# Continuous variables without missing values: confirmatory factor analysis

## Contents



## 1. Introduction

To illustrate all the different cases and the different steps in the analysis the classical example of confirmatory factor analysis of nine psychological variables (NPV) from the Holzinger-Swineford (1939) study will be used. The nine variables is a subset of 26 variables administered to 145 seventh- and eighth-grade children in the Grant-White school in Chicago. The nine tests are (with the original variable number in parenthesis):

- **VIS PERC** Visual Perception (V1)
- **CUBES** Cubes (V2)
- **LOZENGES** Lozenges (V4)
- **PAR COMP** Paragraph Comprehension (V6)
- **SEN COMP** Sentence Completion (V7)
- **WORDMEAN** Word meaning (V9)
- **ADDITION** Addition (V10)
- **COUNTDOT** Counting dots (V12)
- **SCCAPS** Straight-curved capitals (V13)

It is hypothesized that these variables have three correlated common factors: visual perception here called Visual, verbal ability here called Verbal and speed here called Speed such that the first three variables measure Visual, the next three measure Verbal, and the last three measure Speed. A path diagram of the model to be estimated is given in Figure 1.

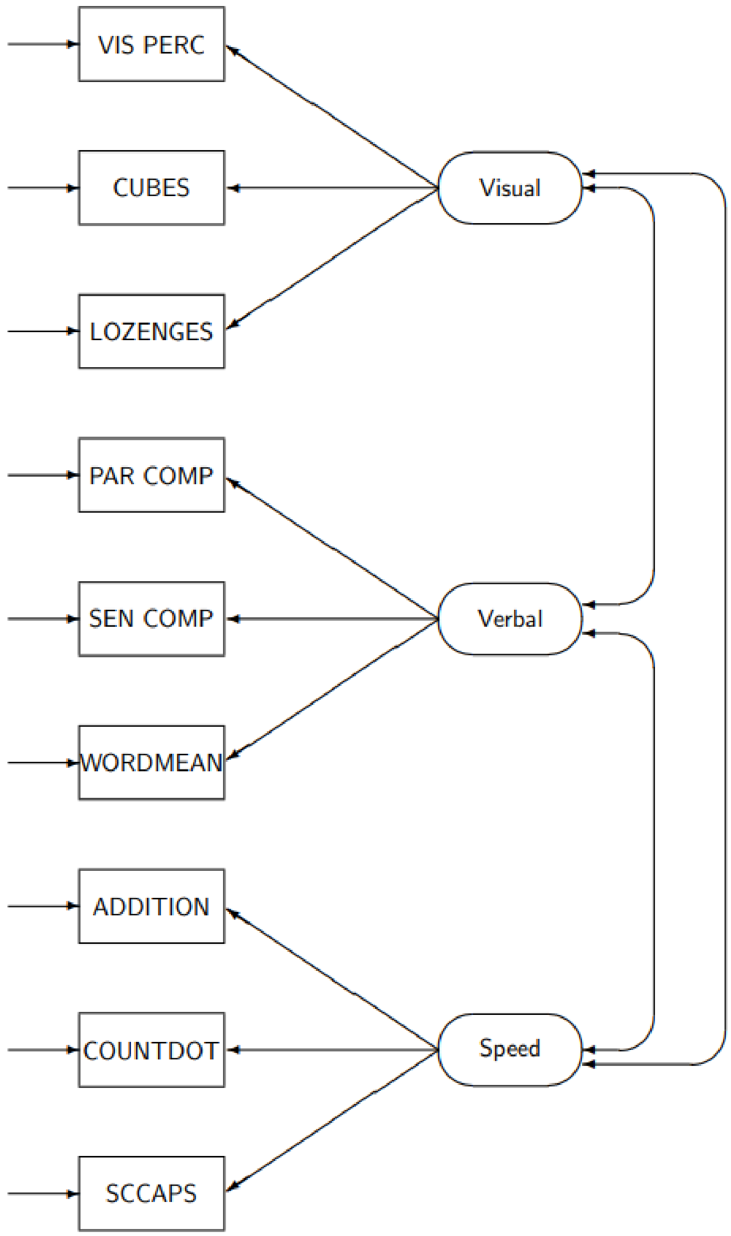


**Figure 1: Confirmatory Factor Analysis Model for Nine Psychological Variables**

Suppose the data is available in a text file **npv.dat** with the names of the variables in the first line. The first few lines of the data file looks like this[1]

