PROC SURVFIT and PROC SURVTEST: An Update

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Introduction

The general topic is estimation and comparison of survival curves. The survival curve is simply the estimated proportion surviving from time 0 to t. Time 0 may be birth, the time of diagnosis of a particular disease, time of assignment to treatment, time of kidney transplant, etc. Subsequent to time 0, we record the time to the event of interest. This may be death, remission of symptoms, tumor shrinkage, another diagnosis, etc. Not all persons will necessarily be observed until the event of interest has occurred. We refer to these observation times as right censored. The methods addressed below, which estimate and compare survival curves, allow the utilization of persons who have censored observation times. If one is interested in estimating the proportion surviving 5 years following some surgical procedure, for example, it is not necessary to exclude patients who had surgery less than 5 years ago. The aim is to utilize all the information.

Below we describe two SAS procedures to estimate (PROC SURVFIT) and compare (PROC SURVTEST) survival curves.

I. PROC SURVFIT

In a previous SUGI presentation we described the proposed SURVFIT procedure (1). Since that time, we have completed the procedure and have had it in use for over a year. There are some minor changes between what was proposed and the final product. It has recently been submitted with ample documentation to SAS Institute as a supplemental procedure.

The SURVFIT procedure estimates the survival curve by either the Kaplan-Meier (K-M) or actuarial method (2). The Kaplan-Meier method is also called the product limit estimator. SURVFIT produces a life table and optionally an arithmetic or 1- or 2-cycle semi-log plot of \( P \) (the estimated probability of survival from time 0 to \( t \)) vs. time. Optionally, an output data set of the life table may be created.

One unique feature of SURVFIT is the ability to compute the expected survival curve. Generally, the expected survival curve is useful when death is the endpoint of interest. It reflects the survival experience of a group of persons of like age and sex in some reference population.

Numerous reference populations are incorporated into the procedure. The conditional probability of surviving to age \( x+1 \), given survival to \( x \), is stored for ages 0-109, separately for males and females (2). For calendar years 1950, 1960 and 1970, we have the Minnesota and U.S. white population life tables. Also incorporated are sex-specific life tables for the white population of the West North Central (WNC) region of the U.S. for the 61 single calendar years between 1910 and 1970, inclusive. The West North Central Region of the U.S. encompasses the states of Minnesota, Iowa, Missouri, Kansas, Nebraska, North and South Dakota. The individual calendar year life tables were obtained by interpolating with a high order polynomial regression model between successive 10-year, census life tables. Collectively, these 61 life tables are referred to as the 'cohort' life tables. When requesting expected survival using 'cohort', the expected survival is based not only on persons of like age and sex in the reference population, but also of like calendar year at time 0. Use of the 'cohort' would be more important when subjects' age and sex specific death rates change meaningfully over calendar years spanned by the entire study. The reference populations included in SURVFIT all have as their endpoint, death from all causes. The user can, with relative ease, incorporate any single calendar year reference life table to be used in calculating expected survival. This feature facilitates the calculation of expected survival for endpoints other than death, for cause of death specific expected survival, and perhaps others.

Depending on the options selected, several variables need to exist on the data set. If no expected survival is requested, the only variables required are a variable reflecting observation time and an event variable indicating whether or not the observed time corresponds to an event of interest or censored observation. When 'cohort' expected survival is requested, variables denoting time, event, sex, age, and calendar year at time 0 are required.

We have adopted the convention that, if the assumed variable name exists on the data set, it is not necessary to code that with the procedure. The procedure will also deal directly with SAS dates and perform internally the appropriate subtractions and some limited edits. For example, the date at last follow-up must exceed the date at time zero.

Because the K-M survival curve always uses days as intervals, the life table printout may be very large for large data sets with lengthy follow-up. The interval statement was included to address this problem. It controls the length of interval used when printing the K-M life table. It does not affect, for the K-M method, the way the calculations are performed. For the actuarial method, since calculations for it are specific to the length of the intervals, the interval statement directly dictates the form of the results.
The SAS statements with a brief description and sample output are given below. All variables, except the sex variable and BY-variables, must be numeric. For formulae and other specifics, please refer to the documentation accompanying the supplemental procedure or our previous presentation.

