
- 1 specifies a global threshold chosen by using the minimax criterion of Donoho and Johnstone (1994).
- 2 specifies a global threshold defined by using the universal criterion of Donoho and Johnstone (1994).
- 3 specifies an adaptive method where the thresholds at each level i are chosen to minimize an approximation of the L^2 risk in estimating the true data values by using the reconstruction with thresholded coefficients (Donoho and Johnstone 1995).

- 4 specifies a hybrid method of Donoho and Johnstone (1995). The universal threshold as specified by *opt[2]=2* is used at levels where most of the detail coefficients are essentially zero. The risk minimization method as specified by *opt[2]=4* is used at all other levels.

opt[3] specifies the value of the global user-supplied threshold if *opt[2]=1*. It is ignored if *opt[2] ≠ 1*.

opt[4] specifies the number of levels starting at the highest detail coefficient level at which thresholding is to be applied. If this value is negative or missing, thresholding is applied at all levels in *decomp*.

Some common examples of threshold options specifications are:

opt={1 3 . -1}; specifies hard thresholding with a minimax threshold applied at all levels in the decomposition. This threshold is named “*RiskShrink*” in Donoho and Johnstone (1994).

opt={2 2 . -1}; specifies soft thresholding with a universal threshold applied at all levels in the decomposition. This threshold is named “*VisuShrink*” in Donoho and Johnstone (1994).

opt={2 4 . -1}; specifies soft thresholding with level dependent thresholds which minimize the Stein Unbiased Estimate of Risk (SURE). This threshold is named “*SureShrink*” in Donoho and Johnstone (1995).

level is an optional scalar argument that specifies the level at which the reconstructed data are to be returned. If this argument is not specified then the reconstructed data are returned at the top level defined in *decomp*.

The WAVIFT subroutine returns

result a vector obtained by inverting, after thresholding the detail coefficients, the discrete wavelet transform encoded in *decomp*. The row or column orientation of *result* is the same as that of the input data specified in the corresponding WAVFT subroutine. If you specify the optional *level* argument, *result* contains the reconstruction at the specified level, otherwise the reconstruction corresponds to the top level in the decomposition.

An example is available in the documentation for the WAVFT subroutine.

WAVPRINT Call

CALL WAVPRINT(*decomp*, *request* < , *options* >);

The WAVPRINT subroutine is used to display the information that is encoded in a wavelet decomposition.

The required input arguments are

decomp specifies a wavelet decomposition that has been computed by using a call to the WAVFT subroutine.

request specifies a scalar that indicates what information is to be displayed.

You can specify different optional arguments depending on the value of *request*:

request=1 displays information about the wavelet family used to perform the wavelet transform. No additional arguments need to be specified.

request=2 displays the detail coefficients by level. Valid syntax is

CALL WAVPRINT(*decomp*, 2 < , *lower* > < , *upper* >);

The optional arguments are as follows:

lower specifies the lowest level to be displayed. The default value of *lower* is the lowest level in *decomp*.

upper specifies the upper level to be displayed. The default value of *upper* is the highest detail level in *decomp*.

request=3 displays the scaling coefficients by level. Valid syntax is

CALL WAVPRINT(*decomp*, 3 < , *lower* > < , *upper* >);

The optional arguments are as follows:

lower and specifies the lowest level to be displayed. The default value of *lower* is the lowest level in *decomp*.

upper specifies the upper level to be displayed. The default value of *upper* is the top level in *decomp*.

request=4 displays thresholded detail coefficients by level. Valid syntax is

CALL WAVPRINT(*decomp*, 4 < , *opt* > < , *lower* > < , *upper* >);

The optional arguments are as follows:

opt specifies the thresholding to be applied to the displayed detail coefficients. See the [WAVIFT](#) subroutine for details. If you omit this argument, no thresholding is applied.

lower specifies the lowest level to be displayed. The default value of *lower* is the lowest level in *decomp*.

upper specifies the upper level to be displayed. The default value of *upper* is the highest detail level in *decomp*.

An example is available in the documentation for the [WAVFT](#) subroutine.

WAVTHRSH Call

CALL WAVTHRSH(*decomp*, *opt*);

The wavelet threshold (WAVTHRSH) subroutine thresholds the detail coefficients in a wavelet decomposition.

The required input arguments are

- decomp* specifies a wavelet decomposition that has been computed by using a call to the [WAVFT](#) subroutine.
- opt* refers to an options vector that specifies the thresholding algorithm used. See the [WAVIFT](#) subroutine for a description of this options vector.

On return, the detail coefficients encoded in *decomp* are replaced by their thresholded values. Note that this action is not reversible. If you want to retain the original detail coefficients, you should not use the [WAVTHRSH](#) subroutine to do thresholding. Rather, you should supply the thresholding argument where appropriate in the [WAVIFT](#), [WAVGET](#), and [WAVPRINT](#) subroutines.

An example is available in the documentation for the [WAVFT](#) subroutine.

WINDOW Statement

```
WINDOW  <CLOSE=window-name>  <window-options>  <GROUP=group-name  field-specs>
          <... GROUP=group-name field-specs> ;
```

The **WINDOW** statement defines and opens a window on the display and can include a number of fields. The [DISPLAY statement](#) actually writes values to the window. The following fields can be specified in the **WINDOW** statement:

window-name

specifies a name 1 to 8 characters long for the window. This name is displayed in the upper left border of the window.

CLOSE=*window-name*

closes the window.

window-options

control the size, position, and other attributes of the window. The attributes can also be changed interactively with window commands such as [WGROW](#), [WDEF](#), [WSHRINK](#), and [COLOR](#). A description of the window options follows.

GROUP=*group-name*

starts a repeating sequence of groups of fields defined for the window. The *group-name* specification is a name 1 to 8 characters long used to identify a group of fields in a later [DISPLAY statement](#).

field-specs

are a sequence of field specifications made up of positionals, field operands, formats, and options. These are described in the next section.

The following window options can be specified in the **WINDOW** statement:

CMNDLINE=*name*

specifies the name of a variable in which the command line entered by the user will be stored.

COLOR=*operand*

specifies the background color for the window. The *operand* is either a quoted character literal, a

name, or an operand. The valid values are “WHITE,” “BLACK,” “GREEN,” “MAGENTA,” “RED,” “YELLOW,” “CYAN,” “GRAY,” and “BLUE.” The default value is “BLACK.”

COLUMNS=operand

specifies the starting number of columns for the window. The *operand* is either a literal number, a variable name, or an expression in parentheses. The default value is 78 columns.

ICOLUMN=operand

specifies the initial starting column position of the window on the display. The *operand* is either a literal number or a variable name. The default value is column 1.

IROW=operand

specifies the initial starting row position of the window on the display. The *operand* is either a literal number or a variable name. The default value is row 1.

MSGLINE=operand

specifies the message to be displayed on the standard message line when the window is made active. The *operand* is almost always the name of a variable, but a character literal can be used.

ROWS=operand

determines the starting number of rows of the window. The *operand* is either a literal number, the name of a variable that contains the number, or an expression in parentheses that yields the number. The default value is 23 rows.

Both the WINDOW and [DISPLAY statements](#) accept field specifications, which have the following general form:

< positionals > field-operand < format > < field-options > ;

The arguments to these statements are as follows:

<i>positionals</i>	are directives determining the position on the screen to begin the field. There are four kinds of positionals; any number of positionals are accepted for each field operand.
<i># operand</i>	specifies the row position; that is, it moves the current position to column 1 of the specified line. The <i>operand</i> is either a number, a name, or an expression in parentheses.
<i>/</i>	specifies that the current position move to column 1 of the next row.
<i>@ operand</i>	specifies the column position. The <i>operand</i> is either a number, a name, or an expression in parentheses. The @ directive should come after the # position if # is specified.
<i>+ operand</i>	specifies a skip of columns. The <i>operand</i> is either a number, a name, or an expression in parentheses.
<i>field-operand</i>	is a character literal in quotes or the name of a variable that specifies what is to go in the field.
<i>format</i>	is the format used for display, the value, and the informat applied to entered values. If no format is specified, then the standard numeric or character format is used.
<i>field-options</i>	specify the attributes of the field as follows:

PROTECT=YES

P=YES

specifies that the field is protected; that is, you cannot enter values in the field. If the field operand is a literal, it is already protected.

COLOR=operand

specifies the color of the field. The *operand* is a literal character value in quotes, a variable name, or an expression in parentheses. The colors available are “WHITE,” “BLACK,” “GREEN,” “MAGENTA,” “RED,” “YELLOW,” “CYAN,” “GRAY,” and “BLUE.” Note that the color specification is different from that of the corresponding DATA step value because it is an operand rather than a name without quotes. The default value is “BLUE.”

XMULT Function

XMULT(*matrix1*, *matrix2*);

The XMULT function computes the matrix product like the matrix multiplication operator (*) except XMULT uses extended precision to accumulate sums of products. You should use the XMULT function only when you need great accuracy.

The following program uses the XMULT function:

```
a=1e13;
b=1e13;
c=100*a;
a=a+1;
x=c || a || b || c;
y=c || a || (-b) || (-c);

z=xmult(x,y`); /* correct answer */
print z [format=16.0];

wrong = x * y`; /* loss of precision */
print wrong [format=16.0];
```

Z

200000000000001

WRONG

19997367730176

XSECT Function

XSECT(*matrix1* <, *matrix2*, ..., *matrix15*>);

The XSECT function returns as a row vector the sorted set (without duplicates) of the element values that are present in all of its arguments. This set is the intersection of the sets of values in its argument matrices. When the intersection is empty, the XSECT function returns a null matrix (zero rows and zero columns). There can be up to 15 arguments, which must all be either character or numeric.

For characters, the element length of the result is the same as the shortest of the element lengths of the arguments. For comparison purposes, shorter elements are padded on the right with blanks.

For example, the following statements return the result shown:

```
a={1 2 4 5};
b={3 4};
c=xsect(a,b);
```

C	1 row	1 col	(numeric)
		4	

YIELD Function

YIELD(*times*, *flows*, *freq*, *value*);

The YIELD function returns a scalar that contains yield-to-maturity of a cash-flow stream based on frequency and value specified.

times	is an n -dimensional column vector of times. Elements should be nonnegative.
flows	is an n -dimensional column vector of cash flows.
freq	is a scalar that represents the base of the rates to be used for discounting the cash flows. If positive, it represents discrete compounding as the reciprocal of the number of compoundings. If zero, it represents continuous compounding. No negative values are accepted.
value	is a scalar that is the discounted present value of the cash flows.

The present value relationship can be written as

$$P = \sum_{k=1}^K c(k)D(t_k)$$

where P is the present value of the asset, $\{c(k)\}_{k=1, \dots, K}$ is the sequence of cash flows from the asset, t_k is the time to the k th cash flow in periods from the present, and $D(t)$ is the discount function for time t .

With continuous compounding:

$$D(t) = e^{-yt}$$

With discrete compounding:

$$D(t) = (1 + fy)^{-t/f}$$

where $f > 0$ is the frequency, the reciprocal of the number of compoundings per unit time period, and y is the yield-to-maturity. The YIELD function solves for y .

For example, the following statements produce the output shown in Figure 23.297:

```
timesn = T(do(1, 100, 1));
flows = repeat(10, 100);
freq = 50;
value = 682.31027;
yield = yield(timesn, flows, freq, value);
print yield;
```

Figure 23.297 Yield to Maturity

yield
0.01

Base SAS Functions Accessible from SAS/IML Software

You can call most functions available in Base SAS software from SAS/IML programs. If you call a Base SAS function with a matrix argument, the function will usually act elementwise on each element of the matrix.

The following Base SAS functions are either not available from SAS/IML software, or behave differently from the Base SAS function of the same name.

Function	Comment
CALL CATS	return variable must be preinitialized
DIF n	not supported; use the SAS/IML DIF function instead.
DIM	not supported
HBOUND	not supported
LAG n	not supported; use the SAS/IML LAG function instead.
LBOUND	not supported
MOD	base function performs “fuzzing;” the SAS/IML function does not

PUT	Use the PRINT statement instead
CALL PRXNEXT	return variables must be preinitialized
CALL PRXPOSN	return variables must be preinitialized
CALL PRXSUBSTR	return variables must be preinitialized
CALL RXCHANGE	return variables must be preinitialized
CALL RXMATCH	return variables must be preinitialized
CALL RXSUBSTR	return variables must be preinitialized
CALL SCAN	return variables must be preinitialized
CALL SCANQ	return variable must be preinitialized
VVALUE	not applicable: interrogates DATA step variables
VVALUEX	not applicable: interrogates DATA step variables
VNEXT	not applicable: interrogates DATA step variables

There are also some Base SAS features that are not supported by the SAS/IML language. For example, the DATA step permits N-literals (strings that end with 'N') to be interpreted as the name of a variable, but the SAS/IML language does not.

The following Base SAS functions can be called from SAS/IML. The functions are documented in the *SAS Language Reference: Dictionary*. In some cases, SAS/IML does not accept all variations in the syntax. For example, SAS/IML does not accept the OF keyword as a way to generate an argument list in a function.

The functions displayed in *italics* are documented elsewhere in this user's guide. These functions operate on matrices in addition to scalar values, as do many of the mathematical and statistical functions.