’VIS PERC’ CUBES LOZENGES ’PAR COMP’ ’SEN COMP’ WORDMEAN ADDITION COUNTDOTS SCCAPS

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| 33 | 22 | 17 | 8 | 17 | 10 | 65 | 98 | 195 |
| 34 | 24 | 22 | 11 | 19 | 19 | 50 | 86 | 228 |
| 29 | 23 | 9 | 9 | 19 | 11 | 114 | 103 | 144 |
| 16 | 25 | 10 | 8 | 25 | 24 | 112 | 122 | 160 |
| 30 | 25 | 20 | 10 | 23 | 18 | 94 | 113 | 201 |
| 36 | 33 | 36 | 17 | 25 | 41 | 129 | 139 | 333 |
| 28 | 25 | 9 | 10 | 18 | 11 | 96 | 95 | 174 |

[1] If a name contains spaces or other special characters, put the name within ’ ’ as shown.

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| 30 | 25 | 11 | 11 | 21 | 8 | 103 | 114 | 197 |
| 20 | 25 | 6 | 9 | 21 | 16 | 89 | 101 | 178 |
| 27 | 26 | 6 | 10 | 16 | 13 | 88 | 107 | 137 |
| 32 21 | 8 | 1 | 7 | 11 | 103 | 136 | 154 | |

## 2. Creating a LISREL Data System File

For most analyses with LISREL it is convenient to to work with a LISREL **data system file** of the type *.**lsf**. LISREL can import data from many formats such as SAS, SPSS, STATA, and EXCEL. LISREL can also import data in text format with spaces (***.dat** or ***.raw**), commas (***.csv**) or tab characters (*.txt) as delimiters between entries. The data is then stored as a LISREL data system file **.lsf**. First, we illustrate how to import a text file with spaces as delimiters. The procedure is the same for all other types of files. Importation of data from external sources is described in the PRELIS Guide.

Since the data in this example is a text file with spaces as delimiters, an easy way to create a **.lsf** file is by running the following simple PRELIS syntax file

```
DA NI=9
RA=NPV.DAT LF CO All
OU RA=NPV.LSF
```

LF is a new PRELIS option to tell PRELIS that the labels are in the first line(s) of the data file.

## 3. Estimating the Model by Maximum Likelihood

With the **npv.lsf** file on hand, one can estimate the model by normal theory maximum likelihood[2]. The first SIMPLIS file is (see file **npv1a.spl**):

```
Estimation of the NPV Model by Maximum Likelihood
Raw Data from File npv.lsf
Latent Variables: Visual Verbal Speed Relationships:
’VIS PERC’ - LOZENGES = Visual
’PAR COMP’ - WORDMEAN = Verbal ADDITION - SCCAPS = Speed
Path Diagram
End of Problem
```

One can also include a line

```
Path Diagram
```

to display path diagrams with parameter estimates, standard errors, and *t*-values.

The sample covariance matrix **S** is given as

```
        Covariance Matrix

            VIS PERC      CUBES   LOZENGES   PAR COMP   SEN COMP   WORDMEAN
            --------   --------   --------   --------   --------   --------
 VIS PERC     47.801
    CUBES     10.013     19.758
```

[2] The term normal theory maximum likelihood is used to mean that the estimation of the model is based on the assumption that the variables have a multivariate normal distribution.

```
LOZENGES     25.798     15.417     69.172
PAR COMP      7.973      3.421      9.207     11.393
SEN COMP      9.936      3.296     11.092     11.277     21.616
WORDMEAN     17.425      6.876     22.954     19.167     25.321     63.163
ADDITION     17.132      7.015     14.763     16.766     28.069     33.768
COUNTDOT     44.651     15.675     41.659      7.357     19.311     20.213
  SCCAPS    124.657     40.803    114.763     39.309     61.230     79.993

        Covariance Matrix

           ADDITION   COUNTDOT     SCCAPS
           --------   --------   --------
ADDITION    565.593
COUNTDOT    293.126    440.792
  SCCAPS    368.436    410.823   1371.618

Total Variance = 2610.906 Generalized Variance = 0.106203D+17

Largest Eigenvalue = 1734.725 Smallest Eigenvalue = 3.665

Condition Number = 21.756
```

