PROC FACTOR: A Tool for Extracting Hidden Gems from a Mountain of Variables

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ABSTRACT

Factor analysis is a data-reduction statistical technique used to probe underlying interrelationships in Likert-type variables. SAS® provides an excellent tool, in the form of PROC FACTOR, for unraveling insights contained in subjective or perceptive survey responses. The procedure reduces the number of original variables into a few common components capable of accounting for most of the variability in the data set.

Using a data set from a national agricultural and food policy preference survey, this paper will demonstrate, step-by-step, how to do exploratory factor analysis including the use of the most popular PROC FACTOR options (METHOD=, ROTATE=, SCREE, MINEIGEN=, FLAG=, NFACT=, OUT=) available within the procedure. Important sections of the program output will be highlighted including the proper presentation and interpretation of results. Beginners and intermediate level users with some knowledge of statistics would benefit from this presentation. We used Base SAS® and SAS/STAT® to perform the analyses.

INTRODUCTION

One of the easiest and most popular techniques for obtaining information on human behavioral preferences and similarities or the lack of them is the inclusion of Likert-type scales (e.g. agree, not sure, disagree, or strongly disagree) in survey questionnaires. The traditional approach to analyzing the data is to use measures of central tendency, which does not account for correlation occurring between scale level responses. Such a shortcoming leaves out the more important aspect of detecting unobservable patterns very useful in describing behavioral traits shared within and/or uniquely associated with some groups of respondents. One procedure for analyzing subjective perceptions to gain insights from survey responses is through factor analysis.

Factor analysis extracts a small number of latent variables (or constructs) which quantify the underlying commonality from among a larger set of observed variables. From the initial correlation matrix generated by PROC FACTOR, the procedure plugs in values, henceforth called “loading”, in a matrix using the observed variables as rows, and the extracted constructs as columns. Factor loading and their subsequent interpretation are determined not only by their relative values within but also across constructs.

PROCEDURE

Sixteen Likert-type variables from a national agricultural and food policy preference survey were used for a factor analysis. Each question has a response range of 1 (strongly agree) to 5 (strongly disagree). Figure 1 shows some sample questions from the survey.

1. All meat products sold at retail should carry instructions for proper storage and cooking (Check one).
__Strongly agree __Agree __Not sure
__Disagree __Strongly disagree

2. Food inspections should be strengthened to ensure safer and better quality foods (Check one).
__Strongly agree __Agree __Not sure
__Disagree __Strongly disagree

3. When government regulations reduce the value of farm property, the owner should be compensated for this loss (Check one).
__Strongly agree __Agree __Not sure
__Disagree __Strongly disagree

Figure 1. Sample Likert-type questions lifted from a survey.

```
PROC FACTOR DATA=LL.AGPOL METHOD=ML MINEIGEN=1
SCREE REORDER ROTATE=VARIMAX FLAG=.40
OUT=LL.AGFACT;
VAR SA5--S14;
RUN;
```

Figure 2. Typical invocation of a PROC FACTOR procedure with options.

PROC FACTOR was invoked using the SIMPLE, METHOD=ML, PRIORS=SMC, MINEIGEN=1, SCREE, ROTATE=VARIMAX, FLAG=.40, and OUT options (Fig. 2). The SIMPLE option produces simple statistics helpful in flagging outliers and abnormal entries. The METHOD=ML requests that the maximum likelihood method be used for the initial factor extraction. PRIORS=SMC requests that the procedure use squared multiple correlation between a given input variable and the other variables for the variable’s prior communality estimate. MINEIGEN=1 option dictates that the procedure retain only factors that have eigenvalues of 1.00 or greater. This requirement ensures that only components, which can account for the variance of at least one variable, are retained.

```
PROC FACTOR DATA=LL.AGPOL METHOD=ML NFACT=4
SCREE REORDER ROTATE=VARIMAX FLAG=.40
OUT=LL.AGFACT;
VAR SA5--S14;
RUN;
```

Figure 3. PROC FACTOR invocation using the NFACT option.

Initial factor extraction does not always yield meaningful constructs. Therefore, it is not unusual to use the NFACT= option after a run using MINEIGEN= option to force the creation of other possible components. The factor procedure above requests that four common factors be extracted by using the NFACT=4 option (Fig. 3).

