

Assignment 1 SEM

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Simple linear regression for a continuous observed dependent variable with two covariates

Reading the ex3.1.dat file

```
## 'data.frame': 500 obs. of 3 variables:
## $ V1: num -0.355 0.562 0.316 3.347 -0.122 ...
## $ V2: num 0.573 -0.368 -0.577 1.089 -0.694 ...
## $ V3: num -0.175 1.09 0.425 1.149 -0.767 ...

## [1] 500 3

##      V1      V2      V3
## 1 -0.354517 0.573051 -0.175230
## 2 0.561655 -0.368095 1.090042
## 3 0.315551 -0.577052 0.425472
## 4 3.347049 1.088520 1.149353
## 5 -0.122389 -0.694153 -0.766538
## 6 -0.251276 -0.017487 -1.367410

## [1] "V1" "V2" "V3"
```

Creating names for the variables present in the dataset

```
## [1] "y1" "x1" "x3"
```

Scaling the whole dataset

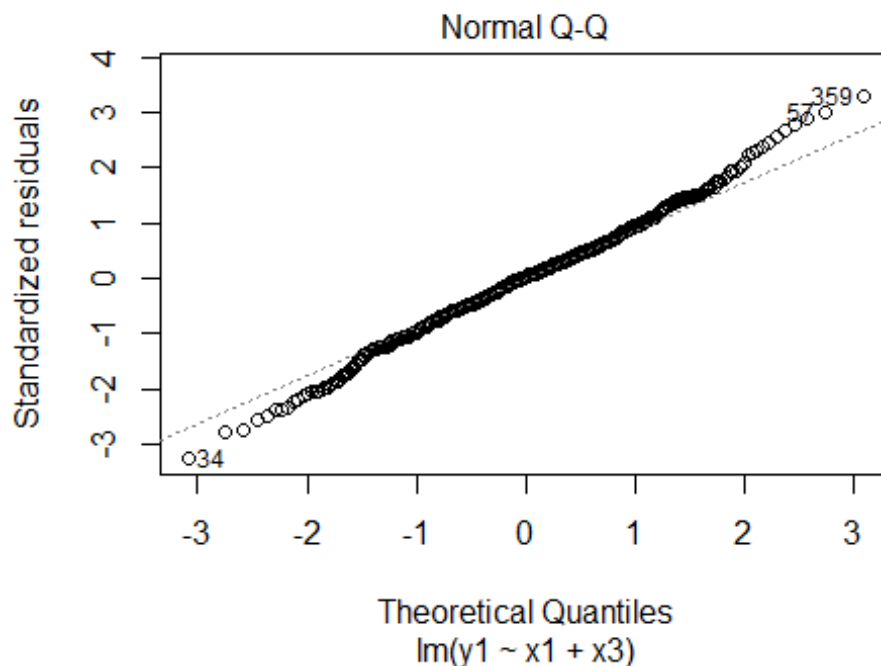
```
##      y1      x1      x3
## Min.   :-2.96235 Min.   :-3.00587 Min.   :-3.162585
## 1st Qu.: -0.65139 1st Qu.: -0.71754 1st Qu.: -0.727682
## Median : -0.03607 Median : 0.02093 Median : 0.001914
## Mean   : 0.00000 Mean   : 0.00000 Mean   : 0.000000
## 3rd Qu.: 0.70002 3rd Qu.: 0.72063 3rd Qu.: 0.777791
## Max.   : 2.97848 Max.   : 2.78874 Max.   : 2.979475

## [1] "matrix"
```

Regression model with diagnostic plot

```
##
## Call:
## lm(formula = y1 ~ x1 + x3, data = data1_scaled)
```

```
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -2.02847 -0.37032  0.01512  0.36459  2.05378
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) 1.752e-17  2.802e-02   0.00    1
## x1          6.534e-01  2.806e-02  23.29 <2e-16 ***
## x3          4.092e-01  2.806e-02  14.58 <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.6265 on 497 degrees of freedom
## Multiple R-squared:  0.609, Adjusted R-squared:  0.6075
## F-statistic: 387.1 on 2 and 497 DF,  p-value: < 2.2e-16
```



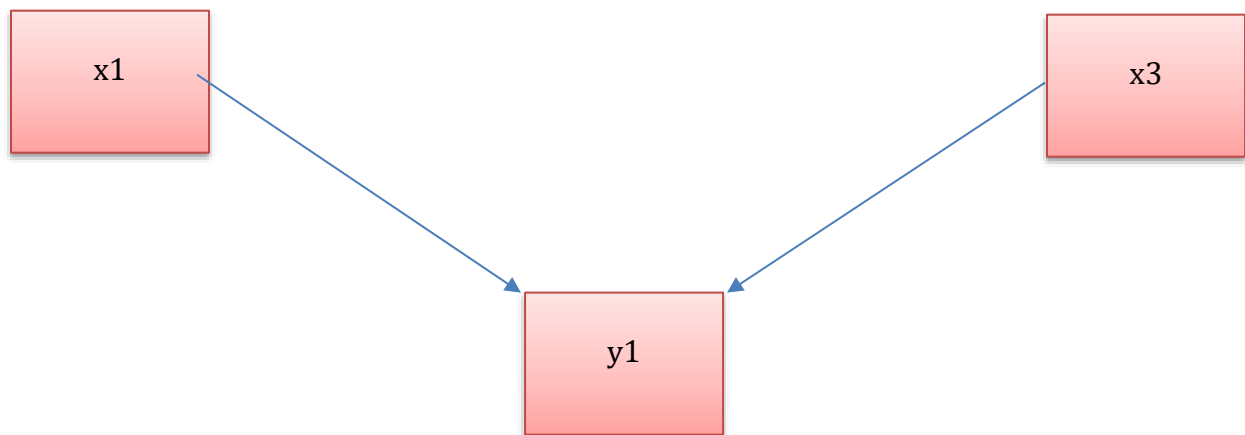
Interpretation

The higher the t-value, the better it is. The model shows t-value for x1 (23.2) and x3 (14.6) which should be more than 2, thus, fairly reliable coefficient as a predictor. The relation of y1 with x1 and x3 exists as p-value is less than the pre-determined statistical significance level (0.05). The standard error should be less than 2.5% to have the required precision. In

our model, the Standard Error is 2.806×10^{-2} for x_1 and x_3 . The R-square value is 0.60. The variation of dependent variable with two covariates seems to be 60 %.