The total variance is the sum of the diagonal elements of **S** and the generalized variance is the determinant of **S** which equals the product of all the eigenvalues of **S**. The largest and smallest eigenvalues of **S** are also given. These quantities are useful in principal components analysis. The condition number is the square root of the ratio of the largest and smallest eigenvalue. A small condition number indicates multicollinearity in the data. If the condition number is very small LISREL gives a warning. This might indicate that one or more variables are linear or nearly linear combinations of other variables.

LISREL gives parameter estimates, standard errors, *Z*-values, *P*-values and $R^2$ for the measurement equations as follows:

```
LISREL Estimates (Maximum Likelihood)

         Measurement Equations

 VIS PERC = 4.678*Visual, Errorvar.= 25.915, R² = 0.458
Standerr  (0.624)                  (4.582)
Z-values   7.499                    5.656
P-values   0.000                    0.000

   CUBES = 2.296*Visual, Errorvar.= 14.487, R² = 0.267
Standerr  (0.408)                  (1.981)
Z-values   5.622                    7.313
P-values   0.000                    0.000

LOZENGES = 5.769*Visual, Errorvar.= 35.896, R² = 0.481
Standerr  (0.751)                  (6.660)
Z-values   7.684                    5.390
P-values   0.000                    0.000

PAR COMP = 2.922*Verbal, Errorvar.= 2.857 , R² = 0.749
Standerr  (0.237)                  (0.589)
Z-values   12.312                   4.854
P-values   0.000                    0.000
```

```
SEN COMP = 3.856*Verbal, Errorvar.= 6.749 , R² = 0.688
Standerr  (0.333)                   (1.165)
Z-values   11.590                    5.792
P-values   0.000                     0.000

WORDMEAN = 6.567*Verbal, Errorvar.= 20.034, R² = 0.683
Standerr  (0.569)                   (3.419)
Z-values   11.532                    5.859
P-values   0.000                     0.000

ADDITION = 15.676*Speed, Errorvar.= 319.868, R² = 0.434
Standerr  (2.012)                   (48.754)
Z-values   7.792                     6.561
P-values   0.000                     0.000

COUNTDOT = 16.709*Speed, Errorvar.= 161.588, R² = 0.633
Standerr  (1.752)                   (38.166)
Z-values   9.535                     4.234
P-values   0.000                     0.000

  SCCAPS = 25.956*Speed, Errorvar.= 697.900 , R² = 0.491
Standerr  (3.117)                   (116.524)
Z-values   8.328                     5.989
P-values   0.000                     0.000
```

By default LISREL standardizes the latent variables. This seems most reasonable since the latent variables are unobservable and have no definite scale. The correlations among the latent variables, with standard errors and *Z*-values are given as follows

```
 Correlation Matrix of Independent Variables

             Visual     Verbal      Speed
           --------   --------   --------
  Visual      1.000

  Verbal      0.541      1.000
            (0.085)
              6.355

   Speed      0.523      0.336      1.000
            (0.094)    (0.091)
              5.562      3.674
```

These estimates have been obtained by maximizing the likelihood function $L$ under multivariate normality. Therefore it is possible to give the log-likelihood values at the maximum of the likelihood function. It is common the report the value of $-2\ln(L)$, sometimes called deviance, instead of $L$. LISREL gives the value $-2\ln(L)$ for the estimated model and for a saturated model. A saturated model is a model where the mean vector and covariance matrix of the multivariate normal distribution are unconstrained.