PROC SURVFIT options;

Options
[DATA=data_set name]
[DATA= data set name] indicates method, Kaplan-Meier
[ACT] (default) or actuarial
[USERDS=user data set] user supplied data set of conditional probabilities of surviving 1 year for each sex for ages 0-109.
[DATES] specifies that the relevant dates are provided from which time, age and calendar year at time 0, as needed, are derived. No dates is default.
[NOPRINT] specifies that life table or plots will not be printed. Useful when creating an output data set. Default is to print.
[OUTPUT OUT=data_set name] specifies that an output data set is desired. The user supplied data set name is optional. Variables are automatically named and included in the output data set, appropriate for the options selected. They basically capture all the information from the life table, the method and any BY-variables. When expected survival is requested with the K-M method, 13 variables plus BY-variables will be included. For the K-M method, the number of observations corresponds roughly to the number of unique observation times.

VAR NAMES [keyword 1= var name 1
keyword 2= var name 2 ... ];

If a required variable exists on the data set with a variable name the same as the keyword, it is not necessary to code it into the VARNAMES statement. Hence, the VARNAMES statement is, in fact, optional.

Keywords
TIME=time_variable specifies observation time in days.
EVENT=event_indicator_variable
1=censored or withdrawn; i.e. event of interest has not occurred (for survival implies alive)
2=event of interest has occurred at the observation time specified above (for survival implies dead)
SEX=sex_indicator_variable
numeric: 1=male and 2=female
M'=male and 'F'=female
AGE=age_variable
indicates subject's age, in years, at time 0.
CALYR=calendar_year_at_time_0_variable
a 2- or 4-digit number. If two-digit, the first two digits are assumed to be 19. Values before 1910 or after 1970 are treated as 1910 and 1970, respectively, since this corresponds to the range of life tables available under the COHORT option.

DATEB=SAS_date_of_birth_variable
DATEZ=SAS_date_at_time_zero_variable
DATEFU=SAS_date_at_last_follow-up_variable

When COHORT expected survival is requested, the user must indicate, in addition to EVENT and SEX, either TIME, AGE and CALYR, or the DATE option on the PROC statement and DATEB, DATEZ and DATEFU. When expected other than COHORT is requested, CALYR is not needed, but all three date variables are. Without expected survival, only TIME and EVENT or the DATE option on the PROC statement, DATEZ, and DATEFU are needed.

INTERVAL i 1 OF d 1, i 2 OF d 2, ..., i 20 OF d 20: The entire interval statement is optional. If present, it specifies the number and length of intervals starting at time 0. The statement is of the form i; intervals of length d· days where i· and Jd. are ... J 11 11 positive integers with 1<J <20. The default interval is 1 day for the K-M method and 365 days for the actuarial method. For K-M, INTERVAL only affects the printing of the life table.
PLOT options;

Options

ARITH results in arithmetic plot of the observed and expected survival curve. The ordinate, ranging from 0 to 1, is the estimated probability of surviving from time 0 to t years, plotted against t, in years.

ONE results in a one-cycle, semi log 10 plot. The ordinate takes on values corresponding to survival probabilities between 0.10 and 1.00, omitting those below 0.10.

TWO similar to ONE except that the ordinate range is now 0.01 to 1.00.

MAXT=t specifies the maximum time value, in years, to be plotted on the abscissa. This is useful in making a series of uniform plots. If not specified, the abscissa takes on values from 0 to the nearest whole year greater than or equal to the end of the last interval in the life table.

Expected survival, if requested, is plotted on the same plot as the observed. One or more plot options may be specified in a single plot statement, resulting in multiple plots. There is no feature in this procedure to produce more than one observed survival curve on a single plot. We do not plan to submit this latter procedure to SAS Institute as a supplemental procedure.

BY by variables;
As with most procedures, the ability to execute SURVFIT separately for various groups is available. As usual, the data set must be sorted.

DATA;
INPUT FOLLOWUP STATUS SEX $ AGE_DX;
CARDS;
7 1 F 27
21 2 M 51
180 2 M 62
260 2 F 58
380 1 M 24
678 1 F 29
596 2 M 65
PROC SURVFIT POP=US1970 OUTPUT;
VARNAMES TIME=FOLLOWUP EVENT=STATUS AGE=AGE_DX;
PLOT ARITH;
TITLE EXAMPLE OF SURVFIT PROCEDURE;
PROC PRINT;

Comment: Observations with missing values are omitted and a tally is presented. Other minor edits are performed and noted. Program limits include 5000 intervals and <10 years of follow-up. The expected survival capability may be felt to be limiting for some situations, as no accommodation is made for including a race dimension in the reference populations. The ability to update the cohort reference populations with current census life tables has been incorporated. A user with moderate programming talents could also insert a different set of cohort life tables into the procedure.