The normal Q-Q plot is used to determine whether the residuals are normally distributed or not. The residuals in this plot were slightly deviated from the diagonal line in both the upper and lower tail. Points 34, 57 and 359 seems to be little off here. The residuals were approximately normally distributed.

Factor Mapping



Exploratory factor analysis with continuous factor indicators

Reading the dataset

```
## 'data.frame': 500 obs. of 12 variables:
## $ V1 : num -0.378 1.118 0.195 1.492 -0.442 ...
## $ V2 : num 0.0759 1.7535 -0.6006 -0.2235 -0.4476 ...
## $ V3 : num -0.628 2.177 -1.482 -0.396 1.083 ...
## $ V4 : num -0.88 0.642 -0.312 0.94 -0.648 ...
## $ V5 : num -2.7 1.72 -2.04 0.6 0.67 ...
## $ V6 : num 0.79 0.127 -1.114 2.825 0.577 ...
## $ V7 : num 0.36942 -0.32402 -0.63162 -1.96677 0.00115 ...
## $ V8 : num 0.678 0.634 -1.035 -0.725 -0.198 ...
## $ V9 : num 1.85932 0.17849 -0.00555 0.21327 -0.79722 ...
## $ V10: num 1.887 -0.761 -0.559 -0.647 0.281 ...
## $ V11: num 0.447 -1.0819 1.1913 0.0502 -0.291 ...
## $ V12: num 0.6782 -0.7933 0.1789 -1.059 -0.0991 ...
```

```
##          V1          V2          V3          V4          V5          V6          V7
## 1 -0.378137  0.075915 -0.628122 -0.880031 -2.703588  0.789544  0.369423
## 2  1.118025  1.753513  2.177335  0.642068  1.722000  0.127374 -0.324017
## 3  0.194822 -0.600631 -1.481951 -0.311791 -2.044864 -1.113668 -0.631615
## 4  1.491893 -0.223520 -0.395545  0.939834  0.600017  2.824590 -1.966773
## 5 -0.441761 -0.447650  1.082701 -0.647520  0.669891  0.576646  0.001154
## 6  1.138741  0.517782  0.134229  0.198726  1.479790  1.516361 -1.424818
##          V8          V9          V10         V11         V12
## 1  0.677649  1.859322  1.886903  0.447027  0.678236
## 2  0.634312  0.178495 -0.760867 -1.081870 -0.793253
## 3 -1.034981 -0.005553 -0.558788  1.191310  0.178950
## 4 -0.725317  0.213274 -0.646794  0.050215 -1.059023
## 5 -0.198322 -0.797221  0.280672 -0.290995 -0.099085
## 6  2.138852  1.618477 -1.519581 -0.792117  0.042684

## [1] 500 12

## [1] "V1" "V2" "V3" "V4" "V5" "V6" "V7" "V8" "V9" "V10" "V11"
## [12] "V12"
```

Creating names for variables

```
## [1] "y1" "y2" "y3" "y4" "y5" "y6" "y7" "y8" "y9" "y10" "y11"
## [12] "y12"

##          y1          y2          y3          y4          y5          y6          y7
## 1 -0.378137  0.075915 -0.628122 -0.880031 -2.703588  0.789544  0.369423
## 2  1.118025  1.753513  2.177335  0.642068  1.722000  0.127374 -0.324017
## 3  0.194822 -0.600631 -1.481951 -0.311791 -2.044864 -1.113668 -0.631615
## 4  1.491893 -0.223520 -0.395545  0.939834  0.600017  2.824590 -1.966773
## 5 -0.441761 -0.447650  1.082701 -0.647520  0.669891  0.576646  0.001154
## 6  1.138741  0.517782  0.134229  0.198726  1.479790  1.516361 -1.424818
##          y8          y9          y10         y11         y12
## 1  0.677649  1.859322  1.886903  0.447027  0.678236
## 2  0.634312  0.178495 -0.760867 -1.081870 -0.793253
## 3 -1.034981 -0.005553 -0.558788  1.191310  0.178950
## 4 -0.725317  0.213274 -0.646794  0.050215 -1.059023
## 5 -0.198322 -0.797221  0.280672 -0.290995 -0.099085
## 6  2.138852  1.618477 -1.519581 -0.792117  0.042684
```

The dataset has 500 obs. of 12 variables. The variables names are y1-y12.

Assessing the Factorability of the Data

- *Bartlett's Test of Sphericity*

```
## R was not square, finding R from data

## $chisq
## [1] 1420.056
##
```

```
## $p.value
## [1] 3.016298e-253
##
## $df
## [1] 66
```

Bartlett's test is statistically significant. It suggests that some of the variables are correlated with each other.