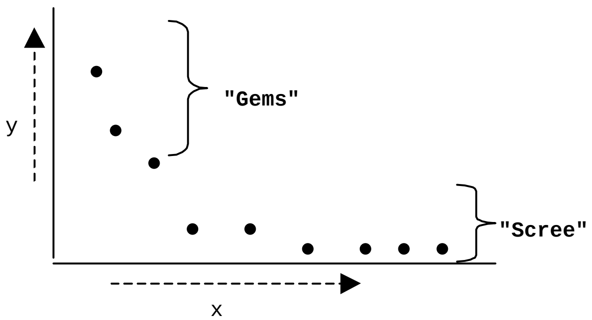

Figure 4. A hypothetical scree plot.

SCREE is a graphical presentation of the relative sizes of the eigenvalues associated with each extracted factor. The eigenvalues (y) are posted on the vertical axis while the component numbers (x) are located on the horizontal axis (Fig 4). One usually retains the few factors ("gems") that graphically separate themselves from the rest of the pack ("scree") which has piled up near the base of the graph. This option visually reinforces a decision to keep or not to keep extracted factors in conjunction with meeting the other imposed criteria (e.g. MINEIGEN=1).

VAR	FACTOR1	FACTOR2	VAR	FACTOR1	FACTOR2
SA6	-3	30	SA6	-3	30
SA7	19	38	SA7	19	38
SA8	42	13	SA8	42*	13
SA9	60	-1	SA9	60*	-1
SB1	16	46	SB1	16	46*
(Without FLAG= option)			(With FLAG= option)		

Figure 5. Flagged and unflagged factor patterns.

The FLAG=.40 enables marking with "*" all loadings with an absolute value of .40 (user entered) or greater considered significant by the researcher. This makes it easy to spot high loading of each input variable on every extracted factor. A comparison of flagged and unflagged factor patterns is shown above (Figure 5). The more variables you have, the more you will appreciate the benefit of using this option. (NOTE: Values indicated in the figure were rounded to the nearest integer and multiplied by 100 using the ROUND option. This makes for an easier reading of loaded coefficients). FLAG= may also be used with the REORDER option which places each variable that loaded high on the same factor next to each other.

VAR	FACT1	FACT2	FACT3	VAR	FACT1	FACT2	FACT3
SB2	12	35	24	SB2	42*	13	3
SB3	0	39	46*	SB3	60*	-1	-3
SB4	8	47*	37	SB4	59*	13	3
SI1	65*	-11	0	SB5	-1	6	90*
SI2	54*	-41*	8	SB6	4	68*	-7
(Before rotation)				(After rotation)			

Figure 6. Rotated and unrotated factor patterns (VARIMAX method).

ROTATE=VARIMAX specifies a varimax rotation which results in orthogonal or uncorrelated components. VARIMAX simplifies factor structure by maximizing the loading of input variables on one factor while minimizing the loading for all other remaining factors. The result is a simplified structure characterized by extreme value loading in factor matrix columns such that if one variable loaded very high (cutoff value for this demo, =>.40) on one factor, loading for the rest of the factors will have values of near-zero (Fig. 6).

The OUT= option produces a new data set containing all the information from the original data set plus the factor scores of the extracted and retained components in the current analysis. Choose this option if you intend to use the result of the PROC FACTOR output in subsequent data analyses.

PROC FACTOR… A STEP AT A TIME

The essential ingredients and steps followed to obtain a final solution from an orthogonal factor analysis were:

Sample Size
A minimum of 100 respondents or 5 times the number of variables, whichever is larger, is required for a valid factor analysis run. Since not all observations will be usable, it is prudent to have much more than the minimum number of observations when collecting the data. This demonstration had more than 1111 observations, 1083 of which were used. Obviously, 100 observations would have been sufficient.

Direction is Important!
Prior to running the procedure, all input variables have to be checked so all of them have the same ordinal direction. In the case of the "strongly agree-strongly disagree" rating, make sure that strongly agree is consistently assigned a scale value of 1 and the strongly disagree gets a scale value of 5 for all Likert-

type questions. Inconsistent assignment of rating values will result in negative correlation for some and positive correlation for others making interpretation difficult and complicated.