The log-likelihood values are given in the output as

```
                               Log-likelihood Values

                        Estimated Model         Saturated Model
                        ---------------         ---------------
```

```
 Number of free parameters(t)        21                        45
 -2ln(L)                        6706.910                  6655.724
 AIC (Akaike, 1974)*            6748.910                  6745.724
 BIC (Schwarz, 1978)*           6811.276                  6879.365

*LISREL uses AIC= 2t - 2ln(L) and BIC = tln(N)- 2ln(L)
```

LISREL also give the values of AIC and BIC. These can be used for the problem of selecting the "best" model from several a priori specified models. One then chooses the model with the smallest AIC or BIC. The original papers of Akaike (1974) and Schwarz (1978) define AIC and BIC in terms of ln($L$) but LISREL uses −2ln($L$) and the formulas:

$$AIC = 2t - 2\ln(L), \quad (1)$$

$$BIC = t\ln(N) - 2\ln(L), \quad (2)$$

where $t$ is the number of free parameters in the model and $N$ is the total sample size.

## 4. Testing the Model

Various chi-square statistics are used for testing structural equation models. If normality holds and the model is fitted by the maximum likelihood (ML) method, one such chi-square statistic is obtained as $N$ times the minimum of the ML fit function, where $N$ is the sample size. An asymptotically equivalent chi-square statistic can be obtained from a general formula developed by Browne (1984) and using an asymptotic covariance matrix estimated under multivariate normality. These chi-square statistics are denoted $C_1$ and $C_2(NT)$, respectively. They are valid under multivariate normality of the observed variables and if the model holds.

For this analysis, LISREL gives the two chi-square values $C_1$ and $C_2(NT)$ as

```
Degrees of Freedom for (C1)-(C2)                         24
 Maximum Likelihood Ratio Chi-Square (C1)                 51.187 (P = 0.0010)
 Browne's (1984) ADF Chi-Square (C2_NT)                   48.615 (P = 0.0021)
```

## 5. Robust Estimation

The analysis just described assumes that the variables have a multivariate normal distribution. This assumption is questionable in many cases. Although the maximum likelihood parameter estimates are considered to be robust against non-normality, their standard errors and chi-squares are affected by non-normality. It is therefore recommended to use the maximum likelihood method with robustified standard errors and chi-squares, which is called Robust Maximum Likelihood. To do so just include a line

```
Robust Estimation
```

anywhere between the second line and the last line, see file **npv2a.spl**. This gives the following information about the distribution of the variables.

```
Total Sample Size(N) =    145

 Univariate Summary Statistics for Continuous Variables

 Variable     Mean  St. Dev.  Skewness  Kurtosis  Minimum Freq.  Maximum Freq.
 --------     ----  --------   -------  --------  ------- -----  ------- -----
```

```
 VIS PERC   29.579     6.914    -0.119    -0.046   11.000     1   51.000     1
    CUBES   24.800     4.445     0.239     0.872    9.000     1   37.000     2
 LOZENGES   15.966     8.317     0.623    -0.454    3.000     2   36.000     1
 PAR COMP    9.952     3.375     0.405     0.252    1.000     1   19.000     1
 SEN COMP   18.848     4.649    -0.550     0.221    4.000     1   28.000     1
 WORDMEAN   17.283     7.947     0.729     0.233    2.000     1   41.000     1
 ADDITION   90.179    23.782     0.163    -0.356   30.000     1  149.000     1
 COUNTDOT  109.766    20.995     0.698     2.283   61.000     1  200.000     1
   SCCAPS  191.779    37.035     0.200     0.515  112.000     1  333.000     1
```

This shows that the range of the variables are quite different, reflecting the case that they are composed of different number of items. For example, PAR COMP has a range of 1 to 19, whereas SCCAPS has a range of 112 to 333. This is also reflected in the means and standard deviations.

LISREL also gives tests of univariate and multivariate skewness and kurtosis.

```
Test of Univariate Normality for Continuous Variables

             Skewness         Kurtosis      Skewness and Kurtosis

 Variable Z-Score P-Value   Z-Score P-Value   Chi-Square P-Value

 VIS PERC  -0.604   0.546     0.045   0.964        0.367   0.833
    CUBES   1.202   0.229     1.843   0.065        4.842   0.089
 LOZENGES   2.958   0.003    -1.320   0.187       10.491   0.005
 PAR COMP   1.995   0.046     0.761   0.447        4.559   0.102
 SEN COMP  -2.646   0.008     0.693   0.489        7.483   0.024
 WORDMEAN   3.385   0.001     0.720   0.472       11.977   0.003
 ADDITION   0.826   0.409    -0.937   0.349        1.560   0.458
 COUNTDOT   3.263   0.001     3.325   0.001       21.699   0.000
   SCCAPS   1.008   0.313     1.273   0.203        2.638   0.267
```

The output file **npv2a.out** gives the same parameter estimates as before but different standard errors. As a consequence, *t*-values and *P*-values are also different. The parameter estimates and the two sets of standard errors are given in Table 1.