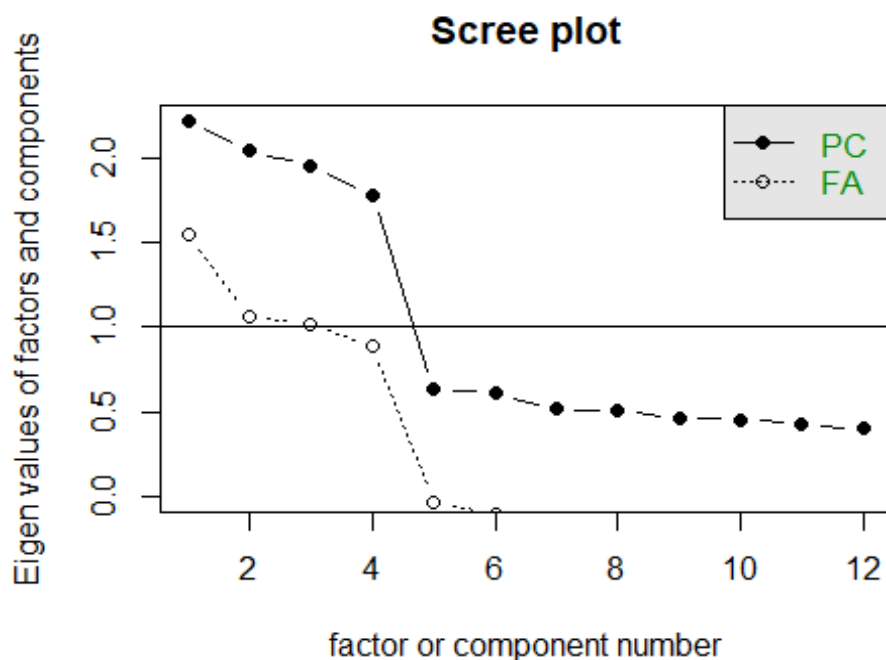
- *Kaiser-Meyer-Olkin (KMO)*

```
## Kaiser-Meyer-Olkin factor adequacy
## Call: KMO(r = data2)
## Overall MSA = 0.67
## MSA for each item =
##   y1   y2   y3   y4   y5   y6   y7   y8   y9  y10  y11  y12
## 0.67 0.63 0.67 0.70 0.64 0.68 0.69 0.69 0.69 0.69 0.65 0.72
```

The minimum acceptable value is 0.50, but the recommended value is 0.60 before undertaking a factor analysis. The overall KMO for this dataset is 0.67 suggests that the factor analysis can be performed.

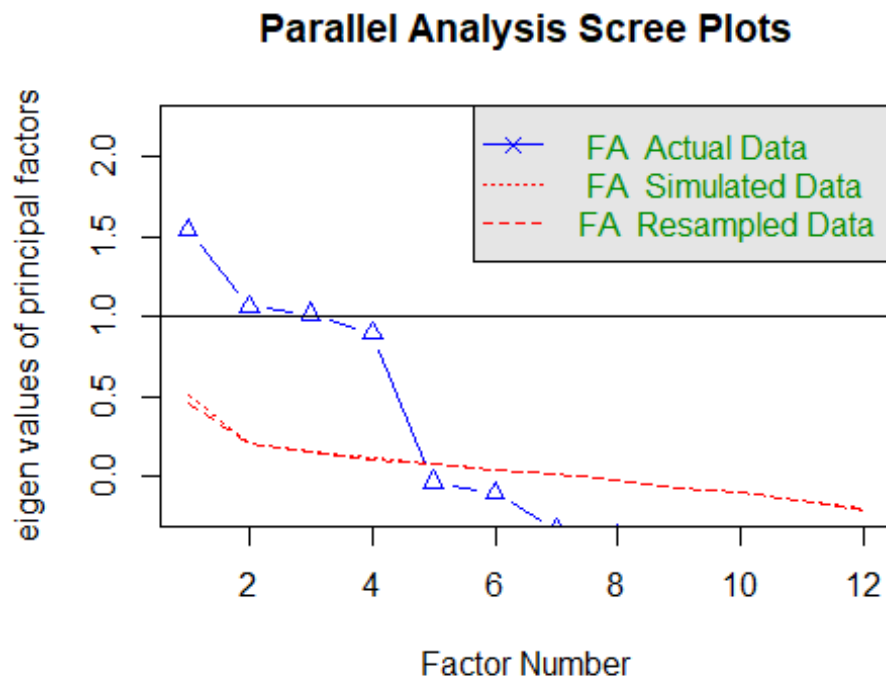
Determining the Number of Factors to Extract

- *Scree plot*



Eigenvalues are a measure of the amount of variance accounted for by a factor. The last point to fall on this line represents the last factor that can be extracted. As per the results of the scree plot, I would probably conclude that there are four factors in this dataset.

- *Parallel Analysis*



```
## Parallel analysis suggests that the number of factors = 4 and the number of components = NA
```

The blue line in the parallel analysis shows the observed eigenvalues and the red dotted line shows the random eigenvalues. Each point on the blue line that lies above the simulated data line (red line) is a factor that has to be extracted. Here 4 factors lie above the corresponding simulated data line. So, I will compare all the 4 factors to see the interpretability.

Factor Analysis

The aim of the factor analysis is to reduce the number of variables and to interpret the results.

- *Factor analysis with 1 factor*

```

## Factor Analysis using method = minres
## Call: fa(r = data2, nfactors = 1, rotate = "oblimin", fm = "minres")
## Standardized loadings (pattern matrix) based upon correlation matrix
##      MR1      h2  u2 com
## y1 -0.01 0.00012 1.00  1
## y2  0.04 0.00187 1.00  1
## y3  0.02 0.00037 1.00  1
## y4 -0.27 0.07120 0.93  1
## y5 -0.26 0.06679 0.93  1
## y6 -0.27 0.07445 0.93  1
## y7 -0.07 0.00552 0.99  1
## y8 -0.10 0.01039 0.99  1
## y9 -0.08 0.00627 0.99  1
## y10 0.64 0.40697 0.59  1
## y11 0.70 0.48620 0.51  1
## y12 0.64 0.41356 0.59  1
##
##              MR1
## SS loadings    1.54
## Proportion Var 0.13
##
## Mean item complexity = 1
## Test of the hypothesis that 1 factor is sufficient.
##
## The degrees of freedom for the null model are 66 and the objective function was 2.87 with Chi Square of 1420.06
## The degrees of freedom for the model are 54 and the objective function was 2.16
##
## The root mean square of the residuals (RMSR) is 0.18
## The df corrected root mean square of the residuals is 0.2
##
## The harmonic number of observations is 500 with the empirical chi square 2170.62 with prob < 0
## The total number of observations was 500 with Likelihood Chi Square = 1064.4 with prob < 1.5e-187
##
## Tucker Lewis Index of factoring reliability = 0.087
## RMSEA index = 0.195 and the 90 % confidence intervals are 0.184 0.204
## BIC = 728.81
## Fit based upon off diagonal values = 0.29
## Measures of factor score adequacy
##
##              MR1
## Correlation of (regression) scores with factors 0.85
## Multiple R square of scores with factors        0.72
## Minimum correlation of possible factor scores    0.44