Bitwise Logical Operation Functions

BAND	returns the bitwise logical AND of two arguments
BLSHIFT	performs a bitwise logical left shift of an argument by a specified amount
BNOT	returns the bitwise logical NOT of an argument
BOR	returns the bitwise logical OR of two arguments
BRSHIFT	performs a bitwise logical right shift of an argument by a specified amount
BXOR	returns the bitwise logical EXCLUSIVE OR of two arguments

Character and Formatting Functions

ANYALNUM	searches a character string for an alphanumeric character and returns the first position at which it is found
ANYALPHA	searches a character string for an alphabetic character and returns the first position at which it is found

ANYCNTRL	searches a character string for a control character and returns the first position at which it is found
ANYDIGIT	searches a character string for a digit and returns the first position at which it is found
ANYFIRST	searches a character string for a character that is valid as the first character in a SAS variable name under VALIDVARNAME=V7, and returns the first position at which that character is found
ANYGRAPH	searches a character string for a graphical character and returns the first position at which it is found
ANYLOWER	searches a character string for a lowercase letter and returns the first position at which it is found
ANYNAME	searches a character string for a character that is valid in a SAS variable name under VALIDVARNAME=V7, and returns the first position at which that character is found
ANYPRINT	searches a character string for a printable character and returns the first position at which it is found
ANYPUNCT	searches a character string for a punctuation character and returns the first position at which it is found
ANYSpace	searches a character string for a white-space character (blank, horizontal and vertical tab, carriage return, line feed, form feed) and returns the first position at which it is found
ANYUPPER	searches a character string for an uppercase letter and returns the first position at which it is found
ANYXDIGIT	searches a character string for a hexadecimal character that represents a digit and returns the first position at which that character is found
BYTE	returns one character in the ASCII or EBCDIC collating sequence
CAT	concatenates character strings without removing leading or trailing blanks
CATS	concatenates character strings and removes leading and trailing blanks
CALL CATS	concatenates character strings and removes leading and trailing blanks
CATT	concatenates character strings and removes trailing blanks
CALL CATT	concatenates character strings and removes trailing blanks
CATX	concatenates character strings, removes leading and trailing blanks, and inserts separators
CALL CATX	concatenates character strings, removes leading and trailing blanks, and inserts separators
CHOOSEC	returns a character value that represents the results of choosing from a list of arguments
CHOOSEN	returns a numeric value that represents the results of choosing from a list of arguments
COLLATE	returns an ASCII or EBCDIC collating sequence character string
COMPARE	returns the position of the left-most character by which two strings differ, or returns 0 if there is no difference
COMPBL	removes multiple blanks from a character string

CALL COMPCOST	sets the costs of operations for later use by the COMPGED function
COMPGED	compares two strings by computing the generalized edit distance
COMPLEV	compares two strings by computing the Levenshtein edit distance
COMPRESS	removes specific characters from a character string
COUNT	counts the number of times that a specific substring of characters appears within a character string that you specify
COUNTC	counts the number of specific characters that either appear or do not appear within a character string that you specify
COUNTQ	counts the number of “words” and quoted strings in a character expression
COUNTW	counts the number of words in a character expression
FIND	searches for a specific substring of characters within a character string that you specify
FINDC	searches for specific characters that either appear or do not appear within a character string that you specify
IFC	returns a character value that matches an expression
IFN	returns a numeric value that matches an expression
INDEX	searches a character expression for a string of characters
INDEXC	searches a character expression for specific characters
INDEXW	searches a character expression for a specified string as a word
INPUTC	applies a character informat at run time
INPUTN	applies a numeric informat at run time
LEFT	left aligns a character expression
LENGTH	returns the length of a character string
LENGTHC	returns the length of a character string, including trailing blanks
LENGTHM	returns the amount of memory (in bytes) that is allocated for a character string
LENGTHN	returns the length of a nonblank character string, excluding trailing blanks, and returns 0 for a blank character string
LOWCASE	converts all letters in an argument to lowercase
CALL MISSING	assigns a missing value to the specified character or numeric variable
NLITERAL	converts a character string that you specify to a SAS name literal (N-literal)
NOTALNUM	searches a character string for a nonalphanumeric character and returns the first position at which it is found
NOTALPHA	searches a character string for a nonalphabetic character and returns the first position at which it is found
NOTCNTRL	searches a character string for a character that is not a control character and returns the first position at which it is found
NOTDIGIT	searches a character string for any character that is not a digit and returns the first position at which that character is found
NOTFIRST	searches a character string for an invalid first character in a SAS variable name under VALIDVARNAME=V7, and returns the first position at which that character is found
NOTGRAPH	searches a character string for a nongraphical character and returns the first position at which it is found

NOTLOWER	searches a character string for a character that is not a lowercase letter and returns the first position at which that character is found
NOTNAME	searches a character string for an invalid character in a SAS variable name under VALIDVARNAME=V7, and returns the first position at which that character is found
NOTPRINT	searches a character string for a nonprintable character and returns the first position at which it is found
NOTPUNCT	searches a character string for a character that is not a punctuation character and returns the first position at which it is found
NOTSPACE	searches a character string for a character that is not a white-space character (blank, horizontal and vertical tab, carriage return, line feed, form feed) and returns the first position at which it is found
NOTUPPER	searches a character string for a character that is not an uppercase letter and returns the first position at which that character is found
NOTXDIGIT	searches a character string for a character that is not a hexadecimal digit and returns the first position at which that character is found
NVALID	checks a character string for validity for use as a SAS variable name in a SAS statement
PROPCASE	converts all words in an argument to proper case
PUTC	applies a character format at run time
PUTN	applies a numeric format at run time
REPEAT	repeats a character expression
REVERSE	reverses a character expression
RIGHT	right aligns a character expression
SCAN	selects a given word from a character expression
CALL SCAN	returns the position and length of a given word from a character expression
CALL SCANQ	returns the position and length of a given word from a character expression, and ignores delimiters that are inside quotation marks
ROUNDEX	encodes a string to facilitate searching
SPEDIS	determines the likelihood of two words matching, expressed as the asymmetric spelling distance between the two words
STRIP	returns a character string with all leading and trailing blanks removed
SUBPAD	returns a substring that has specified length and is padded with blanks, if necessary
SUBSTRN	returns a substring, allowing a result with a length of zero
SUBSTR	extracts substrings of character expressions
TRANSLATE	replaces specific characters in a character expression
TRANWRD	replaces or removes all occurrences of a word in a character string
TRIM	removes trailing blanks from character expressions and returns one blank if the expression is missing
TRIMN	removes trailing blanks from character expressions and returns a null string (zero blanks) if the expression is missing
UPCASE	converts all letters in an argument to uppercase
UUIDGEN	returns the short or binary form of a Universal Unique Identifier (UUID)

VERIFY	returns the position of the first character that is unique to an expression
--------	---

Character String Matching Functions and Subroutines

CALL RXCHANGE	changes one or more substrings that match a pattern
CALL RXFREE	frees memory allocated by other regular expression (RX) functions and CALL routines
RXMATCH	finds the beginning of a substring that matches a pattern
RXPARSE	parses a pattern
CALL RXSUBSTR	finds the position, length, and score of a substring that matches a pattern
CALL PRXCHANGE	performs a pattern matching substitution
CALL PRXDEBUG	enables Perl regular expressions in a DATA step to send debug output to the SAS log
CALL PRXFREE	frees unneeded memory that was allocated for a Perl regular expression
PRXMATCH	searches for a pattern match and returns the position at which the pattern is found
CALL PRXNEXT	returns the position and length of a substring that matches a pattern and iterates over multiple matches within one string
PRXPAREN	returns the last bracket match for which there is a match in a pattern
PRXPARSE	compiles a Perl regular expression that can be used for pattern matching of a character value
CALL PRXPOSN	returns the start position and length for a capture buffer
CALL PRXSUBSTR	returns the position and length of a substring that matches a pattern

Date and Time Functions

DATDIF	returns the number of days between two dates
DATE	returns the current date as a SAS date value
DATEJUL	converts a Julian date to a SAS date value
DATEPART	extracts the date from a SAS datetime value
DATETIME	returns the current date and time of day as a SAS datetime value
DAY	returns the day of the month from a SAS date value
DHMS	returns a SAS datetime value from date, hour, minute, and seconds
HMS	returns a SAS time value from hour, minute, and seconds
HOURL	returns the hour from a SAS time or datetime value
INTCK	returns the integer number of time intervals in a given time span
INTNX	advances a date, time, or datetime value by a given interval, and returns a date, time, or datetime value
JULDATE	returns the Julian date from a SAS date value
JULDATE7	returns a seven-digit Julian date from a SAS date value

MDY	returns a SAS date value from month, day, and year values
MINUTE	returns the minute from a SAS time or datetime value
MONTH	returns the month from a SAS date value
QTR	returns the quarter of the year from a SAS date value
SECOND	returns the second from a SAS time or datetime value
TIME	returns the current time of day
TIMEPART	extracts a time value from a SAS datetime value
TODAY	returns the current date as a SAS date value
WEEKDAY	returns the day of the week from a SAS date value
YEAR	returns the year from a SAS date value
YRDIF	returns the difference in years between two dates
YYQ	returns a SAS date value from the year and quarter

Descriptive Statistics Functions and Subroutines

CMISS	returns the number of nonmissing values
CSS	returns the corrected sum of squares
CV	returns the coefficient of variation
GEOMEAN	returns the geometric mean
EUCLID	returns the Euclidean norm of the nonmissing arguments
GEOMEANZ	returns the geometric mean without fuzzing the values of the arguments that are approximately 0
HARMEAN	returns the harmonic mean
HARMEANZ	returns the harmonic mean without fuzzing the values of the arguments that are approximately 0
IQR	returns the interquartile range
KURTOSIS	returns the kurtosis
LARGEST	returns the k th largest nonmissing value
LPNORM	returns the L_p norm of the nonmissing arguments
MAX	returns the largest value
MAD	returns the median absolute deviation from the median
MEDIAN	computes median values
MEAN	returns the arithmetic mean (average)
MIN	returns the smallest value
N	returns the number of nonmissing values
ORDINAL	returns any specified order statistic
PCTL	computes percentiles
RANGE	returns the range of values
RMS	returns the root mean square
SKEWNESS	returns the skewness
SMALLEST	returns the k th smallest nonmissing value
SUM	returns the sum of the nonmissing arguments
STD	returns the standard deviation
CALL STDIZE	standardizes the values of one or more variables
STDERR	returns the standard error of the mean

SUMABS	returns the sum of the absolute values of the nonmissing arguments
USS	returns the uncorrected sum of squares
VAR	returns the variance

Double-Byte Character String Functions

Many of the Base SAS character functions have analogous companion functions that take double-byte character strings (DBCS) as arguments. These functions (for example, KCOMPARE, KCVT, KINDEX, and KSUBSTR) are accessible from SAS/IML. See the *SAS Language Reference: Dictionary* for a complete list of DBCS functions.

External Files Functions

DROPNOTE	deletes a note marker from a SAS data set or an external file and returns a value
EXIST	verifies the existence of a SAS data library member
FAPPEND	appends the current record to the end of an external file and returns a value
FCLOSE	closes an external file, directory, or directory member, and returns a value
FCOL	returns the current column position in the File Data Buffer (FDB)
FDELETE	deletes an external file or an empty directory
FEXIST	verifies the existence of an external file associated with a fileref and returns a value
FGET	copies data from the File Data Buffer (FDB) into a variable and returns a value
FILEEXIST	verifies the existence of an external file by its physical name and returns a value
FILENAME	assigns or deassigns a fileref for an external file, directory, or output device and returns a value
FILEREF	verifies that a fileref has been assigned for the current SAS session and returns a value
FINFO	returns the value of a file information item
FNOTE	identifies the last record that was read and returns a value that FPOINT can use
FOPEN	opens an external file and returns a file identifier value
FOPTNAME	returns the name of an item of information about a file
FOPTNUM	returns the number of information items that are available for an external file
FPOINT	positions the read pointer on the next record to be read and returns a value
FPOS	sets the position of the column pointer in the File Data Buffer (FDB) and returns a value

FPUT	moves data to the File Data Buffer (FDB) of an external file, starting at the FDB's current column position, and returns a value
FREAD	reads a record from an external file into the File Data Buffer (FDB) and returns a value
FREWIND	positions the file pointer to the start of the file and returns a value
FRLen	returns the size of the last record read, or, if the file is opened for output, returns the current record size
FSEP	sets the token delimiters for the FGET function and returns a value
FWRITE	writes a record to an external file and returns a value
MOPEN	opens a file by directory identifier and member name, and returns the file identifier or a 0
PATHNAME	returns the physical name of a SAS data library or of an external file, or returns a blank
SYSMSG	returns the text of error messages or warning messages from the last data set or external file function execution
SYSRC	returns a system error number

File I/O Functions

ATTRC	returns the value of a character attribute for a SAS data set
ATTRN	returns the value of a numeric attribute for the specified SAS data set
CEXIST	verifies the existence of a SAS catalog or SAS catalog entry and returns a value
CLOSE	closes a SAS data set and returns a value
CUROBS	returns the observation number of the current observation
DROPNOTE	deletes a note marker from a SAS data set or an external file and returns a value
DSNAME	returns the SAS data set name that is associated with a data set identifier
EXIST	verifies the existence of a SAS data library member
FETCH	reads the next nondeleted observation from a SAS data set into the Data Set Data Vector (DDV) and returns a value
FETCHOBS	reads a specified observation from a SAS data set into the Data Set Data Vector (DDV) and returns a value
GETVARC	returns the value of a SAS data set character variable
GETVARN	returns the value of a SAS data set numeric variable
LIBNAME	assigns or deassigns a libref for a SAS data library and returns a value
LIBREF	verifies that a libref has been assigned and returns a value
NOTE	returns an observation ID for the current observation of a SAS data set
OPEN	opens a SAS data set and returns a value
PATHNAME	returns the physical name of a SAS data library or of an external file, or returns a blank

POINT	locates an observation identified by the NOTE function and returns a value
REWIND	positions the data set pointer at the beginning of a SAS data set and returns a value
SYSMSG	returns the text of error messages or warning messages from the last data set or external file function execution
SYSRC	returns a system error number
VARFMT	returns the format assigned to a SAS data set variable
VARINFMT	returns the informat assigned to a SAS data set variable
VARLABEL	returns the label assigned to a SAS data set variable
VARLEN	returns the length of a SAS data set variable
VARNAME	returns the name of a SAS data set variable
VARNUM	returns the number of a variable's position in a SAS data set
VARTYPE	returns the data type of a SAS data set variable

Financial Functions

COMPOUND	returns compound interest parameters
CONVX	returns the convexity for an enumerated cash flow
CONVXP	returns the convexity for a periodic cash flow stream
DACCDB	returns the accumulated declining balance depreciation
DACCDBSL	returns the accumulated declining balance with conversion to a straight-line depreciation
DACCSL	returns the accumulated straight-line depreciation
DACCSYD	returns the accumulated sum-of-years-digits depreciation
DACCTAB	returns the accumulated depreciation from specified tables
DEPDB	returns the declining balance depreciation
DEPDBSL	returns the declining balance with conversion to a straight-line depreciation
DEPSL	returns the straight-line depreciation
DEPSYD	returns the sum-of-years-digits depreciation
DEPTAB	returns the depreciation from specified tables
DUR	returns the modified duration for an enumerated cash flow
INTRR	returns the internal rate of return as a decimal
IRR	returns the internal rate of return as a percentage
MORT	returns amortization parameters
NETPV	returns the net present value as a decimal
NPV	returns the net present value as a percentage
PVP	returns the present value for a periodic cash flow stream
SAVING	returns the future value of a periodic saving
YIELDP	returns the yield-to-maturity for a periodic cash flow stream

Macro Functions and Subroutines

CALL RESOLVE	resolves the value of a text expression at execution time
SYMGET	returns the character value of a macro variable
SYMGETN	returns the numeric value of a macro variable
SYMEXIST	indicates the existence of a macro variable
CALL SYMPUT	sets the character value of a macro variable
CALL SYMPUTX	assigns a value to a macro variable and removes both leading and trailing blanks

Mathematical Functions and Subroutines

ALLCOMB	generates all combinations of n elements taken k at a time
ALLPERM	generates all permutations of n elements
ABS	returns the absolute value
AIRY	returns the Airy function
BETA	returns the value of the beta function.
COALESCE	returns the first non-missing value from a list of numeric arguments
COALESCEC	returns the first non-missing value from a list of character arguments
COMB	returns the number of combinations of n items taken r at a time
COMPFUZZ	returns the result of a fuzzy comparison of numeric values
CONSTANT	returns some machine and mathematical constants
CNONCT	returns the noncentrality parameter from a chi-squared distribution
DAIRY	returns the derivative of the Airy function
DEVIANC	returns the deviance from a specified distribution
DIGAMMA	returns the DIGAMMA function
ERF	returns the normal error function
ERFC	returns the complementary normal error function
EXP	returns the exponential function
FACT	returns the factorial of an integer
FNONCT	returns the noncentrality parameter of an F distribution
GAMMA	returns the gamma function
IBESSEL	returns a modified Bessel function
JBESSEL	returns a Bessel function
LOGBETA	returns the logarithm of the beta function
LGAMMA	returns the natural logarithm of the gamma function
LOG	returns the natural (base e) logarithm
LOG2	returns the logarithm base 2
LOG10	returns the logarithm base 10
CALL LOGISTIC	returns the logistic value of each argument
MOD	returns the remainder value
RANCOMB	returns random combinations of n elements taken k at a time