II. PROC SURVTST

The purpose of PROC SURVTST is to compare survival curves. The original version of this procedure currently exists in SAS as a supplemental procedure. This original version of SURVTST was described at a previous SUGI meeting (14) What we discuss below are the improvements in the procedure that we are in the
process of making. The statistical development has been completed. We plan to have the revised SURVTEST procedure completed, tested, and sent to SAS Institute as a supplemental procedure, by mid 1983. The available test statistics will be greatly expanded, while the statements and output will be quite similar to the original version.

What follows is a summary of the changes. Linear rank test statistics include the Gehan-Wilcoxon (GW) and the GP,Y class of statistics where p>0, y>0. Special cases of GP,Y are the log-rank test (LR) (p=0, y=0) and Peto-Peto-Wilcoxon (PPW) (p=1, y=0). These linear rank tests have been developed for K=2 sample situations, with corresponding one-sample goodness-of-fit statistics defined, as well. For one-sample tests, the GP,Y is available for p>0, y>0, 1. For K=2 sample situations, versions of the GP,Y and GW test statistics are also available for testing departures from a prespecified proportional hazards model where the proportionality condition need not be unity.

For testing the equality of two survival curves, a generalized Smirnov (GS) test statistic and a class of K=2 statistics, p=0, y=0, which are non-linear supremum-type rank statistics, have been included.

The procedure will facilitate the one-sample goodness of fit procedure statistics by allowing the user to specify the variable name containing a particular survival function.

A. Statistical Development

A1. Notation. Assume the following data is available on the kth individual, k=1,...,N, where N indicates the total number of individuals over all samples. Let the kth individual’s observation time (in days) be denoted by Xk and let zk be an event indicator denoting whether the observation time is an event time (zk=1) or a censorship time (zk=0). For K=2 sample situations, versions of the GP,Y and GW test statistics are also available for testing departures from a prespecified proportional hazards model where the proportionality condition need not be unity.

For testing the equality of two survival curves, a generalized Smirnov (GS) test statistic and a class of K=2 statistics, p=0, y=0, which are non-linear supremum-type rank statistics, have been included.

The procedure will facilitate the one-sample goodness of fit procedure statistics by allowing the user to specify the variable name containing a particular survival function.

A2. Model. Denote the true survival distribution for the ith sample by Si(t), which is simply the probability that an individual in sample i will survive from time 0 to time t. If we denote the cumulative hazard function in sample i by Ai(t), it follows that

Si(t) = exp{-Ai(t)}. Individuals in the ith sample then have hazard function

\[ \frac{d}{dt} \lambda_i(t) = \lambda_i(t). \]

To help interpret the meaning of the hazard function, consider a small \( \Delta t \). Then \( \lambda_i(t) \Delta t \) essentially represents the probability of death occurring in the interval \( t \) to \( t+\Delta t \), given survival to \( t \).

Let \( \lambda_i(t) \) denote the probability an individual in sample i is not censored before time t. Assuming statistical independence between the causes of death and censorship, it follows that the distribution of observation times in the ith sample is given by

\[ S_i(t) = \exp{-\Lambda_i(t)}. \]

With the exception of one important special case, all test procedures were developed to test the hypothesis that all r samples have equivalent survival distributions; that is,

\[ H_0: S_i(t) = S(t), \quad i=0,...,r-1, \quad (1) \]

where \( S(t) \) is unspecified. The exception to this is that the two-sample linear rank tests to be discussed can be employed more generally to...
the test of hypothesis

\[ H_0': \lambda_1(t) = \lambda_0(t)e^{\theta_0} \]  

(2)

for some fixed \( \theta_0 \). Of course, \( H_0' \) reduces to \( H_0 \) when \( \theta_0 = 0 \).

A3. Two-sample linear rank tests. As background, these test statistics are called rank tests because they depend on time only to the extent necessary to rank deaths and censored observations. A rank test statistic is invariant under any monotone transformation of the data because such a transformation does not alter the ranks. They are called linear because such statistics can be written as linear functions of the ranks.