```

- *Applying cutoff (0.3) to improve visibility*

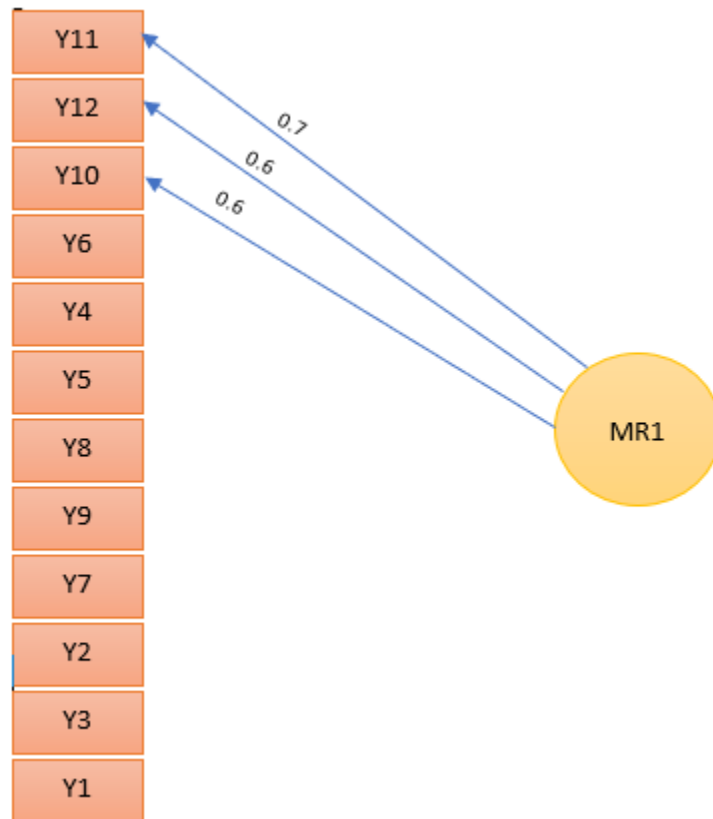
```
##
## Loadings:
##      MR1
## y1
## y2
## y3
## y4
## y5
## y6
## y7
## y8
## y9
## y10  0.638
## y11  0.697
## y12  0.643
##
##                      MR1
## SS loadings      1.544
## Proportion Var  0.129
```

- *Applying factanal function*

```
##
## Call:
## factanal(x = data2, factors = 1, rotation = "varimax")
##
## Uniquenesses:
##   y1   y2   y3   y4   y5   y6   y7   y8   y9  y10  y11  y12
## 0.999 0.999 1.000 0.983 0.986 0.983 1.000 0.998 0.999 0.524 0.392 0.556
##
## Loadings:
##      Factor1
## y1
## y2
## y3
## y4 -0.132
## y5 -0.116
## y6 -0.132
## y7
## y8
## y9
## y10 0.690
## y11 0.780
## y12 0.666
##
##                      Factor1
## SS loadings      1.581
## Proportion Var   0.132
##
## Test of the hypothesis that 1 factor is sufficient.
```



```
## The chi square statistic is 1042.03 on 54 degrees of freedom.
## The p-value is 6.04e-183
```



Factor mapping

- *Adequacy test* (Validating the model with 1 factor analysis)

The root mean square of residuals (RMSR) is 0.18 and this value should be closer to 0. Next, the RMSEA (root mean square error of approximation) index is 0.195 and it should be below 0.05. Finally, the Tucker-Lewis Index (TLI) is 0.087, not an acceptable value, it should be over 0.9.

The significance level is very small indicating hypothesis of good model fit is rejected.

- ***Factor analysis with 2 factors***

```
## Factor Analysis using method = minres
## Call: fa(r = data2, nfactors = 2, rotate = "oblimin", fm = "minres")
## Standardized loadings (pattern matrix) based upon correlation matrix
##      MR1  MR2    h2    u2 com
## y1  0.08  0.00 0.0062 0.99 1.0
```

```

## y2  0.02  0.05  0.0026  1.00  1.3
## y3 -0.03  0.02  0.0011  1.00  1.5
## y4  0.03 -0.26  0.0669  0.93  1.0
## y5  0.02 -0.25  0.0626  0.94  1.0
## y6  0.06 -0.26  0.0705  0.93  1.1
## y7  0.73  0.02  0.5394  0.46  1.0
## y8  0.72 -0.02  0.5222  0.48  1.0
## y9  0.71  0.01  0.5012  0.50  1.0
## y10 -0.01  0.64  0.4157  0.58  1.0
## y11  0.00  0.71  0.5056  0.49  1.0
## y12  0.01  0.66  0.4290  0.57  1.0
##
##
##          MR1  MR2
## SS loadings      1.57 1.55
## Proportion Var    0.13 0.13
## Cumulative Var    0.13 0.26
## Proportion Explained 0.50 0.50
## Cumulative Proportion 0.50 1.00
##
## With factor correlations of
##          MR1  MR2
## MR1  1.00 -0.02
## MR2 -0.02  1.00
##
## Mean item complexity = 1.1
## Test of the hypothesis that 2 factors are sufficient.
##
## The degrees of freedom for the null model are 66 and the objective function was 2.87 with Chi Square of 1420.06
## The degrees of freedom for the model are 43 and the objective function was 1.38
##
## The root mean square of the residuals (RMSR) is 0.14
## The df corrected root mean square of the residuals is 0.18
##
## The harmonic number of observations is 500 with the empirical chi square 1346.53 with prob < 3.6e-254
## The total number of observations was 500 with Likelihood Chi Square = 680.22 with prob < 1.5e-115
##
## Tucker Lewis Index of factoring reliability = 0.276
## RMSEA index = 0.173 and the 90 % confidence intervals are 0.161 0.184
## BIC = 412.99
## Fit based upon off diagonal values = 0.56
## Measures of factor score adequacy
##
##          MR1  MR2
## Correlation of (regression) scores with factors 0.88 0.85
## Multiple R square of scores with factors 0.77 0.73
## Minimum correlation of possible factor scores 0.53 0.45