CALL RANPERK	randomly permutes the values of the arguments, and returns a permutation of k out of n values
RANPERM	returns random permutations of n elements
PERM	returns the number of permutations of n items taken r at a time
SIGN	returns the sign of a value
CALL SOFTMAX	returns the softmax value for each argument
SQRT	returns the square root of a value
TNONCT	returns the value of the noncentrality parameter from the student's t distribution
TRIGAMMA	returns the value of the TRIGAMMA function

Probability Functions

CDF	computes cumulative distribution functions
LOGCDF	returns the logarithm of a left cumulative distribution function
LOGPDF	computes the logarithm of a probability function
LOGSDF	computes the logarithm of a survival function
PDF	computes probability density functions
POISSON	returns the probability from a Poisson distribution
PROBBETA	returns the probability from a beta distribution
PROBBNML	returns the probability from a binomial distribution
PROBBNRM	returns the probability from the bivariate normal distribution
PROBCHI	returns the probability from a chi-squared distribution
PROBF	returns the probability from an F distribution
PROBGAM	returns the probability from a gamma distribution
PROBHYP	returns the probability from a hypergeometric distribution
PROBMC	returns a probability or a quantile from various distributions for multiple comparisons of means
PROBNEGB	returns the probability from a negative binomial distribution
PROBNORM	returns the probability from the standard normal distribution
PROBT	returns the probability from a t distribution
SDF	computes a survival function

Quantile Functions

BETAINV	returns a quantile from the beta distribution
CINV	returns a quantile from the chi-squared distribution
FINV	returns a quantile from the F distribution
GAMINV	returns a quantile from the gamma distribution
PROBIT	returns a quantile from the standard normal distribution
QUANTILE	returns the quantile from the specified distribution
TINV	returns a quantile from the t distribution

Random Number Functions and Subroutines

NORMAL	returns a random variate from a normal distribution
RANBIN	returns a random variate from a binomial distribution
RANCAU	returns a random variate from a Cauchy distribution
RAND	returns a random variate from a specified distribution. (See the RANDGEN subroutine .)
RANEXP	returns a random variate from an exponential distribution
RANGAM	returns a random variate from a gamma distribution
RANNOR	returns a random variate from a normal distribution
RANPOI	returns a random variate from a Poisson distribution
RANTBL	returns a random variate from a tabled probability
RANTRI	returns a random variate from a triangular distribution
RANUNI	returns a random variate from a uniform distribution
CALL STREAMINIT	specifies a seed value to use for subsequent random number generation by the RAND function. (See the RANDSEED subroutine .)
UNIFORM	returns a random variate from a uniform distribution

State and Zip Code Functions

FIPNAME	converts FIPS codes to uppercase state names
FIPNAMEL	converts FIPS codes to mixed-case state names
FIPSTATE	converts FIPS codes to two-character postal codes
STFIPS	converts state postal codes to FIPS state codes
STNAME	converts state postal codes to uppercase state names
STNAMEL	converts state postal codes to mixed-case state names
ZIPCITY	returns a city name and the two-character postal code that corresponds to a zip code
ZIPCITYDISTANCE	returns the geodetic distance between two zip code locations
ZIPFIPS	converts zip codes to FIPS state codes
ZIPNAME	converts zip codes to uppercase state names
ZIPNAMEL	converts zip codes to mixed-case state names
ZIPSTATE	converts zip codes to state postal codes

Trigonometric and Hyperbolic Functions

ARCOS	returns the arccosine
ARSIN	returns the arcsine
ATAN	returns the arctangent
ATAN2	returns the arc tangent of two numeric variables
COS	returns the cosine

COSH	returns the hyperbolic cosine
SIN	returns the sine
SINH	returns the hyperbolic sine
TAN	returns the tangent
CALL TANH	returns the hyperbolic tangent of each argument
TANH	returns the hyperbolic tangent

Truncation Functions

CEIL	returns the smallest integer \geq the argument
CEILZ	returns the smallest integer that is greater than or equal to the argument, using zero fuzzing
FLOOR	returns the largest integer \leq the argument
FLOORZ	returns the largest integer that is less than or equal to the argument, using zero fuzzing
FUZZ	returns the nearest integer if the argument is within 1E-12
INT	returns the integer portion of a value
INTZ	returns the integer portion of the argument, using zero fuzzing
MODZ	returns the remainder from the division of the first argument by the second argument, using zero fuzzing
ROUND	rounds a value to the nearest round-off unit
ROUNDE	rounds the first argument to the nearest multiple of the second argument, and returns an even multiple when the first argument is halfway between the two nearest multiples
ROUNDZ	rounds the first argument to the nearest multiple of the second argument, with zero fuzzing
TRUNC	returns a truncated numeric value of a specified length

Web Tools

HTMLDECODE	decodes a string that contains HTML numeric character references or HTML character entity references and returns the decoded string
HTMLENCODE	encodes characters by using HTML character entity references and returns the encoded string
URLDECODE	returns a string that was decoded by using the URL escape syntax
URLENCODE	returns a string that was encoded by using the URL escape syntax

References

- Abramowitz, M. and Stegun, I. A. (1972), *Handbook of Mathematical Functions*, New York: Dover Publications.
- Aiken, R. C. (1985), *Stiff Computation*, New York: Oxford University Press.
- Al-Baali, M. and Fletcher, R. (1985), “Variational Methods for Nonlinear Least Squares,” *Journal of the Operations Research Society*, 36, 405–421.
- Al-Baali, M. and Fletcher, R. (1986), “An Efficient Line Search for Nonlinear Least Squares,” *Journal of Optimization Theory and Applications*, 48, 359–377.
- Ansley, C. (1979), “An Algorithm for the Exact Likelihood of a Mixed Autoregressive-Moving Average Process,” *Biometrika*, 66, 59–65.
- Ansley, C. F. (1980), “Computation of the Theoretical Autocovariance Function for a Vector ARMA Process,” *Journal of Statistical Computation and Simulation*, 12, 15–24.
- Ansley, C. F. and Kohn, R. (1986), “A Note on Reparameterizing a Vector Autoregressive Moving Average Model to Enforce Stationary,” *Journal of Statistical Computation and Simulation*, 24, 99–106.
- Barnett, V. and Lewis, T. (1978), *Outliers in Statistical Data*, New York: John Wiley & Sons.
- Barreto, H. and Maharry, D. (2006), “Least Median of Squares and Regression Through the Origin,” *Computational Statistics and Data Analysis*, 50, 1391–1397.
- Barrodale, I. and Roberts, F. D. K. (1974), “Algorithm 478: Solution of an Overdetermined System of Equations in the L_1 -Norm,” *Communications ACM*, 17, 319–320.
- Bates, D., Lindstrom, M., Wahba, G., and Yandell, B. (1987), “GCVPACK-Routines for Generalized Cross Validation,” *Communications in Statistics: Simulation and Computation*, 16, 263–297.
- Beale, E. M. L. (1972), “A Derivation of Conjugate Gradients,” in F. A. Lootsma, ed., *Numerical Methods for Nonlinear Optimization*, London: Academic Press.
- Beaton, A. E. (1964), *The Use of Special Matrix Operations in Statistical Calculus*, Princeton: Educational Testing Service.
- Bickart, T. A. and Picel, Z. (1973), “High Order Stiffly Stable Composit Multistep Methods for Numerical Integration of Stiff Differential Equations,” *BIT*, 13, 272–286.
- Bishop, Y. M. M., Fienberg, S. E., and Holland, P. W. (1975), *Discrete Multivariate Analysis: Theory and Practice*, Cambridge, MA: MIT Press.
- Box, G. E. P. and Jenkins, G. M. (1976), *Time Series Analysis: Forecasting and Control*, Revised Edition, San Francisco: Holden-Day.
- Breiman, L. (1995), “Better Subset Regression Using the Nonnegative Garrote,” *Technometrics*, 37, 373–384.
- Brockwell, P. J. and Davis, R. A. (1991), *Time Series: Theory and Methods*, Second Edition, New York: Springer-Verlag.

- Brownlee, K. A. (1965), *Statistical Theory and Methodology in Science and Engineering*, New York: John Wiley & Sons.
- Charnes, A., Frome, E. L., and Yu, P. L. (1976), "The Equivalence of Generalized Least Squares and Maximum Likelihood Estimation in the Exponential Family," *Journal of the American Statistical Association*, 71, 169–172.
- Christensen, R. (1997), *Log-Linear Models and Logistic Regression*, Second Edition, New York: Springer-Verlag.
- Chung, C. F. (1996), "A Generalized Fractionally Integrated ARMA Process," *Journal of Time Series Analysis*, 2, 111–140.
- Cox, D. R. and Hinkley, D. V. (1974), *Theoretical Statistics*, London: Chapman & Hall.
- Daubechies, I. (1992), *Ten Lectures on Wavelets*, Volume 61, CBMS-NSF Regional Conference Series in Applied Mathematics, Philadelphia, PA: Society for Industrial and Applied Mathematics.
- Davies, L. (1992), "The Asymptotics of Rousseeuw's Minimum Volume Ellipsoid Estimator," *The Annals of Statistics*, 20, 1828–1843.
- De Jong, P. (1991), "Stable Algorithms for the State Space Model," *Journal of Time Series Analysis*, 12, 143–157.
- DeBoor, C. (1981), *A Practical Guide to Splines*, New York: Springer-Verlag.
- Dennis, J. E., Gay, D. M., and Welsch, R. E. (1981), "An Adaptive Nonlinear Least-Squares Algorithm," *ACM Transactions on Mathematical Software*, 7, 348–368.
- Dennis, J. E. and Mei, H. H. W. (1979), "Two New Unconstrained Optimization Algorithms Which Use Function and Gradient Values," *Journal of Optimization Theory Applications*, 28, 453–482.
- Donelson, J. and Hansen, E. (1971), "Cyclic Composite Predictor-Corrector Methods," *SIAM Journal on Numerical Analysis*, 8, 137–157.
- Donoho, D. L. and Johnstone, I. M. (1994), "Ideal Spatial Adaptation via Wavelet Shrinkage," *Biometrika*, 81, 425–455.
- Donoho, D. L. and Johnstone, I. M. (1995), "Adapting to Unknown Smoothness via Wavelet Shrinkage," *Journal of the American Statistical Association*, 90, 1200–1224.
- Duchon, J. (1976), "Fonctions-Spline et Esperances Conditionnelles de Champs Gaussiens," *Ann. Sci. Univ. Clermont Ferrand II Math.*, 14, 19–27.
- Emerson, P. L. (1968), "Numerical Construction of Orthogonal Polynomials from a General Recurrence Formula," *Biometrics*, 24, 695–701.
- Eskow, E. and Schnabel, R. B. (1991), "Algorithm 695: Software for a New Modified Cholesky Factorization," *ACM Transactions on Mathematical Software*, 17, 306–312.
- Fletcher, R. (1987), *Practical Methods of Optimization*, Second Edition, Chichester, UK: John Wiley & Sons.

- Fletcher, R. and Xu, C. (1987), "Hybrid Methods for Nonlinear Least Squares," *Journal of Numerical Analysis*, 7, 371–389.
- Forsythe, G. E., Malcom, M. A., and Moler, C. B. (1967), *Computer Solution of Linear Algebraic Systems*, Chapter 17, Englewood Cliffs, NJ: Prentice-Hall.
- Furnival, G. M. and Wilson, R. W. (1974), "Regression by Leaps and Bounds," *Technometrics*, 16, 499–511.
- Gaffney, P. W. (1984), "A Performance Evaluation of Some FORTRAN Subroutines for the Solution of Stiff Oscillatory Ordinary Differential Equations," *Association for Computing Machinery, Transactions on Mathematical Software*, 10, 58–72.
- Gay, D. M. (1983), "Subroutines for Unconstrained Minimization," *ACM Transactions on Mathematical Software*, 9, 503–524.
- Gentleman, W. M. and Sande, G. (1966), "Fast Fourier Transforms for Fun and Profit," *AFIPS Proceedings of the Fall Joint Computer Conference*, 19, 563–578.
- George, J. A. and Liu, J. W. (1981), *Computer Solutions of Large Sparse Positive Definite Systems*, Englewood Cliffs, NJ: Prentice-Hall.
- Geweke, J. and Porter-Hudak, S. (1983), "The Estimation and Application of Long Memory Time Series Models," *Journal of Time Series Analysis*, 4, 221–238.
- Gill, E. P., Murray, W., Saunders, M. A., and Wright, M. H. (1984), "Procedures for Optimization Problems with a Mixture of Bounds and General Linear Constraints," *ACM Transactions on Mathematical Software*, 10, 282–298.
- Golub, G. H. (1969), "Matrix Decompositions and Statistical Calculations," in R. C. Milton and J. A. Nelder, eds., *Statistical Computation*, New York: Academic Press.
- Golub, G. H. and Van Loan, C. F. (1989), *Matrix Computations*, Second Edition, Baltimore: Johns Hopkins University Press.
- Gonin, R. and Money, A. H. (1989), *Nonlinear L_p -Norm Estimation*, New York: Marcel Dekker.
- Goodnight, J. H. (1979), "A Tutorial on the Sweep Operator," *The American Statistician*, 33, 149–158.
- Graybill, F. A. (1969), *Introduction to Matrices with Applications in Statistics*, Belmont, CA: Wadsworth.
- Grizzle, J. E., Starmer, C. F., and Koch, G. G. (1969), "Analysis of Categorical Data by Linear Models," *Biometrics*, 25, 489–504.
- Hadley, G. (1962), *Linear Programming*, Reading, MA: Addison-Wesley.
- Harvey, A. C. (1989), *Forecasting, Structural Time Series Models and the Kalman Filter*, Cambridge: Cambridge University Press.
- Harville, D. A. (1997), *Matrix Algebra from a Statistician's Perspective*, New York: Springer-Verlag.
- Hocking, R. R. (1985), *The Analysis of Linear Models*, Belmont, CA: Brooks/Cole.
- Jenkins, M. A. and Traub, J. F. (1970), "A Three-Stage Algorithm for Real Polynomials Using Quadratic Iteration," *SIAM Journal of Numerical Analysis*, 7, 545–566.