If the observed variables are non-normal, one can use the same formula from Browne (1984) using an asymptotic covariance matrix (ACM)[3] estimated under non-normality. This chi-square, often called the ADF (Asymptotically Distribution Free) chi-square statistic, is denoted $C_2(NNT)$ in LISREL. It has been found in simulation studies that the ADF statistic does not work well because it is difficult to estimate the ACM accurately unless *N* is huge, see e.g, Curran, West, & Finch (1996).

[3] The ACM is an estimate of the covariance matrix of the sample variances and covariances. Under non-normality this involves estimates of fourth-order moments.

**Table 1: Parameter Estimates, Normal Standard Errors, and Robust Standard Errors**

| Factor Loading | Parameter Estimates | Standard Errors Normal | Robust |
|---|---|---|---|
| VIS PERC on Visual | 4.678 | 0.624 | 0.696 |
| CUBES on Visual | 2.296 | 0.408 | 0.377 |
| LOZENGES on Visual | 5.769 | 0.751 | 0.728 |
| PAR COMP on Verbal | 2.992 | 0.237 | 0.251 |
| SEN COMP on Verbal | 3.856 | 0.333 | 0.332 |
| WORDMEAN on Verbal | 6.567 | 0.569 | 0.575 |
| ADDITION on Speed | 15.676 | 2.012 | 1.836 |
| COUNTDOT on Speed | 16.709 | 1.752 | 1.781 |
| SCCAPS on Speed | 25.956 | 3.117 | 3.088 |
| Factor Correlations | | | |
| Verbal vs Visual | 0.541 | 0.085 | 0.094 |
| Verbal vs Speed | 0.523 | 0.094 | 0.100 |
| Verbal vs Speed | 0.336 | 0.091 | 0.115 |

Satorra & Bentler (1988) proposed another approximate chi-square statistic $C_3$, often called the SB chi-square statistic, which is $C_1$ multiplied by a scale factor which is estimated from the sample and involves estimates of the ACM both under normality and non-normality. The scale factor is estimated such that $C_3$ has an asymptotically correct mean even though it does not have an asymptotic chi-square distribution. In practice, $C_3$ is conceived of as a way of correcting $C_1$ for the effects of non-normality and $C_3$ is often used as it performs better than the ADF test $C_2(NT)$ in LISREL, particularly if $N$ is not very large, see e.g., Hu, Bentler, & Kano (1992).

Satorra & Bentler (1988) also mentioned the possibility of using a Satterthwaite (1941) type correction which adjusts $C_1$ such that the corrected value has the correct asymptotic mean and variance. This type of fit measure has not been much investigated, neither for continuous nor for ordinal variables. However, this type of chi-square fit statistic has been implemented in LISREL, where it is denoted $C_4$. For our present example, these appear in the output as

```
Degrees of Freedom for (C1)-(C3),C(5)                24
 Maximum Likelihood Ratio Chi-Square (C1)             51.187 (P = 0.0010)
 Browne's (1984) ADF Chi-Square (C2_NT)               48.615 (P = 0.0021)
 Browne's (1984) ADF Chi-Square (C2_NNT)              64.202 (P = 0.0000)
 Satorra-Bentler (1988) Scaled Chi-Square (C3)        49.715 (P = 0.0015)
 Satorra-Bentler (1988) Adjusted Chi-Square (C4)      34.891 (P = 0.0060)
 Degrees of Freedom for C4                            16.844
```

$C_1$ and $C_2(NT)$ are the same as before but with robust estimation LISREL9 also gives $C_2(NNT)$, $C_3$ and $C_4$ so that one can see what the effect of non-normality is. In particular, the difference $C_2(NNT) - C_2(NT)$ can be viewed as an effect of non-nomality.