```

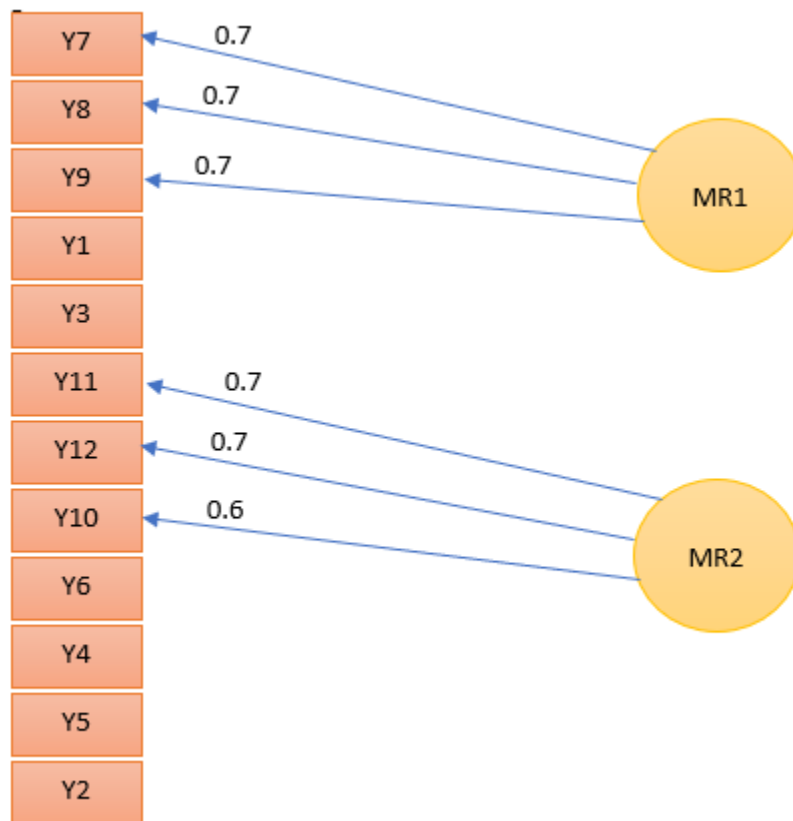
- *Applying cutoff (0.3) to improve visibility*

```
##
## Loadings:
##      MR1      MR2
## y1
## y2
## y3
## y4
## y5
## y6
## y7      0.735
## y8      0.722
## y9      0.708
## y10             0.645
## y11             0.711
## y12             0.655
##
##              MR1      MR2
## SS loadings      1.574 1.548
## Proportion Var 0.131 0.129
## Cumulative Var 0.131 0.260
```

- *Applying factanal function*

```
##
## Call:
## factanal(x = data2, factors = 2, rotation = "varimax")
##
## Uniquenesses:
##      y1      y2      y3      y4      y5      y6      y7      y8      y9      y10      y11      y12
## 0.994 0.999 0.998 0.982 0.987 0.980 0.460 0.473 0.502 0.524 0.392 0.555
##
## Loadings:
##      Factor1 Factor2
## y1
## y2
## y3
## y4 -0.132
## y5 -0.116
## y6 -0.131
## y7             0.735
## y8             0.724
## y9             0.705
## y10 0.690
## y11 0.780
## y12 0.667
##
##              Factor1 Factor2
## SS loadings      1.582 1.572
```

```
## Proportion Var    0.132    0.131
## Cumulative Var    0.132    0.263
##
## Test of the hypothesis that 2 factors are sufficient.
## The chi square statistic is 662.62 on 43 degrees of freedom.
## The p-value is 5.77e-112
```



Factor mapping

- *Adequacy test* (Validating the model with 2 factor analysis)

The root mean square of residuals (RMSR) is 0.14 and this value should be closer to 0. Next, the RMSEA (root mean square error of approximation) index is 0.173 and it should be below 0.05. Finally, the Tucker-Lewis Index (TLI) is 0.276, not an acceptable value considering it should be over 0.9.

The significance level again is very small indicating hypothesis of good model fit is rejected.