Three-variable Loading Per Factor
A factor should be retained only if at least three variables had loaded highly on it. To ensure this loading requirement, allocate more than three questions for each construct to be measured. Of course, this is only possible for surveys that are preplanned to be factor-analyzed. For others where the procedure is an afterthought, this poses a problem. The only choice is either to drop the common factor that does not meet the minimum loading requirement or to re-administer the survey after additional questions for the deficient factor have been added.

Preparation of the Correlation Matrix
Once specified as a procedure of choice, PROC FACTOR automatically generates a correlation matrix from all the input variables contained in the VAR statement.

Initial Factor Method: Maximum Likelihood

Prior Communality Estimates: SMC

SA5	SA6…	SI4
0.124637	0.181014…	0.299978

Prelim Eigenvalues: Total = 10.5261
Average = 0.4576

	1	2	3…	23
Eigenvalue	5.1772	3.8729	1.8821…	-4.4600
Difference	1.3042	1.9908	0.9184…	
Proportion	0.4918	0.3679	0.1788…	-0.0437
Cumulative	0.4918	0.8598	1.0386…	1.0000

3 factors will be retained by the MINEIGEN criterion.

Figure 7. A table of eigenvalues.

Extraction of Initial Factors
Initial factor extraction for the data set was performed using METHOD=ML. An advantage to using this method is that it gives the probability associated with retaining a certain number of common factors. Regardless of the method used, initial extraction always produce orthogonal (uncorrelated) factors.

Rotation to Terminal Solution
Initial extraction rarely produces simple structure. Instead, two- and three-way variable loadings are not uncommon, resulting in a structure too complex to interpret. VARIMAX rotation was used in this demonstration to obtain a simple yet meaningful orthogonal factor loading.

CHOOSING THE NUMBER OF FACTORS TO RETAIN ("DIGGING OUT THE GEMS")

The three key determinants for retaining a certain number of common factors are the position of the factors in the SCREE plot, the proportion of variance accounted for by the individual factor, and the overall interpretability of all retained factors.

Where on the SCREE plot?
What you are looking for here is the break or jump in eigenvalues that separate the "scree" from the "gems". For this survey's SCREE plot, there could be 3 or 4 likely candidate factors for retention. Since more than one break can occur in the plot, decisions based on SCREE plot position should be reinforced with the use of the other two determinants discussed elsewhere.

How much is a factor worth?
The hierarchical position of factors in the table of eigenvalues is determined by the proportion of common variance in the data set accounted for by the individual factors. The intersection of the label “Proportion”in the table and the factor number on top gives the amount of variation attributed to that particular factor. Fig. 7 indicates that FACTOR1 accounts for 49% of the variance, FACTOR2 has 37%, and FACTOR3 accounts for 18%. Total of these three values would not exactly add up to 100% due to errors in estimating the squared multiple correlation values (prior communality estimates). There is no hard and fast rule on the amount of contribution that a factor needs in order for it to be retained. Although still arbitrary, values of at least 10% for individual components and 70-80% for the cumulative (combined) percent of variance are commonly used. Such is a judgement call, arrived at only after careful consideration of the other two determinants.

Is the factor meaningful enough?
Neither being on top of the SCREE plot nor accounting for a large variation assures an extracted factor of being retained. The crucial test of becoming a common factor is its interpretability. Primarily, it has to have:

1) At least 3 input variables loading highly on it.

2) For each input variable that loaded highly, it has to have a maximized loading on itself and a minimized loading on the others, after rotation. This is usually referred to as "having a simple structure".

3) Input variables that loaded highly on it should share the same conceptual perspective which are distinctly different from the dimensions shared, addressed, and measured by the other variables that loaded highly on the other components.

Would you be able to intellectually synthesize and describe the commonality of all the variables that loaded high on a factor? Could you relate it with the other extracted factors and variables (both original and derived)? Needless to say, this facet is usually left at your (or the researcher's) discretion.