- Jennrich, R. I. and Moore, R. H. (1975), "Maximum Likelihood Estimation by Means of Nonlinear Least Squares," *American Statistical Association, 1975 Proceedings of the Statistical Computing Section*.
- Kaiser, H. F. and Caffrey, J. (1965), "Alpha Factor Analysis," *Psychometrika*, 30, 1–14.
- Kastenbaum, M. A. and Lamphiear, D. E. (1959), "Calculation of Chi-Square to Test the No Three-Factor Interaction Hypothesis," *Biometrics*, 15, 107–122.
- Kohn, R. and Ansley, C. F. (1982), "A Note on Obtaining the Theoretical Autocovariances of an ARMA Process," *Journal of Statistical Computation and Simulation*, 15, 273–283.
- Korff, F. A., Taback, M. A. M., and Beard, J. H. (1952), "A Coordinated Investigation of a Food Poisoning Outbreak," *Public Health Reports*, 67, 909–913.
- Kruskal, J. B. (1964), "Multidimensional Scaling by Optimizing Goodness of Fit to a Nonmetric Hypothesis," *Psychometrika*, 29, 1–27.
- Lee, W. and Gentle, J. E. (1986), "The LAV Procedure," *SUGI Supplemental Library User's Guide*.
- Lewart, C. R. (1973), "Algorithm 463: Algorithms SCALE1, SCALE2, and SCALE3 for Determination of Scales on Computer Generated Plots," *Communications of the ACM*, 16(10), 639–640, available at <http://portal.acm.org/citation.cfm?id=362375.362417>.
- Lindström, P. and Wedin, P. A. (1984), "A New Line-Search Algorithm for Nonlinear Least-Squares Problems," *Mathematical Programming*, 29, 268–296.
- Madsen, K. and Nielsen, H. B. (1993), "A Finite Smoothing Algorithm for Linear L_1 Estimation," *SIAM Journal on Optimization*, 3, 223–235.
- Mallat, S. (1989), "Multiresolution Approximation and Wavelets," *Transactions of the American Mathematical Society*, 315, 69–88.
- McKean, J. W. and Schrader, R. M. (1987), "Least Absolute Errors Analysis of Variance," *Statistical Data Analysis - Based on L_1 Norm and Related Methods*.
- McLeod, I. (1975), "Derivation of the Theoretical Autocovariance Function of Autoregressive-Moving Average Time Series," *Applied Statistics*, 24, 255–256.
- Mittnik, S. (1990), "Computation of Theoretical Autocovariance Matrices of Multivariate Autoregressive Moving Average Time Series," *Journal of Royal Statistical Society*.
- Monro, D. M. and Branch, J. L. (1976), "Algorithm AS 117. The Chirp Dis Fourier Transform and General Length," *Applied Statistics*, 351–361.
- Moré, J. J. (1978), "The Levenberg-Marquardt Algorithm: Implementation and Theory," in G. A. Watson, ed., *Lecture Notes in Mathematics*, volume 30, 105–116, Berlin-Heidelberg-New York: Springer-Verlag.
- Moré, J. J. and Sorensen, D. C. (1983), "Computing a Trust-Region Step," *SIAM Journal on Scientific and Statistical Computing*, 4, 553–572.
- Nelder, J. A. and Wedderburn, R. W. M. (1972), "Generalized Linear Models," *Journal of the Royal Statistical Society, Series A*, 135, 370–384.
- Nijenhuis, A. and Wilf, H. S. (1978), *Combinatorial Algorithms*, New York: Academic Press.

- Nussbaumer, H. J. (1982), *Fast Fourier Transform and Convolution Algorithms*, Second Edition, New York: Springer-Verlag.
- Ogden, R. T. (1997), *Essential Wavelets for Statistical Applications and Data Analysis*, Boston: Birkhäuser.
- Osborne, M. R. (1985), *Finite Algorithms in Optimization and Data Analysis*, New York: John Wiley & Sons, Inc.
- Pizer, S. M. (1975), *Numerical Computing and Mathematical Analysis*, Chicago, IL: Science Research Associates.
- Pocock, S. J. (1977), "Group Sequential Methods in the Design and Analysis of Clinical Trials," *Biometrika*, 64, 191–199.
- Pocock, S. J. (1982), "Interim Analyses for Randomized Clinical Trials: The Group Sequential Approach," *Biometrics*, 38, 153–162.
- Powell, M. J. D. (1977), "Restart Procedures for the Conjugate Gradient Method," *Mathematical Programming*, 12, 241–254.
- Powell, M. J. D. (1978), "A Fast Algorithm for Nonlinearly Constrained Optimization Calculations," in G. A. Watson, ed., *Lecture Notes in Mathematics*, volume 630, 144–175, Berlin-Heidelberg-New York: Springer-Verlag.
- Powell, M. J. D. (1982), "VMCWD: A Fortran Subroutine for Constrained Optimization," *DAMTP 1982/NA4*, Cambridge, England.
- Powell, M. J. D. (1992), "A Direct Search Optimization Method That Models the Objective and Constraint Functions by Linear Interpolation," *DAMTP/NA5*, Cambridge, England.
- Ralston, A. and Rabinowitz, P. (1978), *A First Course in Numerical Analysis*, New York: McGraw-Hill.
- Rao, C. R. and Mitra, S. K. (1971), *Generalized Inverse of Matrices and Its Applications*, New York: John Wiley & Sons.
- Reinsch, C. H. (1967), "Smoothing by Spline Functions," *Numerische Mathematik*, 10, 177–183.
- Reinsel, G. C. (1997), *Elements of Multivariate Time Series Analysis*, Second Edition, New York: Springer-Verlag.
- Rice, S. O. (1973), "Efficient Evaluation of Integrals of Analytic Functions by the Trapezoidal Rule," *Bell System Technical Journal*.
- Rousseeuw, P. J. (1984), "Least Median of Squares Regression," *Journal of the American Statistical Association*, 79, 871–880.
- Rousseeuw, P. J. (1985), "Multivariate Estimation with High Breakdown Point," in W. Grossmann, G. Pflug, I. Vincze, and W. Wertz, eds., *Mathematical Statistics and Applications*, 283–297, Dordrecht: Reidel Publishing.
- Rousseeuw, P. J. and Croux, C. (1993), "Alternatives to the Median Absolute Deviation," *Journal of the American Statistical Association*, 88, 1273–1283.

- Rousseeuw, P. J. and Hubert, M. (1996), "Recent Development in PROGRESS," *Computational Statistics and Data Analysis*, 21, 67–85.
- Rousseeuw, P. J. and Hubert, M. (1997), "Recent Developments in PROGRESS," *L₁-Statistical Procedures and Related Topics*.
- Rousseeuw, P. J. and Leroy, A. M. (1987), *Robust Regression and Outlier Detection*, New York: John Wiley & Sons.
- Rousseeuw, P. J. and Van Driessen, K. (1998), *Computing LTS Regression for Large Data Sets*, Technical report, University of Antwerp.
- Rousseeuw, P. J. and Van Driessen, K. (1999), "A Fast Algorithm for the Minimum Covariance Determinant Estimator," *Technometrics*, 41, 212–223.
- Rousseeuw, P. J. and Van Zomeren, B. C. (1990), "Unmasking Multivariate Outliers and Leverage Points," *Journal of the American Statistical Association*, 85, 633–639.
- Schatzoff, M., Tsao, R., and Fienberg, S. (1968), "Efficient Calculation of All Possible Regressions," *Technometrics*, 10(4), 769–779.
- Shampine, L. (1978), "Stability Properties of Adams Codes," *Association for Computing Machinery, Transactions on Mathematical Software*, 4, 323–329.
- Sikorsky, K. (1982), "Optimal Quadrature Algorithms in H_P Spaces," *Numerische Mathematik*, 39, 405–410.
- Sikorsky, K. and Stenger, F. (1984), "Optimal Quadratures in H_P Spaces," *Association for Computing Machinery, Transactions on Mathematical Software*, 3, 140–151.
- Singleton, R. C. (1969), "An Algorithm for Computing the Mixed Radix Fast Fourier Transform," *IEEE Transactions on Audio and Electroacoustics*.
- Sowell, F. (1992), "Maximum Likelihood Estimation of Stationary Univariate Fractionally Integrated Time Series Models," *Journal of Econometrics*, 53, 165–188.
- Squire, W. (1987), "Comparison of Gauss-Hermite and Midpoint Quadrature with the Application of the Voigt Function," *Numerical Integration: Recent Developments*.
- Stenger, F. (1973a), "Integration Formulas Based on the Trapezoidal Formula," *Journal of the Institute of Mathematics and Its Applications*, 12, 103–114.
- Stenger, F. (1973b), "Remarks on Integration Formulas Based on the Trapezoidal Formula," *Journal of the Institute of Mathematics and Its Applications*, 19, 145–147.
- Stenger, F. (1978), "Optimal Convergence of minimum Norm Approximations in H_P ," *Numerische Mathematik*, 29, 345–362.
- Stoer, J. and Bulirsch, R. (1980), *Introduction to Numerical Analysis*, New York: Springer-Verlag.
- Thisted, R. A. (1988), *Elements of Statistical Computing: Numerical Computation*, London: Chapman & Hall.
- Trotter, H. (1962), "Algorithm 115: PERM," *Communications of the ACM*, 5, 434–435.

Wahba, G. (1990), *Spline Models for Observational Data*, Philadelphia: Society for Industrial and Applied Mathematics.

Wang, S. and Tsatis, A. (1987), “Approximately Optimal One Parameter Boundaries for Group Sequential Trials,” *Biometrics*, 43, 193–199.

Wilkinson, J. H. and Reinsch, C. (1971), *Handbook for Automatic Computation: Linear Algebra*, Volume 2, New York: Springer-Verlag.

Woodfield, T. J. (1988), “Simulating Stationary Gaussian ARMA Time Series,” *Computer Science and Statistics: Proceedings of the 20th Symposium on the Interface*.

Young, F. W. (1981), “Quantitative Analysis of Qualitative Data,” *Psychometrika*, 46, 357–388.

Chapter 24

Module Library

Contents

Overview	1065
Contents of IMLMLIB	1066
IMLMLIB and the STORAGE library	1066
Accessing the IML Source Code	1067
Order of Resolution	1067
Error Diagnostics	1068
Modules for Multivariate Random Sampling	1068
Modules Reference	1069
COLVEC Function	1069
EXPMATRIX Function	1070
GBXWSKR Call	1070
GPROBCNT Call	1071
GXYPLOT Call	1071
MEDIAN Function	1072
QUADREG Call	1072
QUARTILE Function	1072
RANDDIRICHLET Function	1073
RANDMULTINOMIAL Function	1074
RANDMVT Function	1076
RANDNORMAL Function	1077
RANDWISHART Function	1078
REGRESS Call	1079
ROWVEC Function	1080
RSUBSTR Function	1080
STANDARD Function	1081
TABPRT Call	1081
References	1081

Overview

IMLMLIB is a library of modules written in the IML language. These modules can be used as though they were built-in functions of IML.

The library contains both functions and subroutines. You can invoke functions in assignment statements or expressions. You can invoke subroutines by using `CALL` or `RUN` statements. IML automatically loads, resolves, and executes a module when you use it.

Contents of IMLMLIB

The library contains the following modules. Many of them are derived from the examples in the IML sample library. Each module is described in detail at the end of this chapter.

COLVEC	converts a matrix into a column vector
CORR	computes correlation coefficients
EXPMATRIX	computes the exponential of a matrix
GBXWHSKR	draws a box-and-whiskers plot
GPROBCNT	draws probability contours for x - y data
GXYPLOT	draws scatter plots of x - y data
MEDIAN	returns the median of numeric data
QUADREG	performs quadratic regression
QUARTILE	computes quartiles
RANDDIRICHLET	generates a random sample from a Dirichlet distribution
RANDMULTINOMIAL	generates a random sample from a multinomial distribution
RANDMVT	generates a random sample from a multivariate Student's t distribution
RANDNORMAL	generates a random sample from a multivariate normal distribution
RANDWISHART	generates a random sample from a Wishart distribution
REGRESS	performs regression analysis
ROWVEC	converts a matrix into a row vector
RSUBSTR	replaces substrings
STANDARD	standardizes numeric data
TABPRT	prints matrices in tabular format

IMLMLIB and the STORAGE library

IML enables you to store and load matrices and modules in your own `STORAGE` library (refer to the chapter on storage features in *SAS/IML Software: Usage and Reference, Version 6*). The IMLMLIB library is different from this `STORAGE` library. IMLMLIB contains predefined modules that can be loaded only by IML.

The STORAGE library, on the other hand, is under the control of the user. You can store and load both matrices and modules. The STORE, LOAD, REMOVE, and RESET STORAGE commands apply only to the STORAGE library. You cannot store additional modules in IMLMLIB.

You can use the SHOW command to obtain information about the IMLMLIB and STORAGE libraries.

- SHOW OPTIONS displays the current settings of both STORAGE and IMLMLIB libraries and their open status.
- SHOW STORAGE displays the contents of the STORAGE library.
- SHOW IMLMLIB displays the contents of the IMLMLIB library.
- SHOW MODULES displays the names of the modules existing in the current environment. These include modules loaded from the STORAGE library or the IMLMLIB library and modules defined in the current session.

Accessing the IML Source Code

The IMLMLIB library is a catalog residing in the SASHELP directory. The catalog contains one entry of type IMOD for each module. Each entry is a module stored in its compiled form.

The SAS/IML source code that defines the modules is available in the catalog SASHELP.IML. There is an entry of type SOURCE for each module. You can view the source code in the program editor window under DMS by using the COPY command and specifying the four-level name:

SASHELP.IML.modulename.SOURCE

The source code is generally followed by examples of its use.

The source code can be edited for customization or enhancements, and can be included in other IML applications. The modules also illustrate a variety of IML features that can be used to solve more complex problems.

Order of Resolution

SAS/IML resolves functions and subroutines in the following order:

- Functions
 1. IML's built-in functions
 2. User-defined IML modules existing in the current environment
 3. STORAGE library, if open
 4. SAS DATA step functions

5. IMLMLIB library

- CALL statement
 1. IML's built-in calls
 2. User-defined IML modules existing in the current environment
 3. STORAGE library, if open
 4. SAS DATA step call
 5. IMLMLIB library
- RUN statement
 1. User-defined IML modules existing in the current environment
 2. STORAGE library, if open
 3. IML's built-in calls
 4. SAS DATA step call
 5. IMLMLIB library

Error Diagnostics

When an error occurs in any IML module, IML pauses in the module and prints error diagnostics with a full traceback that can help in locating the problem. In the case of loaded modules, however, the traceback includes line offsets instead of the absolute SAS LOG line numbers. The offsets can be used to track the problem into the actual source code that originally defined the module. The START statement at the beginning of the module definition is always at offset=1.

Note that offsets apply only to loaded modules. For modules explicitly defined in any given session, absolute line numbers are printed in the traceback.

Modules for Multivariate Random Sampling

For certain kinds of statistical simulations and Bayesian analyses, it is necessary to generate random samples of N observations from multivariate distributions in p variables. SAS/IML software provides the RANDGEN function for generating random samples from univariate distributions. However, the only subroutine for sampling from multivariate distributions is the VNORMAL call, which samples from multivariate normal distributions.

The typical method of generating a multivariate sample is to transform a sample from a related univariate distribution. Thus SAS/IML is a natural choice for generating samples from common multivariate distributions.

The SAS/IML function modules and associated multivariate distributions are as follows:

RANDDIRICHLET

generates a random sample from a Dirichlet distribution (a multivariate generalization of the beta distribution).

RANDMULTINOMIAL

generates a random sample from a multinomial distribution (a multivariate generalization of the binomial distribution).

