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The Skillings–Mack test (Friedman test when there are missing data)

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Abstract. The Skillings–Mack statistic (Skillings and Mack, 1981, *Technometrics* 23: 171–177) is a general Friedman-type statistic that can be used in almost any block design with an arbitrary missing-data structure. The missing data can be either missing by design, for example, an incomplete block design, or missing completely at random. The Skillings–Mack test is equivalent to the Friedman test when there are no missing data in a balanced complete block design, and the Skillings–Mack test is equivalent to the test suggested in Durbin (1951, *British Journal of Psychology, Statistical Section* 4: 85–90) for a balanced incomplete block design. The Friedman test was implemented in Stata by Goldstein (1991, *Stata Technical Bulletin* 3: 26–27) and further developed in Goldstein (2005, *Stata Journal* 5: 285). This article introduces the `skilmack` command, which performs the Skillings–Mack test.

The `skilmack` command is also useful when there are many ties or equal ranks (N.B. the Friedman statistic compared with the χ^2 distribution will give a conservative result), as well as for small samples; appropriate results can be obtained by simulating the distribution of the test statistic under the null hypothesis.

Keywords: `st0167`, `skilmack`, Skillings–Mack, Friedman, block design, nonparametric, unbalanced, missing data, ties

1 Introduction

There are many situations where the assumption of a normally distributed error distribution is not true and hence statisticians need to apply distribution-free methods. A common model for a randomized block design is

$$Y_{ij} = \mu + \beta_i + \tau_j + \epsilon_{ij}$$

where Y_{ij} is the response corresponding to the j th treatment in the i th block, μ is the overall mean, τ_j is the j th treatment effect, and β_i is the i th block effect. The errors, ϵ_{ij} , are independent and identically distributed with some continuous distribution function. Without loss of generality, let there be k treatments and n blocks, and let n_{ij} indicate whether there is an observation for the j th treatment in the i th block. The usual null hypothesis is that the treatment effects are all identical, i.e., $\tau_1 = \dots = \tau_k$. The Friedman test (Friedman 1937) is the distribution-free test for a

completely balanced randomized block design ($n_{ij} = 1 \ \forall i, j$). The Friedman test was implemented in Stata by Goldstein (1991) and further developed in Goldstein (2005). Durbin proposed a Friedman-type test for a balanced incomplete block design (Durbin 1951), and Skillings and Mack (1981) proposed a more general Friedman-type test for an unbalanced incomplete block design with an arbitrary missing-data structure. The missing data can be missing by design or missing completely at random. This article introduces the **skilmack** command, which calculates the Skillings–Mack (SM) test. **skilmack** computes the SM test statistic by using the following steps:

- Remove any block with only one observation.
- Within each block, observations are ranked from 1 to k_i , where k_i is the number of treatments in block i , and when ties occur ranks are averaged.
- The rank for Y_{ij} will be r_{ij} , but when an observation is missing, then the value $(k_i + 1)/2$ is used.
- Compute an adjusted treatment sum, A_j , where

$$A_j = \sum_{i=1}^n \left(\frac{12}{k_i + 1} \right)^{1/2} \left(r_{ij} - \frac{k_i + 1}{2} \right), \quad \text{for } j = 1, \dots, k$$

As in the Friedman test, the SM test begins by reducing the data to within-block ranks. In the Friedman test, the ranks are added within each treatment; however, when there are missing data, it is necessary to center the ranks (by subtracting the average rank for that block). The ranks are then weighted by $\{12/(k_i + 1)\}^{1/2}$. This weight is chosen for two reasons: First, the range of $\{r_{ij} - (k_i + 1)/2\}$ is smaller for blocks with missing data, and the weights attempt to address this imbalance. Second, it produces a simple covariance structure on A_1, \dots, A_k . To complete the calculation of the test statistic, the covariance of the treatment sums is required.