	Unrotated Factor Pattern			Rotated Factor Pattern		
	FACT1	FACT2	FACT3	FACT1	FACT2	FACT3
SA5	12	19	-21	-3	30	8
SA6	10	40*	-10	19	38	3
SA7	-5	21	3	15	13	-9
SA8	5	18	-7	6	19	1
SB2	12	35	24	42*	13	8
SB3	0	39	46*	60*	-1	-3
SB4	8	47*	37	59*	13	3
SB5	15	37	-18	11	41*	8
SB8	4	29	38	48*	-2	2
SB9	0	28	17	31	10	-3
SD1	22	10	-5	4	14	20
SD2	16	54*	-47*	0	73*	5
SD3	8	54*	-41*	4	68*	-3
SE1	7	19	-6	8	20	4
SE2	10	9	4	10	6	8
SF1	9	43*	26	48*	17	4
SF2	4	42*	31	51*	12	-1
SG2	21	39	28	48*	14	16
SI1A	90*	-11	0	-1	6	90*
SI1B	90*	-10	2	1	5	91*
SI2	19	42*	-17	16	46*	11
SI3	8	41*	4	30	29	2
SI4	15	55*	-11	28	50*	5

NOTE: Printed values are multiplied by 100 and rounded to the nearest integer. Values greater than 0.4 have been flagged by an '*'.

Figure 8. Pre- and post-rotation factor patterns for a three-factor solution.

Variable	Label	Conceptual Category
FACTOR1 Loading:		
SB2	Govt regulate farming pract	Regulation
SB3	Cont'n of govt regulation/w	Regulation
SB4	Req farmers to plant grass	Regulation
SF1	Storage/cooking inst for me	Food safety
SF2	Strengthen food inspection	Food safety
SG2	More nutr info on food lab	Nutrition
FACTOR2 Loading:		
SB5	Pay farmers for planting gr	Subsidy
SD2	U.S. to continue subsidy on	Subsidy
SD3	U.S. cont subsidy for value	Subsidy
SI2	Subsidy on plant-derived pr	Subsidy
SI4	Incr funding for empl prgms	Econ Devt
FACTOR3 Loading:		
SI1A	Biotech beneficial for prod	Biotech
SI1B	Biotech beneficial for cons	Biotech

Table 1. Variable loading and associated concepts on a rotated factor pattern as part of a three-factor solution.

ROTATE TO SIMPLIFY

It is very seldom that factors produced during the initial extraction would have a clear-cut loading of input variables. Fig. 8 shows a comparison between an unrotated and a rotated factor pattern. It can be gleaned that without rotation, we could have easily dropped FACTOR1 (just 2 variables had loaded, we need at least 3) and could have retained FACTOR3 (3 variables had loaded moderately). Clearly, the two-way moderate loading exhibited by some of the input variables, such as SD2, made it difficult for us to interpret the pattern. In practice, when a variable exhibits high loading on more than one factor even after a rotation, that variable should be deleted. A good variable should measure only one construct. Rotation made it possible for us to categorically select the factors that deserved to be retained. This was made easy by one-way maximized loading of each variable on the factors they really subscribed to. Based on the number of variables that loaded and the simplicity of exhibited structure, we tentatively retained FACTOR1 and FACTOR2. FACTOR3 was dropped since it did not meet the minimum number of variable loading requirement.

	Unrotated Factor Pattern				Rotated Factor Pattern			
	FAC1	FAC2	FAC3	FAC4	FAC1	FAC2	FAC3	FAC4
SA5	12	16	23	8	29	7	-8	7
SA6	11	38	16	2	38	2	11	15
SA7	-5	21	1	1	13	-9	10	10
SA8	5	16	10	-5	19	1	7	0
SB2	13	37	-17	-25	15	8	46*	6
SB3	1	45*	-41*	-32	1	-3	67*	12
SB4	9	51*	-29	-30	15	2	64*	13
SB5	16	33	24	-3	42*	8	8	6
SB8	5	33	-33	-28	0	2	54*	7
SB9	1	29	-12	-16	11	-4	33	6
SD1	22	9	6	-4	14	20	5	2
SD2	17	47*	54*	-7	73*	4	1	-1
SD3	9	48*	48*	-10	69*	-3	7	-2
SE1	7	18	10	1	20	3	4	6
SE2	10	10	-3	22	4	6	-6	25
SF1	11	49*	-22	32	15	-1	20	58*
SF2	5	50*	-30	37	9	-6	22	65*
SG2	22	45*	-25	31	12	11	21	58*
SI1A	89*	-12	-1	-1	7	89*	-2	7
SI1B	90*	-12	-3	-1	6	91*	0	7
SI2	20	39	23	5	45*	9	7	16
SI3	9	40*	2	13	29	-1	14	29
SI4	15	52*	19	2	50*	3	18	21