- ***Factor analysis with 3 factors***

```

## Factor Analysis using method = minres
## Call: fa(r = data2, nfactors = 3, rotate = "oblimin", fm = "minres")
## Standardized loadings (pattern matrix) based upon correlation matrix
##      MR1   MR2   MR3   h2   u2 com
## y1  0.07 -0.03  0.64 0.417 0.58 1.0
## y2  0.00  0.02  0.78 0.612 0.39 1.0
## y3 -0.06 -0.02  0.64 0.416 0.58 1.0
## y4  0.03 -0.25 -0.06 0.067 0.93 1.1
## y5  0.02 -0.24 -0.11 0.070 0.93 1.4
## y6  0.06 -0.25 -0.07 0.072 0.93 1.3
## y7  0.73  0.02 -0.01 0.540 0.46 1.0
## y8  0.72 -0.02 -0.03 0.527 0.47 1.0
## y9  0.70  0.00  0.04 0.499 0.50 1.0
## y10 -0.01  0.65 -0.04 0.430 0.57 1.0
## y11  0.00  0.72  0.00 0.511 0.49 1.0
## y12  0.01  0.65  0.03 0.428 0.57 1.0
##
##
##      MR1   MR2   MR3
## SS loadings      1.58 1.55 1.46
## Proportion Var    0.13 0.13 0.12
## Cumulative Var    0.13 0.26 0.38
## Proportion Explained 0.34 0.34 0.32
## Cumulative Proportion 0.34 0.68 1.00
##
## With factor correlations of
##      MR1   MR2   MR3
## MR1  1.00 -0.02  0.01
## MR2 -0.02  1.00 -0.01
## MR3  0.01 -0.01  1.00
##
## Mean item complexity = 1.1
## Test of the hypothesis that 3 factors are sufficient.
##
## The degrees of freedom for the null model are 66 and the objective function was 2.87 with Chi Square of 1420.06
## The degrees of freedom for the model are 33 and the objective function was 0.72
##
## The root mean square of the residuals (RMSR) is 0.1
## The df corrected root mean square of the residuals is 0.14
##
## The harmonic number of observations is 500 with the empirical chi square 641.61 with prob < 6.8e-114
## The total number of observations was 500 with Likelihood Chi Square = 353.78 with prob < 2.2e-55
##
## Tucker Lewis Index of factoring reliability = 0.524
## RMSEA index = 0.141 and the 90 % confidence intervals are 0.127 0.153
## BIC = 148.69
## Fit based upon off diagonal values = 0.79

```

```
## Measures of factor score adequacy
##
## Correlation of (regression) scores with factors    MR1  MR2  MR3
## Multiple R square of scores with factors          0.88 0.85 0.87
## Minimum correlation of possible factor scores      0.53 0.46 0.50
```

- *Applying cutoff (0.3) to improve visibility*

```
##
## Loadings:
##      MR1      MR2      MR3
## y1              0.639
## y2              0.782
## y3              0.642
## y4
## y5
## y6
## y7  0.735
## y8  0.725
## y9  0.705
## y10         0.654
## y11         0.715
## y12         0.654
##
##              MR1  MR2  MR3
## SS loadings  1.577 1.553 1.459
## Proportion Var 0.131 0.129 0.122
## Cumulative Var 0.131 0.261 0.382
```

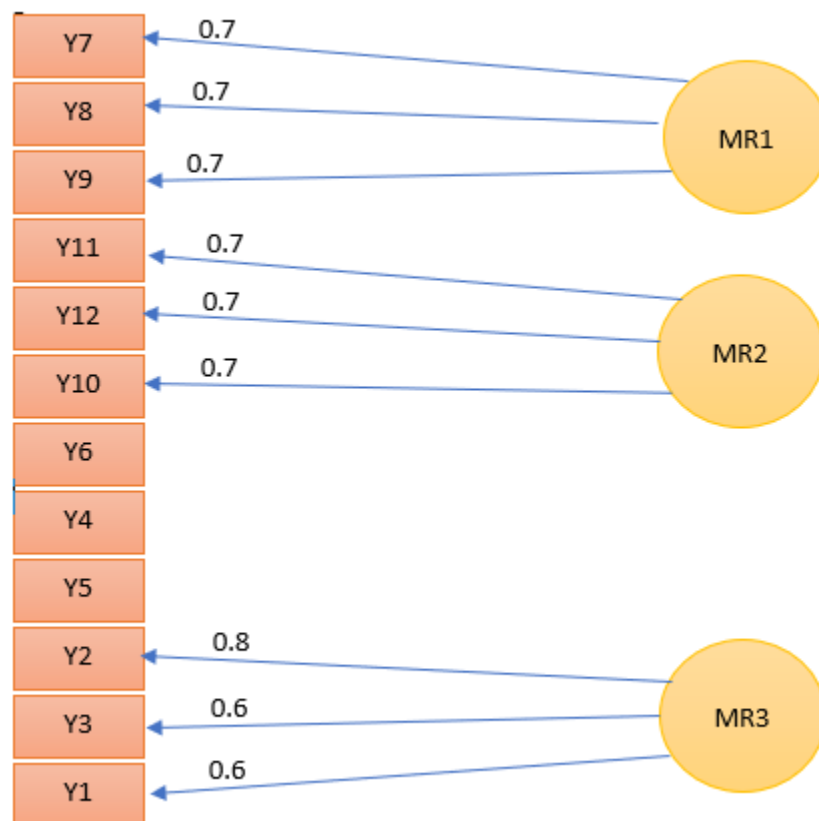
- *Applying factanal function*

```
##
## Call:
## factanal(x = data2, factors = 3, rotation = "varimax")
##
## Uniquenesses:
##   y1   y2   y3   y4   y5   y6   y7   y8   y9   y10  y11  y12
## 0.584 0.353 0.595 0.982 0.983 0.980 0.460 0.470 0.500 0.520 0.394 0.553
##
## Loadings:
##      Factor1 Factor2 Factor3
## y1              0.640
## y2              0.801
## y3              0.633
## y4 -0.132
## y5 -0.118
## y6 -0.133
## y7         0.734
## y8         0.725
## y9         0.704
## y10 0.689
```

```

## y11  0.777
## y12  0.668
##
##               Factor1 Factor2 Factor3
## SS loadings    1.586   1.573   1.466
## Proportion Var  0.132   0.131   0.122
## Cumulative Var  0.132   0.263   0.385
##
## Test of the hypothesis that 3 factors are sufficient.
## The chi square statistic is 335.92 on 33 degrees of freedom.
## The p-value is 7.46e-52

```



Factor mapping

- *Adequacy test* (Validating the model with 3 factor analysis)

The root mean square of residuals (RMSR) is 0.1 and this value should be closer to 0. Next, the RMSEA (root mean square error of approximation) index is 0.141 and it should be below 0.05. Finally, the Tucker-Lewis Index (TLI) is 0.524, again, not an acceptable value considering it's over 0.9.