Setting $\mathbf{A} = (A_1, \dots, A_{k-1})$, the covariance matrix for \mathbf{A} under the null hypothesis, H_0 , is given by

$$\Sigma_0 = \begin{pmatrix} \sum_{t=2}^k \lambda_{1t} & -\lambda_{12} & -\lambda_{13} & \dots & -\lambda_{1,k-1} \\ -\lambda_{12} & \sum_{t \neq 2}^k \lambda_{2t} & -\lambda_{23} & \dots & -\lambda_{2,k-1} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ -\lambda_{1,k-1} & -\lambda_{2,k-1} & -\lambda_{3,k-1} & \dots & \sum_{t \neq k-1}^k \lambda_{k-1,t} \end{pmatrix}$$

where $\lambda_{qt} = \lambda_{tq}$ = (number of blocks in which both treatments q and t are observed). Then the SM statistic is given by

$$SM = \mathbf{A} \Sigma_0^{-1} \mathbf{A}'$$

where Σ_0^{-1} is any generalized inverse for Σ_0 . Under H_0 , $SM \sim \chi_{k-1}^2$ for large n .

There are several situations where it would be appropriate to estimate the distribution of SM values under H_0 , and **skilmack** simulates this distribution.

The χ^2 distribution is inadequate when the sample size is small, and unless n is very large, it is preferable to use simulation to estimate the distribution of SM values under H_0 , particularly for the tail. The χ^2 approximation tends to be conservative. This is especially true for significance levels of 0.01 or less.

For ties, or equal ranks, we will also want to simulate because there is less variation between the weighted sum of centered ranks, A_j , or the sum of ranks in the Friedman test, and so the χ^2 distribution will give conservative p -values.

Unlike with the **friedman** command (Goldstein 2005), for **skilmack** the data are required to be in the more usual long format, i.e., one column for the outcome measure, one for the block identifier or ID, and one for the treatment or within-block repeated variable.

2 The skilmack command

2.1 Syntax

```
skilmack varname [ if ] [ in ], id(varname) repeated(varname) [ covariance
  forcesims(on|off) reps(#) seed(#) notable(noties|tiescov|both) ]
```

2.2 Options

id(varname) is required and specifies the factor variable containing the block identifiers.

repeated(varname) is required and specifies the factor variable containing the treatment identifiers.

covariance specifies that the estimated covariance matrix is used in place of the no-ties covariance matrix. The estimated covariance matrix is the sample covariance matrix of the weighted sum of centered ranks from the simulations.

forcesims(on|off) forces whether simulations are used. Simulations will be run if and only if there are ties, unless overridden by this option.

reps(#) sets the number of simulations. The default is **reps(1000)**.

seed(#) specifies the random-number seed; time is used as the default seed. This option allows an exact replication of the Monte Carlo simulations.

notable(noties|tiescov|both) suppresses the output table produced in the no-ties section or in the case of ties when the **covariance** option is used (or both).

3 Example

The following example was used in Hollander and Wolfe’s book on nonparametric statistical methods (Hollander and Wolfe 1999), which in turn is taken from Brady (1969). The `skilmack` command will be demonstrated using this dataset. (Numbers in parentheses are within-subject ranks.)

Dysfluencies under each condition			
ID	R	A	N
1	3 (1)	5 (2)	15 (3)
2	1 (1)	3 (2)	18 (3)
3	5 (2)	4 (1)	21 (3)
4	2 (1)		6 (2)
5	0 (1)	2 (2)	17 (3)
6	0 (1)	2 (2)	10 (3)
7	0 (1)	3 (2)	8 (3)
8	0 (1)	2 (2)	13 (3)

The SM results from the above data are

```
. skilmack score, id(id) repeated(cond)
Weighted Sum of Centered Ranks
```

cond	N	WSumCRank	SE	WSum/SE
A	7	-1.73	3.74	-0.46
N	8	13.12	3.87	3.39
R	8	-11.39	3.87	-2.94

```

Total                0
Skillings Mack      = 13.281
P-value (No ties) =  0.0013
  N.B. As P-value <0.02, it is likely to be conservative (unless n large).
  Consider obtaining a p-value from a simulated null distribution of SM -
  see options.
```

As cautioned in the output, the p -value did turn out to be conservative, because when we typed `skilmack score, id(id) repeated(cond) forcesims(on) seed(1) reps(100000)`, we got an empirical p -value of 0.

N.B. A large, negative `WSumCRank` (or `WSum/SE`) means a low ranking (e.g., 1) because of typically low scores. This was the case for condition R, which had the fewest dysfluencies.

An informal examination of differences in the repeated measures can be made by comparing the values of `WSum/SE`.