RANDMVT

generates a random sample from a multivariate Student's t distribution.

RANDNORMAL

generates a random sample from a multivariate normal distribution.

RANDWISHART

generates a random sample from a Wishart distribution (a multivariate generalization of the gamma distribution).

All of the modules compute their results by using transformations of univariate random samples generated by the RANDGEN function. Thus you can use the RANDSEED subroutine to set the seed for the modules.

While you can currently sample from a multivariate normal distribution by using the built-in SAS/IML subroutine VNORMAL, VNORMAL does not use the random number seed set in RANDSEED. Thus, to ensure independence and reproducibility of random number streams, the RANDNORMAL function is provided in this package.

For an overview of multivariate sampling, see Gentle (2003).

Modules Reference

COLVEC Function

converts a matrix into a column vector

COLVEC(*matrix*) ;

where *matrix* is any $n \times m$ matrix.

The COLVEC function returns an $nm \times 1$ vector. It converts a matrix into a column vector in row-major order. The returned vector has 1 column and nm rows. The first m elements in the vector correspond to the first row of the input matrix, the next m elements correspond to the second row, and so on.

EXPMATRIX Function

computes the exponential of a matrix

EXPMATRIX(*matrix*);

where *matrix* is any $n \times n$ matrix.

Given a matrix A , the EXPMATRIX function returns an $n \times n$ matrix approximating $e^A = \sum_{k=0}^{\infty} \frac{A^k}{k!}$. The function uses a Padé approximation algorithm as presented in Golub and Van Loan (1989).

Note that this module does not exponentiate each entry of a matrix; for that, use the EXP function.

The following example demonstrates the EXPMATRIX function. For the matrix used in the example, e^{tA} is the matrix $\begin{pmatrix} e^t & te^t \\ 0 & e^t \end{pmatrix}$. Here is the code:

```
A = { 1 1, 0 1 };
t = 3;
X = ExpMatrix( t*A );
ExactAnswer = ( exp(t) || t*exp(t) ) //
( 0      || exp(t) );
print X, ExactAnswer;
```

The output from this code is

```

X
20.085537 60.256611
0 20.085537

EXACTANSWER
20.085537 60.256611
0 20.085537
```

GBXWHSKR Call

draws box-and-whiskers plots

RUN GBXWHSKR(*matrix*);

where *matrix* is any $n \times m$ matrix.

The GBXWHSKR module draws a box-and-whiskers plot for univariate numeric data contained in the specified *matrix*. The box outlines the quartile range, and the minimum, median, and maximum points are labeled on the plot. You cannot produce graphics until you invoke the CALL GSTART statement. The plot created by the GBXWHSKR module remains open for further additions until you specify the CALL

GCLOSE statement, which terminates the current graphics segment. The module source code can be edited for changes, such as adding viewports, text, or colors.

GPROBCNT Call

draws probability contours

RUN GPROBCNT(x , y , p);

The inputs to the GPROBCNT subroutine are as follows:

- x is any $n \times m$ matrix of x values.
- y is a corresponding $n \times m$ matrix of y values.
- p is an optional probability value matrix.

The GPROBCNT module draws one contour curve for each value in the matrix p , which must contain entries between zero and one. If you do not specify the matrix p , contours for the probability values of 0.5, 0.8, and 0.9 are drawn. You cannot produce graphics until you specify the CALL GSTART statement. The contour plot remains open for further additions until you specify the CALL GCLOSE statement, which terminates the current graphics segment. Note that this module cannot be used for general contour plots of three-dimensional data.

GXYPLOT Call

draws a scatter plot of any x - y data

RUN GXYPLOT(x , y);

The inputs to the GXYPLOT subroutine are as follows:

- x is any $n \times m$ matrix of x values.
- y is a corresponding $n \times m$ matrix of y values.

The GXYPLOT module draws a simple scatter plot of any numeric x - y data. Axes with labeled tickmarks are drawn as well. You cannot produce graphics until you specify the CALL GSTART statement. The plot remains open for further additions (such as a title and axis labels) until you specify the CALL GCLOSE statement, which terminates the current graphics segment. The module uses the GPOINT, GXAXIS, and GYAXIS calls to plot the points. The module source code can be edited to specify many of the options available for these calls.

MEDIAN Function

returns the median of numeric data

MEDIAN(*matrix*) ;

where *matrix* is any $n \times m$ matrix.

The MEDIAN function returns the median value for each column in the *matrix*. It computes the median of univariate numeric data contained in the specified *matrix*. When the number of data points is odd, it returns the middle element from the sorted order. When the number of data points is even, it returns the mean of the middle two elements. Missing values are ignored. If all values in a column are missing, the return value for that column is missing.

QUADREG Call

performs quadratic response surface regression

RUN QUADREG(*xopt*, *yopt*, *type*, *parms*, *x*, *y*) ;

The inputs to the GPROBCNT subroutine are as follows:

<i>xopt</i>	Is a returned value that contains $m \times 1$ critical factor values.
<i>yopt</i>	is a returned value that contains the critical response value.
<i>type</i>	is a returned character string that contains the solution type (maximum or minimum).
<i>parms</i>	is a returned value that contains the parameter estimates for the quadratic model.
<i>x</i>	is an $n \times m$ factor matrix, where m is the number of factor variables and n is the number of data points.
<i>y</i>	is an $n \times 1$ response vector.

The QUADREG module fits a regression model with a complete quadratic set of regressions across several factors. The estimated model parameters are divided into a vector of linear coefficients and a matrix of quadratic coefficients to obtain critical factor values that optimize the response. It further determines the type of the optima (maximum, minimum, or saddle point) by computing the eigenvalues of the estimated parameters.

QUARTILE Function

computes quartiles for any univariate numeric data

QUARTILE(*matrix*) ;

where *matrix* is any $n \times m$ matrix.

The QUARTILE function returns a 5×1 column vector for each column in the *matrix*. The column vector contains the minimum, lower quartile, median, upper quartile, and maximum values for the numeric data in the specified *matrix*. Missing values are ignored. If all values in a column are missing, the return values for that column are missing.

RANDDIRICHLET Function

generates a random sample from a Dirichlet distribution

RANDDIRICHLET(*N*, *Shape*);

The inputs are as follows:

N is the number of desired observations sampled from the distribution.

Shape is a $1 \times (p + 1)$ vector of shape parameters for the distribution, $\text{Shape}[i] > 0$.

The Dirichlet distribution is a multivariate generalization of the beta distribution. The RANDDIRICHLET function returns an $N \times p$ matrix that contains N random draws from the Dirichlet distribution.

If $X = \{X_1 X_2 \dots X_p\}$ with $\sum_{i=1}^p X_i < 1$ and $X_i > 0$ follows a Dirichlet distribution with shape parameter $\alpha = \{\alpha_1 \alpha_2 \dots \alpha_{p+1}\}$, then

- the probability density function for x is

$$f(x; \alpha) = \frac{\Gamma(\sum_{i=1}^{p+1} \alpha_i)}{\prod_{i=1}^{p+1} \Gamma(\alpha_i)} \prod_{i=1}^p x_i^{\alpha_i-1} (1 - x_1 - x_2 - \dots - x_p)^{\alpha_{p+1}-1}$$

- if $p = 1$, the probability distribution is a beta distribution.
- if $\alpha_0 = \sum_{i=1}^{p+1} \alpha_i$, then
 - the expected value of X_i is α_i / α_0 .
 - the variance of X_i is $\alpha_i (\alpha_0 - \alpha_i) / (\alpha_0^2 (\alpha_0 + 1))$.
 - the covariance of X_i and X_j is $-\alpha_i \alpha_j / (\alpha_0^2 (\alpha_0 + 1))$.

The following example generates 1000 samples from a two-dimensional Dirichlet distribution. Each row of the returned matrix *x* is a row vector sampled from the Dirichlet distribution. The example then computes the sample mean and covariance and compares them with the expected values. Here are the code and the output:

```
call randseed(1);
n = 1000;
Shape = {2, 1, 1};
x = RANDDIRICHLET(n, Shape);
Shape0 = sum(Shape);
d = nrow(Shape)-1;
s = Shape[1:d];
```

```

Mean = s`/Shape0;
Cov = -s*s` / (Shape0##2*(Shape0+1));
/* replace diagonal elements with variance */
Variance = s#(Shape0-s) / (Shape0##2*(Shape0+1));
do i = 1 to d;
    Cov[i,i] = Variance[i];
end;

SampleMean = x[:,];
n = nrow(x);
y = x - repeat( SampleMean, n );
SampleCov = y`*y / (n-1);
print SampleMean Mean, SampleCov Cov;

```

SampleMean		Mean	
0.4992449	0.2485677	0.5	0.25

SampleCov		Cov	
0.0502652	-0.026085	0.05	-0.025
-0.026085	0.0393922	-0.025	0.0375

For further details about sampling from the Dirichlet distribution, see Kotz, Balakrishnan, and Johnson (2000); Gentle (2003); or Devroye (1986).

RANDMULTINOMIAL Function

generates a random sample from a multinomial distribution

RANDMULTINOMIAL(*N*, *NumTrials*, *Prob*);

The inputs are as follows:

N is the number of desired observations sampled from the distribution.

NumTrials is the number of trials for each observation. $NumTrials[j] \geq 0$, for $j = 1 \dots p$.

Prob is a $1 \times p$ vector of probabilities with $0 < Prob[j] \leq 1$ and $\sum_{j=1}^p Prob[j] = 1$.

The multinomial distribution is a multivariate generalization of the binomial distribution. For each trial, $Prob[j]$ is the probability of event E_j , where the E_j are mutually exclusive and $\sum_{j=1}^p Prob[j] = 1$.

The RANDMULTINOMIAL function returns an $N \times p$ matrix that contains N observations of *NumTrials* random draws from the multinomial distribution. Each row of the resulting matrix is an integer vector $\{X_1 X_2 \dots X_p\}$ with $\sum X_j = NumTrials$. That is, for each row, X_j indicates how many times event E_j occurred in *NumTrials* trials.

If $X = \{X_1 X_2 \dots X_p\}$ follows a multinomial distribution with n trials and probabilities $\rho = \{\rho_1 \rho_2 \dots \rho_p\}$, then

- the probability density function for x is

$$f(x; n, \rho) = \frac{n!}{\prod_{i=1}^p x_i!} \prod_{i=1}^p \rho_i^{x_i}$$

- the expected value of X_i is $n\rho_i$.
- the variance of X_i is $n\rho_i(1 - \rho_i)$.
- the covariance of X_i with X_j is $-n\rho_i\rho_j$.
- if $p = 1$ then X is constant.
- if $p = 2$ then X_1 is Binomial(n, ρ_1) and X_2 is Binomial(n, ρ_2).

The following example generates 1000 samples from a multinomial distribution with three mutually exclusive events. For each sample, 10 events are generated. Each row of the returned matrix x represents the number of times each event was observed. The example then computes the sample mean and covariance and compares them with the expected values. Here are the code and the output:

```
call randseed(1);
prob = {0.3,0.6,0.1};
NumTrials = 10;
N = 1000;
x = RANDMULTINOMIAL(N,NumTrials,prob);

/* population mean and covariance */
Mean = NumTrials * prob;
Cov = -NumTrials*prob*prob;
/* replace diagonal elements of Cov with Variance */
Variance = NumTrials*prob#(1-prob);
do i = 1 to nrow(prob);
    Cov[i,i] = Variance[i];
end;

SampleMean = mean(x);
SampleCov = cov(x);
print SampleMean Mean, SampleCov Cov;
```

SampleMean			Mean		
2.971	5.972	1.057	3	6	1

SampleCov			Cov		
2.0622212	-1.746559	-0.315663	2.1	-1.8	-0.3
-1.746559	2.3775936	-0.631035	-1.8	2.4	-0.6
-0.315663	-0.631035	0.9466977	-0.3	-0.6	0.9

For further details about sampling from the multinomial distribution, see Gentle (2003), or Fishman (1996).

RANDMVT Function

generates a random sample from a multivariate Student's t distribution

RANDMVT(N , DF , $Mean$, Cov);

The inputs are as follows:

- N is the number of desired observations sampled from the multivariate Student's t distribution.
- DF is a scalar value that represents the degrees of freedom for the t distribution.
- $Mean$ is a $1 \times p$ vector of means.
- Cov is a $p \times p$ symmetric positive definite variance-covariance matrix.

The RANDMVT function returns an $N \times p$ matrix that contains N random draws from the Student's t distribution with DF degrees of freedom, mean vector $Mean$, and covariance matrix Cov .

If X follows a multivariate t distribution with ν degrees of freedom, mean vector μ , and variance-covariance matrix Σ , then

- the probability density function for x is

$$f(x; \nu, \mu, \Sigma) = \frac{\Gamma((\nu + p)/2)}{|\Sigma|^{1/2} (\pi \nu)^{p/2} \Gamma(\nu/2)} \left(1 + \frac{(x - \mu) \Sigma^{-1} (x - \mu)^T}{\nu} \right)^{-(\nu + p)/2}$$

- if $p = 1$, the probability density function reduces to a univariate Student's t distribution.
- the expected value of X_i is μ_i .
- the covariance of X_i and X_j is $\frac{\nu}{\nu - 2} \Sigma_{ij}$ when $\nu > 2$.

The following example generates 1000 samples from a two-dimensional t distribution with 7 degrees of freedom, mean vector (1 2), and covariance matrix S. Each row of the returned matrix x is a row vector sampled from the t distribution. The example then computes the sample mean and covariance and compares them with the expected values. Here are the code and the output:

```
call randseed(1);
N = 1000;
DF = 4;
Mean = {1 2};
S = {1 1, 1 5};
x = RandMVT( N, DF, Mean, S );
SampleMean = x[:,];
y = x - SampleMean;
SampleCov = y`*y / (n-1);
Cov = (DF/(DF-2)) * S;
print SampleMean Mean, SampleCov Cov;
```

SampleMean

Mean

1.0768636	2.0893911	1	2
SampleCov		Cov	
1.8067811	1.8413406	2	2
1.8413406	9.7900638	2	10

In the preceding example, the columns (marginals) of x do *not* follow univariate t distributions. If you want a sample whose marginals are univariate t , then you need to scale each column of the output matrix:

```
x = RandMVT( N, DF, Mean, S );
StdX = x / sqrt(diag(S)); /* StdX columns are univariate t */
```

Equivalently, you can generate samples whose marginals are univariate t by passing in a correlation matrix instead of a general covariance matrix.

For further details about sampling from the multivariate t distribution, see Kotz and Nadarajah (2004).

RANDNORMAL Function

generates a random sample from a multivariate normal distribution

```
RANDNORMAL( N, Mean, Cov );
```

The inputs are as follows:

- N is the number of desired observations sampled from the multivariate normal distribution.
- $Mean$ is a $1 \times p$ vector of means.
- Cov is a $p \times p$ symmetric positive definite variance-covariance matrix.

The RANDNORMAL function returns an $N \times p$ matrix that contains N random draws from the multivariate normal distribution with mean vector $Mean$ and covariance matrix Cov .