The significance level using 3 factors is very small indicating hypothesis of good model fit is rejected.

- **Factor analysis with 4 factors**

```
## Factor Analysis using method = minres
## Call: fa(r = data2, nfactors = 4, rotate = "oblimin", fm = "minres")
## Standardized loadings (pattern matrix) based upon correlation matrix
##      MR2  MR1  MR3  MR4  h2  u2  com
## y1  0.07 -0.03  0.64  0.00 0.41 0.59  1
## y2 -0.01  0.03  0.81  0.02 0.65 0.35  1
## y3 -0.06 -0.03  0.63 -0.04 0.41 0.59  1
## y4  0.00 -0.02  0.03  0.65 0.42 0.58  1
## y5 -0.02  0.02 -0.03  0.76 0.57 0.43  1
## y6  0.03 -0.01  0.01  0.67 0.46 0.54  1
## y7  0.73  0.02 -0.01  0.00 0.54 0.46  1
## y8  0.73 -0.02 -0.03  0.00 0.53 0.47  1
## y9  0.71  0.00  0.04 -0.01 0.50 0.50  1
## y10 -0.01  0.69 -0.04  0.00 0.48 0.52  1
## y11  0.00  0.79  0.01  0.02 0.62 0.38  1
## y12  0.01  0.66  0.03 -0.04 0.44 0.56  1
##
##
##      MR2  MR1  MR3  MR4
## SS loadings      1.58 1.54 1.47 1.45
## Proportion Var    0.13 0.13 0.12 0.12
## Cumulative Var    0.13 0.26 0.38 0.50
## Proportion Explained 0.26 0.26 0.24 0.24
## Cumulative Proportion 0.26 0.52 0.76 1.00
##
## With factor correlations of
##      MR2  MR1  MR3  MR4
## MR2  1.00 -0.03  0.01  0.03
## MR1 -0.03  1.00  0.01 -0.12
## MR3  0.01  0.01  1.00 -0.04
## MR4  0.03 -0.12 -0.04  1.00
##
## Mean item complexity = 1
## Test of the hypothesis that 4 factors are sufficient.
##
## The degrees of freedom for the null model are 66 and the objective function was 2.87 with Chi Square of 1420.06
## The degrees of freedom for the model are 24 and the objective function was 0.05
##
## The root mean square of the residuals (RMSR) is 0.01
## The df corrected root mean square of the residuals is 0.02
##
## The harmonic number of observations is 500 with the empirical chi square 13.63 with prob < 0.95
```



```
## The total number of observations was 500 with Likelihood Chi Square = 2
5.51 with prob < 0.38
##
## Tucker Lewis Index of factoring reliability = 0.997
## RMSEA index = 0.013 and the 90 % confidence intervals are 0 0.039
## BIC = -123.64
## Fit based upon off diagonal values = 1
## Measures of factor score adequacy
##
## Correlation of (regression) scores with factors    MR2  MR1  MR3  MR4
## Multiple R square of scores with factors          0.88 0.88 0.87 0.86
## Minimum correlation of possible factor scores      0.77 0.77 0.76 0.75
## Minimum correlation of possible factor scores      0.54 0.54 0.53 0.49
```

- *Applying cutoff (0.3) to improve visibility*

```
##
## Loadings:
##      MR2      MR1      MR3      MR4
## y1              0.637
## y2              0.807
## y3              0.634
## y4                  0.647
## y5                  0.759
## y6                  0.675
## y7 0.735
## y8 0.726
## y9 0.706
## y10           0.692
## y11           0.792
## y12           0.658
##
##              MR2  MR1  MR3  MR4
## SS loadings  1.576 1.543 1.465 1.452
## Proportion Var 0.131 0.129 0.122 0.121
## Cumulative Var 0.131 0.260 0.382 0.503
```

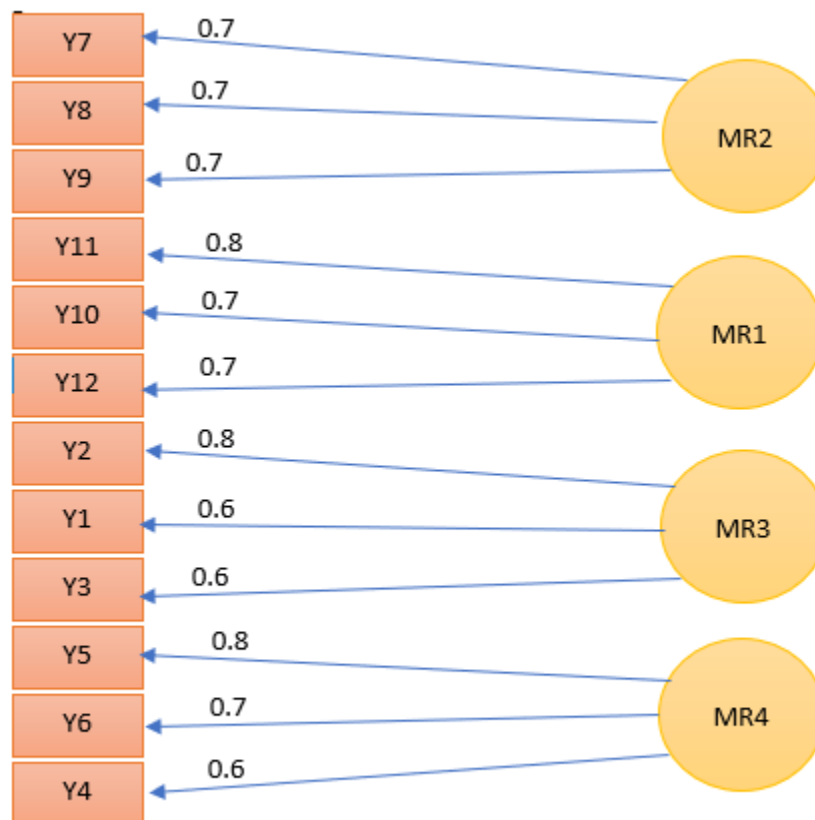
- *Applying factanal function*

```
##
## Call:
## factanal(x = data2, factors = 4, rotation = "varimax")
##
## Uniquenesses:
##   y1   y2   y3   y4   y5   y6   y7   y8   y9  y10  y11  y12
## 0.588 0.346 0.594 0.581 0.424 0.543 0.462 0.470 0.498 0.520 0.376 0.559
##
## Loadings:
##   Factor1 Factor2 Factor3 Factor4
## y1              0.637
## y2              0.807
## y3              0.632
```

```

## y4                                0.645
## y5                                0.757
## y6                                0.673
## y7    0.733
## y8    0.727
## y9    0.706
## y10    0.691
## y11    0.789
## y12    0.659
##
##                               Factor1 Factor2 Factor3 Factor4
## SS loadings                1.576   1.544   1.467   1.453
## Proportion Var             0.131   0.129   0.122   0.121
## Cumulative Var             0.131   0.260   0.382   0.503
##
## Test of the hypothesis that 4 factors are sufficient.
## The chi square statistic is 25.36 on 24 degrees of freedom.
## The p-value is 0.386