NOTE: Printed values are multiplied by 100 and rounded to the nearest integer. Values greater than 0.4 have been flagged by an '*'.

Figure 9. Pre- and post-rotation factor patterns for a four-factor solution.

LOOK FOR MEANINGS…

Extracted components, also known as constructs, are expected to exhibit simple structure after rotation. The trick to naming a factor is to identify all variables that loaded high on a particular factor, and then looking at the predominant theme or content that each of the variables had contributed to that factor. This process of attaching a meaning, as related to the objectives and science of the study, to a retained factor is called "interpretation". For this we need to look at either the variable labels (if meaningful labels were used) of the Rotated Factor Pattern table or go back to the survey questionnaire itself to find out what each loading variable (individual question item) is all about. Table 1 enumerates the variables that loaded. Based on the number of conceptual categories attached to FACTOR1 it is obvious that it would be difficult to come up with a dominant, descriptive content name let alone a unified concept for this factor. FACTOR2 looked okay. Factor3 is liable to be dropped because only 2 variables loaded high on it. This predicament is a clue that we need to try extracting other factors that would most likely polarized the various concepts into more meaningful and cohesive clusters. To explore other solutions, four common factors were extracted with PROC FACTOR using the same set of options but specifying NFACT=4 instead of the MINEIGEN=1.

Variable	Label	Conceptual category
FACTOR1 Loading:		
SB5	Pay farmers for planting grass	Subsidy
SD2	U.S. continue subsidy on ag exp	Subsidy
SD3	U.S. cont subsidy on value adde	Subsidy
SI2	Subsidy on plant-derived fuels	Subsidy
SI4	Incr funding for empl prgms	Econ Dev
FACTOR2 Loading:		
SI1A	Biotech beneficial for producer	Biotech
SI1B	Biotech beneficial for consumer	Biotech
FACTOR3 Loading:		
SB2	Govt regulate farming practices	Regulati
SB3	Cont'n of govt reg on water qua	Regulati
SB4	Req farmers to plant grass str	Regulati
SB8	Req farmers/keep pesti appln	Regulati
FACTOR4 Loading:		
SF1	Storage/cooking instr for	Food safety
SF2	Strengthen food inspecti	Food safety
SG2	More nutr info on food label	Nutrition

Table 2. Variable loading and associated concepts on a rotated factor pattern as part of a three-factor solution.

A comparison between the pre- and a post-rotation factor patterns is shown in Fig. 9. As before, listing down the variables that loaded helps a lot in finding the common thread that holds them together under each factor (Table 2). Having listed the variables, labels, and conceptual categories side by side, it is now easy to assign descriptive names to the retained factors.

DECISION… DECISION… DECISION…

At this point, a decision has to be made whether or not a three-factor model would be sufficient to evaluate producers' preferences and opinions as regards food and agriculture policy. Since FACTOR2 did not meet the minimum variable-loading criterion, can we then discard this "biotechnology" factor? We have seen the increasing role of biotechnology applications in improving food production and enhancing food safety. It also has its own share of controversy… "super" pathogens, milk production "boosters" and animal "cloning" to name a few. Debate on the use and importance of biotechnology would only escalate over time. However, it would indeed be a serious omission if we choose to ignore the producers' sentiment about the issue when we had the chance to hear it. Since this survey was not preplanned for factor analysis, the only way to pursue a four-factor solution is to add new input variables (questions) to the original survey instrument addressing various biotechnology issues, and then administering it to a completely different sample of producers. Thereafter, a factor analysis can be performed on the survey responses to see if a satisfactory four-factor solution is obtainable.