A classic two-sample linear rank statistic to test \( H_0 \) in censored survival data is the log-rank, proposed by Mantel (10). Conditioning on risk set sizes, \( n_0k \) and \( n_1k \), and on the number of events, \( d_k \), occurring at \( T_k \), Mantel proposed forming the difference between the observed and conditionally expected number of events in sample 1 at \( T_k \). The log-rank statistic, as stated in (3), is then proportional to the sum of these differences when the sum is taken over all event times.

\[ \text{log-rank} = \sum_{k=1}^d \left( d_{1k} - \frac{n_{1k}e^{\theta_0}}{n_{0k}e^{\theta_0} + n_{1k}e^{\theta_0}} \right) d_k \]  

(3)

This statistic can be generalized to provide greater sensitivity to survival differences occurring over certain periods by employing a weight function \( \phi(T_k) \). Further generalization to test the more general hypothesis \( H_0': \lambda_1(t) = \lambda_0(t)e^{\theta_0} \) yields

\[ Z(N) = \sum_{k=1}^d \phi(T_k) \left( d_{1k} - \frac{n_{1k}e^{\theta_0}}{n_{0k}e^{\theta_0} + n_{1k}e^{\theta_0}} d_k \right) \]  

(4)

Remembering that \( Z_k \in [0,1] \) in the two sample setting, equivalent formulations for \( Z(N) \), using Lebesgue-Stieltjes integrals, are given by:

\[ Z(N) = \sum_{k=1}^d \left( \Phi([x_k]) - \int_{x_k} d_1(x) \right) \]  

(5)

\[ \Phi([x_k]) = \frac{1}{N} \int_{0}^{N} \int_{x_k} e^{\theta_0} dU \]  

(6)

where (7) follows from (6) by observing that the cumulative hazard estimator \( \hat{\Lambda}_1(x) = \int_{0}^t \frac{N_1(u)}{\hat{F}_1(u)} \) .

We can see from (7) that, when \( \theta_0 = 0 \), these two-sample linear rank statistics are simply a sum (integral) of weighted differences in hazard functions.

The variance, \( \nu \), of \( Z(N) \) can be proposed heuristically using hypergeometric distribution arguments of Mantel (10). Employing the theory of stochastic processes, Gill (7) has verified that the statistic

\[ Z(N) \]  

indeed has a standard normal distribution when \( N \to \infty \), as long as \( \Phi \) satisfies some mild regularity conditions.

As mentioned earlier, the weight function \( \Phi \) enables one to obtain particular sensitivity to survival differences occurring at specific points in time. The following table indicates those weight functions which we are making available and the name of the corresponding test statistic.

<table>
<thead>
<tr>
<th>Test Statistic</th>
<th>Weight Function</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gehan-Wilcoxon</td>
<td>( \Phi(x) = X_2(x)/X_1(x) )</td>
</tr>
<tr>
<td>Peto-Peto Wilcoxon</td>
<td>( \Phi(x) = Y_2(x)/Y_1(x) )</td>
</tr>
<tr>
<td>Harrington-Fleming</td>
<td>( \Phi(x) = \int_{0}^{x} e^{-\theta_0} d\Lambda_1(x) )</td>
</tr>
</tbody>
</table>

Briefly, relative to the log rank test, the Gehan-Wilcoxon and Peto-Peto Wilcoxon provide greater sensitivity to survival differences occurring earlier in time since \( Y_2(x)/Y_1(x) \) and \( X_2(x)/X_1(x) \) are decreasing weight functions.
Harrington-Fleming $G^p$ class includes the log-rank ($p=0$) and Peto-Peto Wilcoxon ($p=1$) as special cases and provides greater sensitivity to early occurring differences the larger one chooses $p$. For the situation in which $859,$ Harrington and Fleming $^{8}$ have found the type of departures from $H_0$ that each of the $G^p$ test produces is fully efficient in detecting. Obviously, the $G^{p, r, Y}$ family provides considerable versatility to the user. Sensitivity to early occurring differences is obtained by taking $p=0, r=0,$ to middle differences by taking $p=1, r=1,$ and to late occurring differences by taking $p=0, r>0.$

\[ A_6. \text{One-sample linear rank, goodness-of-fit tests (e}^{e_0=1}) \]

The class of one-sample goodness-of-fit tests which we present can be obtained from equation (6), with $e_0=0$ and $\xi(x)$ as defined in (9), by letting $N_1=\infty$. The hypothesis to be tested is that the true underlying survival function, $S$, is equal to some specified $S_0$.