If X follows a multivariate normal distribution with mean vector μ and variance-covariance matrix Σ , then

- the probability density function for x is

$$f(x; \mu, \Sigma) = \frac{1}{(2\pi)^{p/2} |\Sigma|^{1/2}} \exp \left(-\frac{(x - \mu) \Sigma^{-1} (x - \mu)^T}{2} \right)$$

- if $p = 1$, the probability density function reduces to a univariate normal distribution.
- the expected value of X_i is μ_i .
- the covariance of X_i and X_j is Σ_{ij} .

The following example generates 1000 samples from a two-dimensional multivariate normal distribution with mean vector (1 2) and a given covariance matrix. Each row of the returned matrix `x` is a row vector sampled from the multivariate normal distribution. The example then computes the sample mean and covariance and compares them with the expected values. Here are the code and the output:

```
call randseed(1);
N = 1000;
Mean = {1 2};
Cov = {2.4 3, 3 8.1};

x = RANDNORMAL( N, Mean, Cov );
SampleMean = x[:,];
y = x - SampleMean;
SampleCov = y`*y / (N-1);
print SampleMean Mean, SampleCov Cov;
```

SampleMean		Mean	
1.0619604	2.1156084	1	2

SampleCov		Cov	
2.5513518	3.2729559	2.4	3
3.2729559	8.7099585	3	8.1

For further details about sampling from the multivariate normal distribution, see Gentle (2003).

RANDWISHART Function

generates a random sample from a Wishart distribution

RANDWISHART(*N*, *DF*, *Sigma*);

The inputs are as follows:

- N* is the number of desired observations sampled from the distribution.
- DF* is a scalar value that represents the degrees of freedom, $DF \geq p$.
- Sigma* is a $p \times p$ symmetric positive definite matrix.

The RANDWISHART function returns an $N \times (p \times p)$ matrix that contains N random draws from the Wishart distribution with DF degrees of freedom. Each row of the returned matrix represents a $p \times p$ matrix.

The Wishart distribution is a multivariate generalization of the gamma distribution. (Note, however, that Kotz, Balakrishnan, and Johnson (2000) suggest that the term “multivariate gamma distribution” should be restricted to those distributions for which the marginal distributions are univariate gamma. This is not

the case with the Wishart distribution.) A Wishart distribution is a probability distribution for nonnegative definite matrix-valued random variables. These distributions are often used to estimate covariance matrices.

If a $p \times p$ nonnegative definite matrix X follows a Wishart distribution with parameters ν degrees of freedom and a $p \times p$ symmetric positive definite matrix Σ , then

- the probability density function for x is

$$f(x; \nu, \Sigma) = \frac{|x|^{(\nu-p-1)/2} \exp(-\frac{1}{2} \text{trace}(x \Sigma^{-1}))}{2^{\nu p/2} |\Sigma|^{\nu/2} \pi^{p(p-1)/4} \prod_{i=1}^p \Gamma(\frac{\nu-i+1}{2})}$$

- if $p = 1$ and $\Sigma = 1$, then the Wishart distribution reduces to a chi-square distribution with ν degrees of freedom.
- the expected value of X is $\nu \Sigma$.

The following example generates 1000 samples from a Wishart distribution with 7 degrees of freedom and 2×2 matrix parameter S . Each row of the returned matrix x represents a 2×2 nonnegative definite matrix. (You can reshape the i th row of x with the SHAPE function.) The example then computes the sample mean and compares them with the expected value. Here are the code and the output:

```
call randseed(1);
N=1000;
DF = 7;
S = {1 1, 1 5};
x = RandWishart( N, DF, S );
Mean = DF * S;
SampleMean = shape( x[:,], 2, 2);
print SampleMean Mean;
```

SampleMean		Mean	
7.0518633	7.2402925	7	7
7.2402925	36.056848	7	35

For further details about sampling from the Wishart distribution, see Johnson (1987).

REGRESS Call

performs regression analysis

RUN REGRESS(x , y , $name$, $\langle tval \rangle$, $\langle l1 \rangle$, $\langle l2 \rangle$, $\langle l3 \rangle$);

The inputs to the REGRESS subroutine are as follows:

x is an $n \times m$ numeric matrix, where m is the number of variables and n is the number of data points.

y	is an $n \times 1$ response vector.
$name$	is an $m \times 1$ matrix of variable names.
$tval$	is an optional t -value.
$l1, l2, l3$	are optional $1 \times m$ vectors that specify linear combinations of coefficients for hypothesis testing.

The REGRESS module does regression analysis and prints results. The design matrix is given by x , and y is the response vector. The $name$ vector identifies each of the variables. If you specify a t -value, the module prints a table of observed and predicted values, residuals, hat diagonal, and confidence limits for the mean and predicted values. If you also specify linear combinations with $l1$, $l2$, and $l3$, the module performs the hypothesis test $\mathbf{H} : l'b = 0$, where b is the vector of parameter estimates.

ROWVEC Function

converts a matrix into a row vector

ROWVEC($matrix$);

where $matrix$ is any $n \times m$ matrix.

The ROWVEC function returns a $1 \times nm$ vector. The specified $matrix$ is converted into a row vector in row-major order. The returned vector has 1 row and nm columns. The first n elements in the vector correspond to the first row of the input matrix, the next n elements correspond to the second row, and so on.

RSUBSTR Function

replaces substrings in each entry of a given matrix

RSUBSTR(x, p, l, r);

The inputs to the RSUBSTR subroutine are as follows:

x	is any $m \times n$ character matrix.
p	is an $m \times n$ matrix or a scalar that determines the starting positions for substrings to be replaced.
l	is an $m \times n$ matrix or a scalar that determines the lengths of substrings to be replaced.
r	is an $m \times n$ matrix or a scalar that specifies the replacement strings.

The RSUBSTR function returns an $m \times n$ matrix with substrings replaced. It replaces or substitutes substrings of the input matrix with new strings. If l is zero, the replacement string in r is simply inserted into the input matrix x at the position indicated by p .

For example, the following statements replace the first two characters of each entry in the matrix X with the corresponding entry in the matrix R:


```

proc iml;
  x = {abc def ghi, jkl mno pqr};
  r = {z y x, w v u};
  p = 1;
  l = 2;
  c=rsubstr(x,p,l,r);
  print x;
  print c;

```

STANDARD Function

standardizes numeric data

STANDARD(*matrix*);

where *matrix* is any $n \times m$ matrix, n is the number of data points, and m is the number of variables.

The STANDARD function returns a standardized $n \times m$ matrix. It standardizes each column of the input matrix, so that the mean of each column is zero and the standard deviation for each column is one.

TABPRT Call

prints matrices in tabular format

RUN TABPRT(*matrix*);

where *matrix* is any $n \times m$ matrix.

The TABPRT module prints any numeric or character matrix in table format. The regular PRINT command output is often difficult to read, especially for large matrices, where individual rows can wrap around. The module source code can be edited for further cosmetic changes, such as alternative format or field width, or for assigning specific row and column labels.

References

- Devroye, L. (1986), *Nonuniform Random Variate Generation*, New York: Springer-Verlag.
- Fishman, G. S. (1996), *Monte Carlo: Concepts, Algorithms, and Applications*, New York: John Wiley & Sons.
- Gentle, J. E. (2003), *Random Number Generation and Monte Carlo Methods*, Second Edition, Berlin: Springer-Verlag.
- Golub, G. H. and Van Loan, C. F. (1989), *Matrix Computations*, Second Edition, Baltimore: Johns Hopkins University Press.

Johnson, M. (1987), *Multivariate Statistical Simulation*, New York: John Wiley & Sons.

Kotz, S., Balakrishnan, N., and Johnson, N. L. (2000), *Continuous Multivariate Distributions, Second Edition*, Wiley-Interscience.

Kotz, S. and Nadarajah, S. (2004), *Multivariate t Distributions and Their Applications*, Cambridge University Press.

Subject Index

A

- ABORT statement
 - exiting PROC IML, [583](#)
- ABS function
 - absolute value, [583](#)
- ADDITION operator
 - adds corresponding matrix elements, [563](#)
- ALL function
 - checking for nonzero elements, [584](#)
- ALLCOMB function
 - generate combinations, [584](#)
- ALLPERM function
 - generate permutations, [586](#)
- ANY function
 - checking for nonzero elements, [587](#)
- APPEND statement
 - SAS data sets, [589](#)
- APPLY function, [592](#)
- ARMACOV call
 - autocovariance sequence, [594](#)
- ARMALIK call
 - log likelihood and residuals, [595](#)
- ARMASIM function
 - simulating univariate ARMA series, [597](#)

B

- Basic time series analysis
 - autocovariance function of ARMA model, [253](#)
 - example, [251](#)
 - generating an ARMA process, [253](#)
 - log-likelihood function of ARMA model, [253](#)
 - overview, [250](#)
- Bessel function
 - finding nonzero roots and derivatives of, [747](#), [748](#)
- Biconjugate Gradient Algorithm, [529](#), [534](#)
- BIN function
 - dividing numeric values into bins, [598](#)
- BLOCK function
 - forming block-diagonal matrices, [600](#)
- Box-and-whiskers plots, [1070](#)
- BRANKS function
 - computing bivariate ranks, [601](#)
- BSPLINE function
 - computing B-spline basis, [602](#)
- BTRAN function

- computing the block transpose, [604](#)

- BYTE function
 - returning values in a computer's character set, [605](#)

C

- CALL statement
 - calling a subroutine or function, [606](#)
- Calling External Modules, [563](#)
- Calling R, [563](#)
- Calling SAS, [563](#)
- CHANGE call
 - replacing text in an array, [607](#)
- CHAR function
 - character representation of a numeric matrix, [607](#)
- Character Manipulation Functions, [553](#)
- CHOOSE function
 - choosing and changing elements, [608](#)
- CLOSE statement
 - closing SAS data sets, [609](#)
- CLOSEFILE statement
 - closing a file, [610](#)
- COMPARISON operator
 - compare matrix elements, [564](#)
- CONCAT function
 - performing elementwise string concatenation, [614](#)
- CONCATENATION operator, horizontal
 - concatenates matrices horizontally, [566](#)
- CONCATENATION operator, vertical
 - concatenates matrices vertically, [567](#)
- Conjugate Gradient Algorithm, [529](#), [531](#)
- CONTENTS function
 - obtaining the variables in SAS data sets, [615](#)
- Control Statements, [559](#)
- CONVEXIT function
 - calculating convexity of noncontingent cash flows, [616](#)
- CORR function
 - computing sample correlations, [616](#)
- COUNTMISS function
 - counting missing values, [618](#)
- COUNTN function
 - counting nonmissing values, [619](#)
- COUNTUNIQUE function
 - counting unique values, [620](#)
- COV function

- computing sample covariances, 621
- COVLAGE function
 - computing autocovariance estimates, 622
- CREATE statement
 - creating new SAS data sets, 623
- CSHAPE function
 - reshaping and repeating character values, 626
- CUPROD function
 - calculating cumulative products, 628
- CUSUM function
 - calculating cumulative sums, 628
- CVEXHULL function
 - finding a convex hull, 629
- D**
- Dataset and File Functions, 560
- DATASETS function
 - obtaining names of SAS data sets, 630
- DELETE call
 - deleting SAS data sets, 630
- DELETE statement
 - marking observations for deletion, 631
- DESIGN function
 - creating a design matrix, 633
- DESIGNF function
 - creating a full-rank design matrix, 634
- DET function
 - computing determinants of a square matrix, 635
- DIAG function
 - creating a diagonal matrix, 635
- DIF function
 - computing difference of lagged values, 636
- DIRECT PRODUCT operator
 - takes the direct product of two matrices, 568
- DISPLAY statement
 - displaying fields in display windows, 637
- DIVISION operator
 - performs elementwise division, 569
- DO DATA statement
 - repeating a loop until, 640
- DO function
 - producing an arithmetic sequence, 638
- DO statement
 - DATA clause, 640
 - grouping statements as a unit, 638
 - UNTIL clause, 641
 - WHILE clause, 642
- DO statement, iterative
 - iteratively executing a DO group, 639
- DO UNTIL statement
 - conditionally executing statements iteratively, 641
- DO WHILE statement

- conditionally executing statements iteratively, 642
- DURATION function
 - calculating modified duration of noncontingent cash flows, 643
- E**
- ECHELON function
 - reducing a matrix to row-echelon normal form, 644
- EDIT statement
 - opening a SAS data set for editing, 644
- EIGEN call
 - computing eigenvalues and eigenvectors, 647
- Eigenvalue Decomposition
 - compared with ODE call, 862
- EIGVAL function
 - computing eigenvalues, 651
- EIGVEC function
 - computing right eigenvectors, 651
- ELEMENT function
 - finding elements that are contained in a set, 652
- ELEMENT MAXIMUM operator
 - selects the larger of two elements, 570
- ELEMENT MINIMUM operator
 - selects the smaller of two elements, 571
- END statement
 - ending a DO loop or DO statement, 653
- ENDSUBMIT statement, 180
- EXECUTE call
 - executing statements immediately, 653
- EXP function
 - calculating the exponential, 654
- Exponential of a matrix, 1070
- ExportDataSetToR subroutine, 193
- ExportMatrixToR subroutine, 193
- F**
- FARMACOV call
 - generating an ARFIMA(p, d, q) process, 657
- FARMAFIT call
 - estimation of an ARFIMA(p, d, q) model, 658
- FARMALIK call
 - computing the log-likelihood for an ARFIMA(p, d, q) model, 660
- FARMASIM call
 - generating an ARFIMA(p, d, q) process, 661
- FDIF call
 - computing a fractionally differenced process, 663
- FFT function
 - computing the finite Fourier transform, 664

FILE statement
 opening or pointing to an external file, 666
 FIND statement
 finding observations, 667
 FINISH statement
 denoting the end of a module, 669
 Forward rates, 669
 Fractionally integrated time series analysis
 ARFIMA modeling, 331
 autocovariance function, 331
 example, 328
 fractional differencing, 331
 generating a fractional time series, 331
 log-likelihood function, 331
 overview, 327
 FREE statement
 freeing matrix storage space, 670
 FULL function
 converting sparse to dense storage, 671

G

GAEND call
 ending a genetic algorithm optimization, 672
 GAGETMEM call
 getting current members of the solution
 population for a genetic algorithm
 optimization, 672
 GAGETVAL call
 getting current solution objective function values
 for a genetic algorithm optimization, 673
 GAINIT call
 creating an initial solution population for a
 genetic algorithm optimization, 674
 GAREEVAL call
 reevaluating the objective function values for a
 solution population of a genetic algorithm
 optimization, 675
 GAREGEN call
 regenerating a solution population by application
 of selection and genetic operators, 675
 GASETCRO call
 setting the crossover operator for a genetic
 algorithm optimization, 676
 GASETMUT call
 setting the mutation operator for a genetic
 algorithm optimization, 680
 GASETOBJ call
 setting the objective function for a genetic
 algorithm optimization, 681
 GASETSEL call
 setting the selection parameters for a genetic
 algorithm optimization, 682
 GASETUP function
 setting up a genetic algorithm optimization
 problem, 683
 GBLKVP call
 defining a blanking viewport, 686
 GBLKVPD call
 deleting the blanking viewport, 686
 GCLOSE call
 closing the graphics segment, 687
 GDELETE call
 deleting a graphics segment, 687
 GDRAW call
 drawing a polyline, 687
 GDRAWL call
 drawing individual lines, 688
 GENEIG call
 generalized eigenproblems, 689
 Genetic Algorithm Functions, 562
 GEOMEAN function
 computes geometric means, 690
 GGRID call
 drawing a grid, 691
 GINCLUDE call
 including graphics segments, 692
 GINV function
 computing generalized inverses, 692
 GOPEN call
 opening graphics segments, 694
 GOTO statement
 jumping to a new statement, 695
 GPIE call
 drawing pie slices, 696
 GPIEXY call
 converting coordinates, 697
 GPOINT call
 plotting points, 698
 GPOLY call
 drawing and filling a polygon, 699
 GPORT call
 defining a viewport, 700
 GPORTPOP call
 popping viewports, 700
 GPORTSTK call
 stacking viewports, 701
 Graphics and Window Functions, 561
 GSCALE call
 calculating round numbers for labeling axes, 701
 GSCRIPT call
 writing multiple text strings, 702
 GSET call
 setting attributes for graphics segments, 703
 GSHOW call
 showing a graph, 704
 GSORTH call