Note that $C_4$ has its own degrees of freedom which is different from the model degrees of freedom. LISREL gives the degrees of freedom for $C_4$ as a fractional number and uses these fractional degrees of freedom to compute the *P*-value for $C_4$.

## 6. Estimation Using Data in Text Form

Since the original data is given in text form in this example, it is not necessary to use a **lsf** file to analyze the data. One can read the text data file **npv.dat** directly into LISREL using the following SIMPLIS syntax file, see file **npv3a.spl**.

```
Estimation of the NPV Model by Robust Maximum Likelihood
Using text data with Labels in the first line
Raw Data from File NPV.DAT
Latent Variables: Visual Verbal Speed
Relationships:
   'VIS PERC' - LOZENGES = Visual
   'PAR COMP' - WORDMEAN = Verbal
   ADDITION - SCCAPS = Speed
Robust Estimation
Options: RS SC MI
Path Diagram
End of Problem
```

The Options line can be used to request additional output, see the SIMPLIS Syntax Guide. In this case, RS means residuals and standardized residuals, SC means completely standardized solution, and MI means modification indices.

## 7. Modifying the Model

The output file **npv3a.out** gives the following information about modification indices

```
       The Modification Indices Suggest to Add the
  Path to  from      Decrease in Chi-Square    New Estimate
 ADDITION  Visual               8.5                -6.90
 COUNTDOT  Verbal               8.3                -4.94
 SCCAPS    Visual              28.4                24.44
 SCCAPS    Verbal              10.8                11.11
```

This suggests that the fit cam be improved by adding a path from Visual to SCCAPS. If this makes sense, one can add this path and rerun the model. This gives a solution where

```
  SCCAPS = 16.559*Visual + 16.274*Speed, Errorvar.= 620.929, R² = 0.547
 Standerr  (3.700)        (3.359)                  (98.281)
 Z-values   4.475          4.845                    6.318
 P-values   0.000          0.000                    0.000

 Degrees of Freedom for (C1)-(C3),C(5)                  23
 Maximum Likelihood Ratio Chi-Square (C1)               28.293 (P = 0.2049)
 Browne's (1984) ADF Chi-Square (C2_NT)                 27.898 (P = 0.2197)
 Browne's (1984) ADF Chi-Square (C2_NNT)                31.701 (P = 0.1065)
 Satorra-Bentler (1988) Scaled Chi-Square (C3)          28.221 (P = 0.2075)
 Satorra-Bentler (1988) Adjusted Chi-Square (C4)        20.437 (P = 0.2342)
 Degrees of Freedom for C4                              16.656
```

indicating a good fit.

## 8. Analyzing Correlations

Factor analysis was mainly developed by psychologists for the purpose of identifying mental abilities by means of psychological testing. Various theories of mental abilities and various procedures for analyzing the correlations among psychological tests emerged.

Following this old tradition, users of LISREL might be tempted to analyze the correlation matrix of the nine psychological variables instead of the covariance matrix as we have done in the previous examples. However, analyzing the correlation matrix by maximum likelihood (ML) is problematic in several ways as pointed out by Cudeck (1989), see also Appendix C in Jöreskog,et.al. (2003). There are three ways to resolve this problem:

**Approach 1** Use the covariance matrix and ML as before and request the completely standardized solution (SC)[4] as was done on the Options line in file **npv3a.spl**. This gives the completely standardized solution in matrix form as

```
Completely Standardized Solution

         LAMBDA-X

              Visual     Verbal      Speed
            --------   --------   --------
 VIS PERC      0.677       - -        - -
    CUBES      0.517       - -        - -
 LOZENGES      0.694       - -        - -
 PAR COMP       - -       0.866       - -
 SEN COMP       - -       0.829       - -
 WORDMEAN       - -       0.826       - -
 ADDITION       - -        - -       0.659
 COUNTDOT       - -        - -       0.796
   SCCAPS       - -        - -       0.701

         PHI

              Visual     Verbal      Speed
            --------   --------   --------
   Visual      1.000
   Verbal      0.541      1.000
    Speed      0.523      0.336      1.000
THETA-DELTA

            VIS PERC      CUBES   LOZENGES   PAR COMP   SEN COMP   WORDMEAN
            --------   --------   --------   --------   --------   --------
               0.542      0.733      0.519      0.251      0.312      0.317

         THETA-DELTA

            ADDITION   COUNTDOT     SCCAPS
            --------   --------   --------
```

[4] LISREL has two kinds of standardized solutions: the standardized solution (SS) in which only the latent variables are standardized and the completely standardized solution (SC) in which both the observed and the latent variables are standardized.

```
              0.566      0.367      0.509
```

The disadvantage with this alternative is that one does not get standard errors for the completely standardized solution.