The statistic's numerator can be shown to be

\[ \sum_{k=1}^{N_0} [-\ln S_0(x_k)]^{Y} \]

\[ \sum_{k=1}^{N_0} [-\ln S_0(x_k)]^{Y} \]

Observe that the statistic continues to be the difference between the sum of weighted expected and weighted observed numbers of deaths.

It can be shown that

\[ N_0^{-1/2} \frac{z(N_0)}{\rho_0, Y} \sim N(0, 1) \]

\[ N_0^{-1/2} \frac{z(N_0)}{\rho_0, Y} \sim N(0, 1) \]

The variance $\sigma^2$ is consistently estimated by

\[ N_0^{-1} \sum_{k=1}^{N_0} [-\ln S_0(x_k)]^{Y} d_AR_0(x_k). \]

Then

\[ \frac{z(N_0)}{\rho_0, Y} \sim N(0, 1) \]

For example, with $p=0, r=0, \gamma=0,$ we have

\[ \frac{\sum_{k=1}^{N_0} [-\ln S_0(x_k)]^{Y}}{N_0} \sim \frac{1}{\sigma^2} \sum_{k=1}^{N_0} [-\ln S_0(x_k)]^{Y} d_AR_0(x_k). \]

By setting $r=0, \gamma=0,$ we obtain the one-sample version of the log-rank test, which is given by

\[ \frac{\sum_{k=1}^{N_0} [-\ln S_0(x_k)]^{Y}}{N_0} \sim \frac{1}{\sigma^2} \sum_{k=1}^{N_0} [-\ln S_0(x_k)]^{Y} d_AR_0(x_k). \]

Note that to calculate these one-sample statistics, one need only specify $(x_k, S_0(x_k))$ for each individual; $k=1, \ldots, N.$ As stated above, the one-sample $G^{p, r, Y}$ test statistics are only available for $p>0, \gamma=0, 1, 2.$
A7. Two-sample Non-linear rank tests. We consider here two-sample supremum-type tests of equality of survival distributions based upon the \(K^a\) class of statistics and the generalized Smirnov test.

First consider the \(K^a\) class. For any fixed non-negative number \(a\), define the statistic

\[
K^a_{N_0, N_1} = \sup_{t} B^a_{N_0, N_1}(t)
\]

where

\[
B^a_{N_0, N_1}(t) = \frac{1}{2} \left( \frac{S_0(t)}{S_1(t)} \right)^{a} \left( \frac{S_1(t)}{S_0(t)} \right)^{1/2} \times 1\{y_0(t) > 0\} d \left( \frac{N_0(t)}{N_1(t)} - \frac{N_1(t)}{N_0(t)} \right)
\]

where in this section \(G^a_1(x) = \exp \left\{ - \frac{N_0(t)}{N_1(t)} \right\} \) and \(G^a_1(x)\) is the corresponding type of estimator of the censoring distribution.

The \(K^a\) statistics are supremum-type statistics which are sensitive to differences in underlying survival distributions which are large at a particular point in time, but may disappear at other time points. The free parameter \(a\) plays a role analogous to the parameter \(p\) in the \(G^p\) statistics. For \(0 < a < 1\), emphasis is placed on changes in the difference between \(S_0\) and \(S_1\) which occur late in time, while if \(a > 1\) emphasis is placed on changes in \(S_0\) and \(S_1\) which occur early in time. The \(K^a\) procedures are more versatile in providing acceptable power to a wide variety of alternatives than are the corresponding linear-rank \(G^p\) procedures.

Another supremum-type test statistic is the generalized Smirnov (GS) test. It is formulated as follows:

\[
GS = \sup_t Y_{N_0, N_1}(t)
\]

where

\[
Y_{N_0, N_1}(t) = \frac{1}{2} \left( \frac{S_0(t)}{S_1(t)} \right)^{a} \left( \frac{S_1(t)}{S_0(t)} \right)^{1/2} \times 1\{y_0(t) > 0\} d \left( \frac{N_0(t)}{N_1(t)} - \frac{N_1(t)}{N_0(t)} \right)
\]

where \(G^a_1(x) = \exp \left\{ - \frac{N_0(t)}{N_1(t)} \right\} \).