- computing the Gram-Schmidt orthonormalization, 704
- GSTART call
 - initializing the graphics system, 706
- GSTOP call
 - deactivating the graphics system, 707
- GSTRLEN call
 - finding the string length, 707
- GTEXT and GVTEXT calls
 - placing text on a graph, 708
- GWINDOW call
 - defining the data window, 709
- GXAXIS and GYAXIS calls
 - drawing an axis, 709
- H**
- HADAMARD function, 711
- HALF function
 - computing Cholesky decomposition, 712
- HANKEL function
 - generating a Hankel matrix, 712
- HARMEAN function
 - computes harmonic means, 714
- HDIR function
 - performing a horizontal direct product, 714
- HERMITE function
 - reducing a matrix to Hermite normal form, 715
- HOMOGEN function
 - solving homogeneous linear systems, 716
- I**
- I function
 - creating an identity matrix, 717
- IF-THEN/ELSE statement
 - conditionally executing statements, 717
- IFFT function
 - computing the inverse finite Fourier transform, 719
- IMLMLIB Module Library
 - modules reference, 1069, 1071–1075, 1077, 1078, 1080, 1081
 - overview, 1065–1067
- ImportDataSetFromR subroutine, 193
- ImportMatrixFromR subroutine, 193
- INDEX CREATION operator
 - creates an index vector, 572
- INDEX statement
 - indexing a variable in a SAS data set, 723
- INFILE statement
 - opening a file for input, 724
- INPUT statement
 - inputting data, 725

- INSERT function
 - inserting one matrix inside another, 726
- INT function
 - truncating a value, 727
- INV function
 - computing a matrix inverse, 728
- Inverses
 - Moore-Penrose inverse, 612, 940, 946–948
- INVUPDT function
 - updating a matrix inverse, 729
- IPF call
 - performing an iterative proportional fit, 731
- ISM TIMSAC packages, 301, 302
- Iterative Algorithm, 743
- ITSOLVER call
 - solving a sparse linear system by using iterative methods, 743

J

- J function
 - creating a matrix of identical values, 747

K

- Kalman filter subroutines
 - covariance filtering and prediction, 310
 - diffuse covariance filtering and prediction, 310
 - diffuse fixed-interval smoothing, 310
 - examples, 310
 - fixed-interval smoothing, 310
 - one-step forecast for SSM, 755
 - one-step predictions, 749, 752
 - overview, 308
 - smoothed estimate, 752
 - smoothed state vectors, 758
 - syntax, 749
- KRONECKER product
 - takes the direct product of two matrices, 568

L

- LABEL
 - quadratic form maximization, 803
- LAG function
 - computing lagged values, 760
- LCP call
 - solving the linear complementarity problem, 765
- Least absolute value regression, 760, 762, 763
- LENGTH function
 - finding the lengths of character matrix elements, 768
- Linear Algebra Functions, 557
- Linear least squares

- full-rank example, 895, 896
- QR decomposition, 922
- rank-deficient solutions, 940, 942–945
- LINK statement
 - jumping to another statement, 769
- LIST statement
 - displaying observations of a data set, 769
- LMS call
 - performing robust regression, 772
- LOAD statement
 - loading modules and matrices, 783
- LOC function
 - finding nonzero elements of a matrix, 784
- LOG function
 - taking the natural logarithm, 785
- LOGICAL operator
 - perform elementwise logical comparisons, 573
- LP call
 - solving the linear programming problem, 785
- LTS call
 - performs robust regression, 787
- LUPDT call, 795
- M**
- MAD function
 - univariate median absolute deviation, 796
- MARG call
 - evaluating marginal totals, 798
- Matrix decomposition
 - Cholesky decomposition, 940–942
 - complete orthogonal decomposition, 587, 611
 - downdating and updating, 921–923, 940
 - QR decomposition, 875, 876, 879, 891–896
- Matrix Inquiry Functions, 552
- Matrix Reshaping Functions, 553
- Matrix Sorting And By-Group Processing Functions, 553
- MATTRIB statement
 - associating printing attributes with matrices, 801
- MAX function
 - finding the maximum value of matrix, 802
- MCD call, 805
- MEAN function
 - computing sample means, 810
- Median computation, 1072
- MIN function
 - finding the smallest element of a matrix, 812
- Minimum Residual Algorithm, 529, 533
- MOD function
 - computing the modulo (remainder), 813
- MODULEI call, 813
- MODULEIC function
 - calling an external function, 814

- MODULEIN function
 - calling an external function, 814
- MULTIPLICATION operator, elementwise
 - performs elementwise multiplication, 574
- MULTIPLICATION operator, matrix
 - performs matrix multiplication, 576
- Multivariate sampling, 1073, 1074, 1076–1078
- MVE call, 815
- N**
- NAME function
 - listing the names of arguments, 821
- NCOL function
 - finding the number of columns of a matrix, 822
- NLENG function
 - finding the size of an element, 822
- Nonlinear optimization subroutines
 - advanced examples, 370
 - conjugate gradient optimization, 826
 - control parameters vector, 367–369
 - double-dogleg optimization, 826–828
 - feasible point computation, 832
 - finite difference approximations, 829, 830, 832
 - finite-difference approximations, 352, 353
 - global vs. local optima, 344, 345
 - hybrid quasi-Newton optimization, 833, 834, 836
 - Kuhn-Tucker conditions, 346
 - least squares methods, 833, 834, 836, 837
 - Levenberg-Marquardt optimization, 836, 837
 - Nelder-Mead simplex optimization, 837, 838, 841
 - Newton-Raphson optimization, 841, 842, 844
 - Newton-Raphson ridge optimization, 844, 846
 - objective function and derivatives, 347–352
 - options vector, 356–360
 - parameter constraints, 354–356
 - printing optimization history, 369, 370
 - quadratic optimization, 851, 852, 855
 - quasi-Newton optimization, 847, 848, 850, 851
 - return codes, 346
 - termination criteria, 360, 362, 364–366
 - trust-region optimization, 855, 856
- NORMAL function
 - generating a pseudorandom normal deviate, 856
- NROW function
 - finding the number of rows of a matrix, 856
- NUM function
 - producing a numeric representation of a character matrix, 857
- Numerical Analysis Functions, 557
- Numerical integration, 896–900, 902
 - adaptive Romberg method, 897

of differential equations, 857, 858, 860, 861,
863, 864
specifying subintervals, 896
two-dimensional integration, 900

O

ODSGRAPH call, 864
OPSCAL Function, 867
Optimization Subroutines, 558
ORPOL function
 generating orthogonal polynomials, 869
Orthogonal factorization, 940–942
Orthogonalization
 by ORTVEC call, 875, 876, 879

P

PAUSE statement
 interrupting module execution, 879
percentiles, 890
PGRAPH call
 producing scatter plots, 880
POLYROOT function
 finding zeros of a real polynomial, 881
POWER operator, elementwise
 raises each element to a power, 576
POWER operator, matrix
 raises a matrix to a power, 577
PRINT statement
 printing matrix values, 881
Printing matrices, 1081
Probability contour plot, 1071
PROD function
 multiplying all elements, 883
PRODUCT function
 multiplying matrices of polynomials, 884
PURGE statement
 removing observations marked for deletion, 885
PUSH call, 886
PUT statement
 writing data to an external file, 887
PV function
 calculating present value, 888

Q

QNTL call
 computing sample quantiles, 890
Quadratic form maximization, 804, 805
quantiles, 890
Quartile computation, 1072
QUEUE call
 queuing SAS statements, 902

QUIT statement
 exiting from PROC IML, 903

R

R language, 189
RANCOMB function
 generate random combinations, 904
RANDGEN call
 generating random numbers, 905
Random multivariate sampling, 1073, 1074,
1076–1078
Random Number Generation, 554
RANDSEED call
 generating random numbers, 913
RANGE function
 finding the range of values, 914
RANK function
 ranking elements of a matrix, 914
RANKTIE function
 ranking elements of a matrix, 917
RANPERM function
 generate permutations, 912
RATES function
 converting interest rates, 919
RATIO function
 dividing matrix polynomials, 920
READ statement
 reading observations from a data set, 925
Reduction Functions, 552
Regression, 1079
 best subsets, 805
 least absolute value, 760, 762, 763
 response surface, 1072
REMOVE function
 discarding elements from a matrix, 928
REMOVE statement
 removing matrices from storage, 929
RENAME call
 renaming SAS data sets, 929
REPEAT function
 creating a new matrix of repeated values, 930
REPLACE statement
 replacing values, 930
RESET statement
 setting processing options, 933
Reshaping matrices, 1069, 1080
Response surface regression, 1072
RESUME statement
 resuming execution, 935
RETURN statement
 returning to caller, 936
ROOT function

- performing the Cholesky decomposition of a matrix, 936
- ROWCAT function
 - concatenating rows without blank compression, 937
- ROWCATC function
 - concatenating rows with blank compression, 938
- RUN statement
 - executing statements in a module, 939
- S**
- SAVE statement
 - saving data, 948
- Scalar Functions, 551
- Scatter plots, 1071
- Sequential tests, 948, 950–952, 954–958, 960
 - group sequential methods, 954, 955
 - minimizing average sample number (ASN), 958, 960
 - randomized clinical trials, 958, 960
 - scaling, 950
 - shifting, 951
- Set Functions, 559
- SETDIF function
 - comparing elements of two matrices, 961
- SETIN statement
 - making a data set current for input, 961
- SETOUT statement
 - making a data set current for output, 962
- SHAPE function
 - reshaping and repeating values, 962
- SHAPECOL function
 - reshaping and repeating values, 964
- SHOW statement
 - printing system information, 965
- SIGN REVERSE operator
 - reverses the signs of elements, 579
- SOLVE function
 - solving a system of linear equations, 965
- SOLVELIN call
 - solving a sparse symmetric linear system by direct decomposition, 966
- SORT call
 - sorting a matrix, 967
- SORT statement
 - sorting a SAS data set, 968
- SORTNDX call
 - creating a sorted index for a matrix, 969
- SOUND call
 - producing a tone, 970
- SPARSE function
 - converting dense to sparse storage, 971
- Sparse Matrix Algorithms, 529, 743
- preconditioners, 529, 966
- Splines, 972, 973, 977–979
 - integration of splines, 977
- SPOT function
 - calculating spot rates, 979
- SQRSYM function
 - converting to a square matrix, 980
- SQRT function
 - calculating the square root, 980
- SQRVECH function
 - converting to a square matrix, 981
- SSQ function
 - calculating the sum of squares, 981
- Standardizing numeric data, 1081
- START statement
 - defining a module, 982
- Statistical Functions, 554
- STD function
 - computing sample standard deviation, 983
- STOP statement
 - stopping execution of statements, 983
- STORAGE function
 - listing names of matrices and modules, 984
- STORE statement
 - storing matrices and modules, 984
- SUBMIT statement, 180
 - parameter substitution, 182, 196
 - R statements, 191
 - submit R statements, 985
 - submit SAS statements, 985
- SUBSCRIPTS
 - select submatrices, 579
- SUBSTR function
 - taking substrings of matrix elements, 987
- Substring replacement, 1080
- SUBTRACTION operator
 - subtracts corresponding matrix elements, 581
- SUM function
 - summing all elements, 987
- SUMMARY statement
 - computing summary statistics, 988
- SVD call
 - computing the singular value decomposition, 991
- SWEEP function
 - sweeping a matrix, 992
- SYMSQR function
 - converting to a symmetric matrix, 995
- T**
- T function
 - transposing a matrix, 995
- TABULATE call

- counting the number of elements in each category, 996
- Time series analysis and control
 - AR model selection, 255, 1016
 - ARMA model prediction, 277, 278, 1014
 - Bayesian constrained least squares, 296–298
 - Bayesian seasonal adjustment, 274, 285, 287, 1005, 1006
 - instantaneous response model, 259, 260, 304–306
 - ISM TIMSAC packages, 301, 302
 - least squares and Householder transformation, 295, 296
 - locally stationary multivariate time series, 1011, 1012
 - locally stationary time series, 1010, 1011
 - minimum AIC method, 255, 258–260, 282–284
 - missing values, 300
 - multivariate time series, 277, 278, 291, 292, 1014
 - nonstationary covariance function analysis, 1015
 - nonstationary data analysis, 261, 263, 265–268, 270, 272–274
 - nonstationary time series, 287–290, 1007, 1009, 1010
 - overview, 253
 - periodic AR model, 1013, 1014
 - roots of AR and MA equations, 280, 281, 1015
 - smoothness priors modeling, 284, 285, 1007, 1009, 1010
 - spectral analysis, 292–295
 - state space and Kalman filter method, 298–300
 - VAR model, 258–260, 304, 305, 1012, 1013
- Time Series Functions, 555
- TOEPLITZ function
 - generating a Toeplitz matrix, 997
- TPSPLINE call
 - computing thin-plate smoothing splines, 998
- TPSPLINEV call
 - evaluating thin-plate smoothing splines, 1000
- TRACE function
 - summing diagonal elements, 1003
- TRANPOSE operator
 - transposes a matrix, 582
- Triangular linear systems, 1004
- TYPE function
 - determining matrix types, 1017
- U
- UNIFORM function
 - generating pseudorandom uniform deviates, 1018
- UNION function
 - performing unions of sets, 1019
- UNIQUE function
 - sorting and removing duplicates, 1019
- UNIQUEBY function
 - processing BY groups in a matrix, 1019
- USE statement
 - opening SAS data sets, 1021
- V
- VALSET call
 - performing indirect assignments, 1023
- VALUE function
 - assigning values, 1024
- VAR Function
 - computing a sample variance, 1024
- VARMACOV Call
 - computing cross-covariance matrices, 1025
- VARMALIK Call
 - computing log-likelihood function, 1026
- VARMASIM Call
 - generating VARMA(p,q) time series, 1028
- VEC operator, 964
- VECDIAG function
 - creating vector from diagonal, 1029
- VECH function, 1029
- Vector time series analysis
 - cross-covariance matrix, 327
 - example, 322, 325
 - generating a multivariate normal, 327
 - generating a multivariate time series, 327
 - log-likelihood function, 327
 - overview, 322
 - roots of VARMA characteristic function, 327
- VNORMAL Call
 - generating multivariate normal random series, 1030
- VTSROOT Call
 - calculating characteristic roots, 1031
- W
- Wavelet Analysis Functions, 562
- WAVFT call
 - computing fast wavelet transform, 1032
- WAVGET call
 - extracting wavelet information, 1035
- WAVIFT call
 - computing inverse fast wavelet transform, 1036
- WAVPRINT call
 - printing wavelet information, 1038
- WAVTHRSH call
 - thresholding wavelet detail coefficients, 1039
- WINDOW statement

opening a display window, [1040](#)