Component	Variable/label	Mean(sd)[1]	Component Loading 1	2	3
1	SB5 Pay farme	2.5 (1.2)	0.42	0.10	0.05
	SD2 U.S. cont	3.0 (1.1)	0.74	0.04	-0.05
	SD3 U.S. cont	3.1 (1.0)	0.68	0.11	-0.07
	SI2 Subsidy	3.1 (1.1)	0.46	0.09	0.13
	SI4 Incr fun	2.7 (1.2)	0.50	0.20	0.19
2	SB2 Govt reg	2.7 (1.2)	0.15	0.46	0.05
	SB3 Cont'n o	3.2 (1.3)	-0.01	0.68	0.09
	SB4 Req farm	3.1 (1.3)	0.13	0.66	0.09
	SB8 Req farm	3.0 (1.2)	-0.01	0.55	0.06
3	SF1 Storage/c	2.4 (1.1)	0.16	0.20	0.59
	SF2 Strength	2.1 (0.9)	0.10	0.19	0.66
	SG2 More nut	2.4 (1.0)	0.14	0.22	0.57
Eigenvalue			4.942	2.440	1.576
Common var explained by each component			0.55	0.27	0.17
Reliability coefficient: ____[2]					
n=1083					

[1] Scale: 1=Strongly agree; 5=Strongly disagree
sd=standard deviation
[2] Cronbach's alpha coefficient goes here.

Table 3. Tabular presentation of a three-factor solution from the survey's factor analysis.

For demonstration purposes, let us assume that we decided on a three-factor solution and that we re-ran the analysis using NFACT=3 with the SI1A and SI1B (biotechnology) variables deleted. The result would be similar to Table 2 except that FACTOR2 was dropped and FACTOR3 became FACTOR2, and FACTOR4 became FACTOR3.

THE ULTIMATE TEST

Once again, each of the components must pass the crucial test of interpretability for the solution to be regarded as satisfactory. The following indicates the test criteria and how they were satisfied by the component factors:

1. **Minimum of three variables per factor:** FACTOR1, FACTOR2, and FACTOR3 had 5, 4, and 3 variables that loaded high on them, respectively.

2. **Simplicity of structure:** All three factors exhibited moderate to high loading of input variables as opposed to the other relatively and consistently low complementary loading.

3. **Variables on each factor should share a conceptual meaning that is distinctly different from those shared and measured by the other variables in the other components.** Each of the retained components described and measured different aspects of the total study, which is exclusive of the others' measurement and conceptual domain.

PRESENTATION AND INTERPRETATION OF RESULT

Table 3 shows one way of presenting the result of a factor analysis. Mean factor scores indicate the position of each variable relative to the rating scale used. All three constructs have eigenvalues greater than 1.0, which means that each of them can explain a fraction of the common variance much larger than that attributable to one variable. The cumulative percent of variance of the three constructs accounts for almost 100% of the common variance in the correlation matrix. This result is not surprising knowing that we had used the NFACT=3 option to force the input variables to load high differentially on only three components. Five variables loaded high on the first component, four on the second, and three on the third component. Interpreting the variable loading and assigning a meaningful description to constructs involves the conceptual distillation of the variables' common attribute and attaching a descriptive name to it. Four variables in FACTOR1 deal with subsidy but even SI4, which proposes to increase funding for employment programs to spur rural economic development, had a hint of being a subsidy program. Thus, naming FACTOR1 as subsidy policy factors seemed most appropriate. All items that loaded on FACTOR2 are about regulations and therefore can be concluded to describe and measure regulatory policy factors while FACTOR3 addresses food safety policy factors.

THE VERDICT

PROC FACTOR procedure enabled us to reduce the number of the original 16 variables into three common factors designated as the subsidy, regulation, and the food safety components. All three passed the interpretability criteria and therefore could be used in place of the original variables in subsequent statistical analyses. While exploratory data analysis is the most popular application of PROC FACTOR, some use it to iteratively refine and confirm their models in the light of new data or current research. Others use the procedure as an intermediate process to develop indices designed to measure constructs that could not be reliably predicted by the original variables. While many more applications of factor analysis have not yet been published, there are still other uses of factor analysis that remain to be discovered.

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TRADEMARK INFORMATION

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