The GS statistic is a versatile test statistic with sensitivity to any survival differences which are large at some point in time, independent of the type of differences existing elsewhere. The corresponding test produced in especially sensitive to departures from \(H_0\) in which the two survival distributions exhibit a substantial difference in their middle range, but possibly have this difference disappear later in time.

In closing this section, it should be observed that a careful study of the operating characteristics of the previously discussed two-sample procedures for testing \(H_0\) has been presented by Fleming and Harrington. This discussion also includes consideration of the impact of the simultaneous use of several of these statistics.

B. Proposed Procedure Layout

```
PROC SURVTEST options;
Options
DATA=data_set_name;
GRHOGAMMA=(\(p_0: p_1\)) \ldots \((p_k: y_k)\);

The notation \(\{p_0: y_1\}\) refers to a set of combinations of \(p_0\)'s and \(y_1\)'s to be used. There is no proposed limit on \(k\). These options are appropriate for 1-, 2- and \(r\)-sample problems.
Examples: GRHOGAMMA=(0:0) would result in a log-rank test or its equivalent for 1- and \(r\)-samples. GRHOGAMMA=(0:0 1 2) is equivalent to coding GRHOGAMMA=(0:0) (0:1) (0:2).

GW indicates Gehan-Wilcoxon. This option is appropriate for 1-, 2- and \(r\)-sample problems.

KALPHA=\(a_1, a_2, \ldots, a_k\) indicates the \(K^a\) statistic with the various \(a_k\)'s indicated. Option appropriate for two-sample problems only.

BETA=\(\beta_1, \beta_2, \ldots, \beta_k\) indicates the \(B\) term described above for testing specific departures from equality of hazards, as described above. The default is BETA=0, which corresponds to testing the equality of the survival. Option (other than default) appropriate for two-sample problems only.

VARNAMES [KEYWORD_i=key_word_variable_name_i];
Keyword
TIME=variable_name_of_observation_time (in days)
EVENT=variable_name_of_event_indicator

indicates whether the observation time is an event (death) time or time of censorship where 1=censor, 2=event.

SOFT=variable_name_of_hypothesized_survival

indicates the expected survival, \(S_0(t)\), used in the one-sample, linear
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rank tests. Is specific to the individual and to the individual's observation time. Option appropriate for one-sample problems only.

Since the availability of test statistics is specific to the number of samples (groups) being compared, we prepared the following table.

<table>
<thead>
<tr>
<th>No. of Samples (Groups)</th>
<th>Test Statistics Available</th>
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<tbody>
<tr>
<td></td>
<td>Gehan-Wilcoxon (GW)</td>
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<td>K² (KALPHA)</td>
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<td></td>
<td>Generalized Smirnov (GS)</td>
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<tr>
<td>1 (BETA=0)</td>
<td>Yes (p&lt;0, γ&gt;0)</td>
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<tr>
<td>2 (BETA=0)</td>
<td>Yes (p&lt;0, γ&gt;0)</td>
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<tr>
<td>≥3</td>
<td>Yes (p&lt;0, γ&gt;0)</td>
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</tbody>
</table>

Computer Output

In general, the output will describe the test statistic and print a table as outlined below.

(test descriptor) **TEST FOR VARIABLES** (time vble, event vble)

(a) **GEOGAMMA**

RHO= GAMMA= <BETA> if # samples=2

<SOFT=vble name> if # samples=1

(b) **Gehan-Wilcoxon**

<BETA> if # samples=2

<SOFT=vble name> if # samples=1

(c) **K-ALPHA**

ALPHA= BETA=0

(d) **GENERALIZED SMIRNOV**

<table>
<thead>
<tr>
<th>SAMPLE</th>
<th>N</th>
<th>OBSERVED</th>
<th>SUM OF WEIGHTED OBSERVED</th>
<th>SUM OF WEIGHTED EXPECTED</th>
<th>(O-E)**2</th>
<th>E</th>
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<tbody>
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</tbody>
</table>

CHI-SQUARE= DF= TWO-TAIL P-VALUE=

Note that the chi-square value will not be the total of the (O-E)**2/E. The latter is printed only to give some indication of the samples in which differences between the weighted observed and expected number of events are most pronounced.
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References