X

XMULT function

performing extended-precision matrix
multiplication, [1042](#)

XSECT function

intersecting sets, [1043](#)

Y

YIELD function

calculating yield-to-maturity of a cash-flow
stream, [1043](#)

Syntax Index

A

- ABORT statement, 583
- ABS function, 583
- ADDITION operator, 563
- ALL function, 584
- ALLCOMB function, 584
- ALLPERM function, 586
- ANY function, 587
- APPCORT call, 587
- APPEND statement, 589
- APPLY function, 592
- ARMACOV call, 594
- ARMALIK call, 595
- ARMASIM function, 597

B

- Basic time series subroutines
 - ARMACOV subroutine, 253
 - ARMALIK subroutine, 253
 - ARMASIM function, 253
 - example, 251
 - overview, 250
 - syntax, 253
- BIN function, 598
- BLOCK function, 600
- BRANKS function, 601
- BSPLINE function, 602
- BTRAN function, 604
- BYTE function, 605

C

- CALL statement, 606
- CHANGE call, 607
- CHAR function, 607
- CHOOSE function, 608
- CLOSE statement, 609
- CLOSEFILE statement, 610
- COLVEC function, 1069
- COMPARISON operator, 564
- COMPORT call, 611
- CONCAT function, 614
- CONCATENATION operator, horizontal, 566
- CONCATENATION operator, vertical, 567
- CONTENTS function, 615
- CONVEXIT function, 616

- CORR function, 616
- COUNTMISS function, 618
- COUNTN function, 619
- COUNTUNIQUE function, 620
- COV function, 621
- COVLAG function, 622
- CREATE statement, 623
- CSHAPE function, 626
- CUPROD function, 628
- CUSUM function, 628
- CVEXHULL function, 629

D

- DATASETS function, 630
- DELETE call, 630
- DELETE statement, 631
- DESIGN function, 633
- DESIGNF function, 634
- DET function, 635
- DIAG function, 635
- DIF function, 636
- DIRECT PRODUCT operator, 568
- DISPLAY statement, 637
- DIVISION operator, 569
- DO DATA statement, 640
- DO function, 638
- DO statement, 638
- DO statement, iterative, 639
- DO UNTIL statement, 641
- DO WHILE statement, 642
- DURATION function, 643

E

- ECHELON function, 644
- EDIT statement, 644
- EIGEN call, 647
- EIGVAL function, 651
- EIGVEC function, 651
- ELEMENT function, 652
- ELEMENT MAXIMUM operator, 570
- ELEMENT MINIMUM operator, 571
- END statement, 653
- ENDSUBMIT statement, 653
- EXECUTE call, 653
- EXP function, 654
- EXPMATRIX function, 1070

EXPORTDATASET call, 655
 EXPORTMATRIX call, 656

F

FARMAOV call, 657
 FARMAFIT call, 658
 FARMALIK call, 660
 FARMASIM call, 661
 FDIF call, 663
 FFT function, 664
 FILE statement, 666
 FIND statement, 667
 FINISH statement, 669
 FORWARD function, 669
 Fractional time series subroutines
 syntax, 331
 Fractionally integrated time series subroutines
 example, 328
 FARMAOV subroutine, 331
 FARMAFIT subroutine, 331
 FARMALIK subroutine, 331
 FARMASIM subroutine, 331
 FDIF subroutine, 331
 overview, 327
 FREE statement, 670
 FULL function, 671

G

GAEND call, 672
 GAGETMEM call, 672
 GAGETVAL call, 673
 GAINIT call, 674
 GAREEVAL call, 675
 GAREGEN call, 675
 GASETCRO call, 676
 GASETMUT call, 680
 GASETOBJ call, 681
 GASETSEL call, 682
 GASETUP function, 683
 GBLKVP call, 686
 GBLKVPD call, 686
 GBXWSKR call, 1070
 GCLOSE call, 687
 GDELETE call, 687
 GDRAW call, 687
 GDRAWL call, 688
 GENEIG call, 689
 GEOMEAN function, 690
 GGRID call, 691
 GINCLUDE call, 692
 GINV function, 692
 GOPEN call, 694

GOTO statement, 695
 GPIE call, 696
 GPIEXY call, 697
 GPOINT call, 698
 GPOLY call, 699
 GPORT call, 700
 GPORTPOP call, 700
 GPORTSTK call, 701
 GPROBCNT call, 1071
 GSCALE call, 701
 GSCRIPT call, 702
 GSET call, 703
 GSHOW call, 704
 GSORTH call, 704
 GSTART call, 706
 GSTOP call, 707
 GSTRLEN call, 707
 GTEXT and GVTEXT calls, 708
 GWINDOW call, 709
 GXAXIS and GYAXIS calls, 709
 GXYPLOT call, 1071

H

HADAMARD function, 711
 HALF function, 712
 HANKEL function, 712
 HARMEAN function, 714
 HDIR function, 714
 HERMITE function, 715
 HOMOGEN function, 716

I

I function, 717
 IF-THEN/ELSE statement, 717
 IFFT function, 719
 IMLMLIB Module Library
 modules reference, 1069, 1071–1075, 1077,
 1078, 1080, 1081
 overview, 1065–1067
 IMPORTDATASETFROMR call, 720
 IMPORTMATRIXFROMR call, 722
 INDEX CREATION operator, 572
 INDEX statement, 723
 INFILE statement, 724
 INPUT statement, 725
 INSERT function, 726
 INT function, 727
 INV function, 728
 INVUPDT function, 729
 IPF call, 731
 ITSOLVER call, 743

J

J function, 747
JROOT function, 747, 748

K

KALCVF call, 311, 318, 320, 749, 752
KALCVS call, 752
KALDFF call, 320, 755
KALDFS call, 758
Kalman filter subroutines
 examples, 310
 KALCVF subroutine, 310
 KALCVS subroutine, 310
 KALDFF subroutine, 310
 KALDFS subroutine, 310
 overview, 308
 syntax, 310, 749
KRONECKER product, 568

L

LAG function, 760
LAV call, 760, 762, 763
LCP call, 765
LENGTH function, 768
LINK statement, 769
LIST statement, 769
LMS call, 772
LOAD statement, 783
LOC function, 784
LOG function, 785
LOGICAL operator, 573
LP call, 785
LTS call, 787
LUPDT call, 795

M

MAD function, 796
MARG call, 798
MATTRIB statement, 801
MAX function, 802
MAXQFORM call, 803–805
MCD call, 805
MEAN function, 810
MEDIAN function, 1072
MIN function, 812
MOD function, 813
MODULEI call, 813
MODULEIC function, 814
MODULEIN function, 814
MULTIPLICATION operator, elementwise, 574
MULTIPLICATION operator, matrix, 576
MVE call, 815

N

NAME function, 821
NCOL function, 822
NLENG function, 822
Nonlinear optimization subroutines
 advanced examples, 370
 details, 344
 introductory examples, 337
 NLPCG Call, 376
 NLPCG call, 826
 NLPDD Call, 380, 383, 400, 827, 828
 NLPDD call, 826
 NLPFDD Call, 390, 829, 832
 NLPFDD call, 829, 830
 NLPFEA call, 832
 NLPHQN Call, 834, 836
 NLPHQN call, 833
 NLPLM Call, 392, 836, 837
 NLPLM call, 836
 NLPNMS Call, 838, 841
 NLPNMS call, 837, 838
 NLPNRA Call, 842, 844
 NLPNRA call, 841
 NLPNRR Call, 377, 846
 NLPNRR call, 844
 NLPQN Call, 386, 387, 404, 848, 850, 851
 NLPQN call, 847
 NLPQUA Call, 852, 855
 NLPQUA call, 851
 NLPTR Call, 372, 389, 856
 NLPTR call, 855
 overview, 335
 syntax, 823
NORMAL function, 856
NROW function, 856
NUM function, 857

O

ODE call, 857, 858, 860, 861, 863, 864
ODSGRAPH call, 864
OK= option
 SUBMIT statement, 985
OPSCAL function, 867
ORPOL function, 869
ORTVEC call, 875, 876, 879

P

PAUSE statement, 879
PGRAF call, 880
POLYROOT function, 881
POWER operator, elementwise, 576

POWER operator, matrix, 577
 PRINT statement, 881
 PROC IML Statement, 12, 537
 PROD function, 883
 PRODUCT function, 884
 PURGE statement, 885
 PUSH call, 886
 PUT statement, 887
 PV function, 888

Q

QNTL call, 890
 QR call, 891–896
 QUAD call, 896–900, 902
 QUADREG call, 1072
 QUARTILE function, 1072
 QUEUE call, 902
 QUIT statement, 903

R

R option
 SUBMIT statement, 985
 RANCOMB function, 904
 RANDDIRICHLET function, 1073
 RANDGEN call, 905
 RANDMULTINOMIAL function, 1074
 RANDMVT function, 1076
 RANDNORMAL function, 1077
 RANDSEED call, 913
 RANDWISHART function, 1078
 RANGE function, 914
 RANK function, 914
 RANKTIE function, 917
 RANPERM function, 912
 RATES function, 919
 RATIO function, 920
 RDODT call, 921–923
 READ statement, 925
 REGRESS call, 1079
 REMOVE function, 928
 REMOVE statement, 929
 RENAME call, 929
 REPEAT function, 930
 REPLACE statement, 930
 RESET statement, 933
 RESUME statement, 935
 RETURN statement, 936
 ROOT function, 936
 ROWCAT function, 937
 ROWCATC function, 938
 ROWVEC function, 1080
 RSUBSTR function, 1080

RUN statement, 939
 RUPDT call, 921–923, 940
 RZLIND call, 940–948

S

SAVE statement, 948
 SEQ call, 948, 950–952, 954–958, 960
 SEQSCALE call, 948, 950–952, 954–958, 960
 SEQSHIFT call, 948, 950–952, 954–958, 960
 SETDIF function, 961
 SETIN statement, 961
 SETOUT statement, 962
 SHAPE function, 962
 SHAPECOL function, 964
 SHOW statement, 965
 SIGN REVERSE operator, 579
 SOLVE function, 965
 SOLVELIN call, 966
 SORT call, 967
 SORT statement, 968
 SORTNDX call, 969
 SOUND call, 970
 SPARSE function, 971
 SPLINE call, 972, 973, 977, 978
 SPLINEC call, 972, 973, 977, 978
 SPLINEV function, 973, 977–979
 SPOT function, 979
 SQRSYM function, 980
 SQRT function, 980
 SQRVECH function, 981
 SSQ function, 981
 STANDARD function, 1081
 START statement, 982
 STD function, 983
 STOP statement, 983
 STORAGE function, 984
 STORE statement, 984
 SUBMIT statement, 985
 OK= option, 985
 R option, 985
 SUBSCRIPTS, 579
 SUBSTR function, 987
 SUBTRACTION operator, 581
 SUM function, 987
 SUMMARY statement, 988
 SVD call, 991
 SWEEP function, 992
 SYMSIZE= option, 12, 537
 PROC IML statement, 12
 SYMSQR function, 995

T

T function, 995
 TABPRT call, 1081
 TABULATE call, 996
 TIMSAC subroutines
 advanced examples, 303
 details, 282
 introductory examples, 255
 overview, 253
 syntax, 282
 TSBAYSEA subroutine, 274, 1005, 1006
 TSDECOMP subroutine, 273, 1007, 1009, 1010
 TSMLOCAR subroutine, 261, 1010, 1011
 TSMLOMAR subroutine, 270, 1011, 1012
 TSMULMAR subroutine, 258–260, 304–306,
 1012, 1013
 TSPEARS subroutine, 1013, 1014
 TSPRED subroutine, 277, 278, 305, 1014
 TSROOT subroutine, 280, 281, 1015
 TSTVCAR subroutine, 1015
 TSUNIMAR subroutine, 1016
 TOEPLITZ function, 997
 TPSPLINE call, 998
 TPSPLNEV call, 1000
 TRACE function, 1003
 TRANSPOSE operator, 582
 TRISOLV function, 1004
 TYPE function, 1017

U

UNIFORM function, 1018
 UNION function, 1019
 UNIQUE function, 1019
 UNIQUEBY function, 1019
 USE statement, 1021

V

VALSET call, 1023
 VALUE function, 1024
 VAR Function, 1024
 VARMACOV Call, 1025
 VARMALIK Call, 1026
 VARMASIM Call, 1028
 VECDIAG function, 1029
 VECH function, 1029
 Vector time series subroutines
 example, 322, 325
 overview, 322
 syntax, 327
 VARMACOV subroutine, 327
 VARMALIK subroutine, 327
 VARMASIM subroutine, 327
 VNORMAL subroutine, 327

VTSROOT subroutine, 327
 VNORMAL Call, 1030
 VTSROOT Call, 1031

W

WAVFT call, 1032
 WAVGET call, 1035
 WAVIFT call, 1036
 WAVPRINT call, 1038
 WAVTHRSH call, 1039
 WINDOW statement, 1040
 WORKSIZE= option, 12, 537
 PROC IML statement, 12

X

XMULT function, 1042
 XSECT function, 1043

Y

YIELD function, 1043

Your Turn

We welcome your feedback.

- If you have comments about this book, please send them to **`yourturn@sas.com`**. Include the full title and page numbers (if applicable).
- If you have comments about the software, please send them to **`suggest@sas.com`**.

SAS® Publishing Delivers!

Whether you are new to the work force or an experienced professional, you need to distinguish yourself in this rapidly changing and competitive job market. SAS® Publishing provides you with a wide range of resources to help you set yourself apart. Visit us online at support.sas.com/bookstore.

SAS® Press

Need to learn the basics? Struggling with a programming problem? You'll find the expert answers that you need in example-rich books from SAS Press. Written by experienced SAS professionals from around the world, SAS Press books deliver real-world insights on a broad range of topics for all skill levels.

support.sas.com/saspress

SAS® Documentation

To successfully implement applications using SAS software, companies in every industry and on every continent all turn to the one source for accurate, timely, and reliable information: SAS documentation. We currently produce the following types of reference documentation to improve your work experience:

- Online help that is built into the software.
- Tutorials that are integrated into the product.
- Reference documentation delivered in HTML and PDF – **free** on the Web.
- Hard-copy books.

support.sas.com/publishing

SAS® Publishing News

Subscribe to SAS Publishing News to receive up-to-date information about all new SAS titles, author podcasts, and new Web site features via e-mail. Complete instructions on how to subscribe, as well as access to past issues, are available at our Web site.

support.sas.com/spn



**THE
POWER
TO KNOW®**