**Approach 2** Use the following PRELIS syntax file to standardize the original variables (file **npv2.prl**):

```
RA=NPV.LSF
SV ALL
OU RA=NPVstd.LSF
```

SV is a new PRELIS command to standardize the variables. One can standardize some of the variables by listing them on the SV line. **npv2.prl** produces a new lsf file **NPVstd.lsf** in which all variables have sample means 0 and sample standard deviations 1.

Then use **NPVstd.lsf** instead of **NPV.LSF** in **npv2a.spl** to obtain a completely standardized solution with robust standard errors.

**Approach 3** Use the sample correlation matrix with robust unweighted least squares (RULS) or with robust diagonally weighted least squares (RDWLS). This will use an estimate of the asymptotic covariance matrix of the sample correlations to obtain correct asymptotic standard errors and chi-squares under non-normality.

The following SIMPLIS command file demonstrates the Approach 3, see file **npv4a.spl**:

```
Estimation of the NPV Model
by Robust Diagonally Weighted Least Squares
Using Correlations
Raw Data from File NPV.LSF
Analyze Correlations
Latent Variables: Visual Verbal Speed
Relationships:
   'VIS PERC' - LOZENGES = Visual
   'PAR COMP' - WORDMEAN = Verbal
   ADDITION - SCCAPS = Speed
Robust Estimation
Options: DWLS
Path Diagram
End of Problem
```

Note the added line

```
Analyze Correlations
```

This gives the standardized solution as

```
LISREL Estimates (Robust Diagonally Weighted Least Squares)

         Measurement Equations


 VIS PERC = 0.726*Visual, Errorvar.= 0.472 , R² = 0.528
 Standerr  (0.0712)                 (0.196)
 Z-values   10.201                   2.408
 P-values   0.000                    0.016
```

```
   CUBES = 0.481*Visual, Errorvar.= 0.769 , R² = 0.231
Standerr  (0.0815)                 (0.184)
Z-values   5.897                    4.175
P-values   0.000                    0.000

LOZENGES = 0.677*Visual, Errorvar.= 0.541 , R² = 0.459
Standerr  (0.0691)                 (0.191)
Z-values   9.794                    2.832
P-values   0.000                    0.005

PAR COMP = 0.863*Verbal, Errorvar.= 0.255 , R² = 0.745
Standerr  (0.0329)                 (0.176)
Z-values   26.257                   1.448
P-values   0.000                    0.147

SEN COMP = 0.836*Verbal, Errorvar.= 0.302 , R² = 0.698
Standerr  (0.0352)                 (0.177)
Z-values   23.743                   1.707
P-values   0.000                    0.088

WORDMEAN = 0.823*Verbal, Errorvar.= 0.323 , R² = 0.677
Standerr  (0.0364)                 (0.177)
Z-values   22.620                   1.826
P-values   0.000                    0.068

ADDITION = 0.611*Speed, Errorvar.= 0.627 , R² = 0.373
Standerr  (0.0662)                (0.185)
Z-values   9.226                   3.384
P-values   0.000                   0.001

COUNTDOT = 0.711*Speed, Errorvar.= 0.494 , R² = 0.506
Standerr  (0.0588)                (0.186)
Z-values   12.094                  2.650
P-values   0.000                   0.008

  SCCAPS = 0.842*Speed, Errorvar.= 0.290 , R² = 0.710
Standerr  (0.0588)                (0.194)
Z-values   14.324                  1.498
P-values   0.000                   0.134

Correlation Matrix of Independent Variables

             Visual     Verbal      Speed
           --------   --------   --------
  Visual      1.000

  Verbal      0.535      1.000
            (0.085)
              6.292

   Speed      0.571      0.379      1.000
            (0.087)    (0.087)
              6.591      4.354
```