4 Simulation

A dataset is simulated by sorting on random numbers, for each individual, to randomly shuffle which data point belongs to which repeat. The sorting on random numbers is not applied where there are missing data to preserve the missing-data structure. A value of the test statistic is then calculated. This process is then repeated (default 1,000 times). The p -value is the proportion of times that randomly generated values of SM are at least as large as the value of SM from the actual data.

If there are ties (equal ranks), average ranks are assigned, e.g., 1.5, 1.5, 3. Assigning average ranks is perhaps the most common way of dealing with ties. However, one may prefer to force ranks to be randomly assigned when they are tied. (This can effectively be done by adding a small random amount to each score.)

The SM statistic can be calculated when there are ties; however, the p -value calculated from the assumed χ^2 null distribution becomes more and more conservative the more ties there are. To provide a more accurate p -value, simulations are used to approximate the distribution of SM values under the null hypothesis, conditional on the particular missing-data structure and tied rankings.

With the `covariance` option, the SM statistic can be redefined by estimating the covariance matrix of the weighted sums of centered ranks and using this in place of the covariance matrix (which is accurate when there are no ties, but not when there are many ties). A new table is produced with different standard errors, and a new SM statistic and p -value are calculated. The tables can be suppressed by using the `notable()` option.

5 Friedman test dealing with ties

Because the SM test is equivalent to the Friedman test in a completely balanced design with no missing data (Skillings and Mack 1981) even when there are ties, `skilmack` can be used to perform the Friedman test when there are ties.

(Continued on next page)

```
. recode score . = 2 /* to create a full dataset with a tie */
(score: 1 changes made)
. skilmack score, id(id) repeated(cond) seed(1) reps(10000)

Weighted Sum of Centered Ranks
```

cond	N	WSumCRank	SE	WSum/SE
A	8	-2.60	4.00	-0.65
N	8	13.86	4.00	3.46
R	8	-11.26	4.00	-2.81

```

Total              0
Skillings Mack      = 13.562
P-value (No ties)   = 0.0011
    N.B. As P-value < 0.02, it is likely to be conservative (unless n large).
    Consider obtaining a p-value from a simulated null distribution of SM -
    see options.

Ties exist. Above SEs and P-value approximate, if not too many ties;
24 rows of [id, score]; 23 different combinations; n(id) = 8

Consider using the p-value below, (which is found from a simulated
    conditional null distribution of SM - see options -
    simulating ..... )
Empirical P-value (Ties) ~ 0.0000
```

Equivalence with the Friedman test is illustrated below.

```
. reshape wide score, i(cond) j(id)
(note: j = 1 2 3 4 5 6 7 8)
```

Data	long	->	wide
Number of obs.	24	->	3
Number of variables	3	->	9
j variable (8 values)	id	->	(dropped)
xij variables:	score	->	score1 score2 ... score8

```

. friedman score*
Friedman = 13.5625
Kendall = 0.8477
P-value = 0.0011
```

There are several things to notice here. First, the SM statistic is the Friedman statistic, and because they have the same approximate χ^2 distribution under the null hypothesis, the p -values (ignoring the issue of ties) are the same. Second, the `skilmack` command gives information on how many ties there are. There were 23 different combinations of (`id`, `score`) (maximum possible 24 and minimum possible 8). Because there were few ties, one could argue that there is little need to get a better approximate null distribution since it will differ only slightly from the χ^2 distribution assumed in the no-ties case. However, a simulated null distribution is desirable here because the dataset and the p -value are small. The p -value conditional on the particular ties, and coming from comparison of the test statistic with the simulated null distribution, should be, and was, lower than the p -value ignoring ties and coming from the χ^2 distribution. The approximate null distribution will differ each time unless the seed is set and will be more accurate with more simulations leading to a more reliable p -value.

6 Summary

The SM test does not seem to be readily available in main statistical packages. `skilmack` is the first Stata implementation of the SM test, which is a generalization of the Friedman test. It is a distribution-free method and can be applied to a variety of situations; for example, it can be used to analyze an incomplete block design. The SM test is equivalent to the Friedman test when there are no missing data. The simulations option allows a more theoretically correct p -value to be estimated when ties exist in the dataset, and this can be used regardless of whether there are missing data.

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