```



Factor mapping
All the four factors having 3 variables loaded.

- *Adequacy test* (Validating the model with 4 factor analysis)

The root mean square of residuals (RMSR) is 0.01 and this value should be closer to 0. Next, the RMSEA (root mean square error of approximation) index is 0.013 and it should be below 0.05. Finally, the Tucker-Lewis Index (TLI) is 0.997, an acceptable value considering it's over 0.9.

The significance level seems promising and has made a huge improvement as compared to the last three models. The p-value (0.386) suggests that the hypothesis of good model fit cannot be rejected.

Final Interpretation

The analysis including 4 factors seems to have perfect model fit for this dataset.

References:

Structural equation models, 2019, week 1 material

<https://www.r-bloggers.com/exploratory-factor-analysis-in-r/>

Assignment 2 SEM

Shweta Goswami

28-01-2019

Exercise 2.1

Draw the graphs, specify and test the hypothesis given on p. 1 of the lecture material. Draw conclusions based on the χ^2 statistic and the CFI, TLI and RMSEA indices.

TITLE: CFA of Academic SC Structure for Grade 7 Adolescents (Byrne 2012, p. 56)

- Reading the ASC7INDM.DAT file

```
CFA <- read.fortran("ASC7INDM.DAT", format=c("40F1.0","X","6F2.0"))
str(CFA)
```

```
## 'data.frame':    265 obs. of  46 variables:
## $ V1 : num  3 4 1 3 3 2 1 1 3 3 ...
## $ V2 : num  4 4 4 3 4 3 1 4 3 3 ...
## $ V3 : num  3 4 4 3 4 3 4 1 4 3 ...
## $ V4 : num  3 4 4 2 4 2 2 1 3 3 ...
## $ V5 : num  3 4 4 3 3 3 4 1 3 2 ...
## $ V6 : num  3 4 1 3 4 2 3 1 2 3 ...
## $ V7 : num  3 4 3 3 4 3 4 1 2 4 ...
## $ V8 : num  4 4 4 4 3 3 4 1 3 4 ...
## $ V9 : num  1 4 1 3 2 2 4 1 3 4 ...
## $ V10: num  3 4 4 3 4 3 3 3 3 4 ...
## $ V11: num  3 4 4 3 3 3 3 2 3 4 ...
## $ V12: num  4 4 1 3 3 2 2 4 3 4 ...
## $ V13: num  2 4 1 3 3 3 4 3 3 4 ...
## $ V14: num  2 4 1 3 4 3 4 2 3 4 ...
## $ V15: num  3 4 1 1 3 1 4 3 3 4 ...
## $ V16: num  3 4 1 4 4 1 1 4 3 4 ...
## $ V17: num  2 4 4 3 3 3 1 2 3 3 ...
## $ V18: num  3 4 1 4 3 3 1 3 3 4 ...
## $ V19: num  3 4 4 3 1 2 4 2 2 3 ...
## $ V20: num  3 4 4 4 3 3 4 1 2 3 ...
## $ V21: num  3 4 4 3 3 1 4 2 2 3 ...
## $ V22: num  3 4 4 4 3 1 4 3 3 4 ...
## $ V23: num  3 4 4 3 3 2 4 3 3 3 ...
## $ V24: num  3 4 1 3 2 2 4 3 3 4 ...
## $ V25: num  6 6 4 5 6 5 1 2 5 4 ...
## $ V26: num  5 6 6 5 5 5 6 1 5 6 ...
## $ V27: num  4 6 6 5 5 5 1 6 6 3 ...
## $ V28: num  6 6 2 6 4 3 6 4 6 6 ...
## $ V29: num  3 6 6 5 3 3 4 4 6 6 ...
## $ V30: num  4 6 4 6 4 2 6 4 6 5 ...
## $ V31: num  4 6 6 5 4 4 6 4 6 6 ...
## $ V32: num  6 6 3 6 4 4 6 6 6 6 ...
## $ V33: num  2 5 6 5 4 4 1 6 5 4 ...
## $ V34: num  6 6 5 6 6 4 6 6 6 6 ...
```

```
## $ V35: num 1 6 4 3 5 5 1 1 5 4 ...
## $ V36: num 5 6 5 5 6 6 6 5 6 6 ...
## $ V37: num 6 6 6 6 3 4 5 3 6 5 ...
## $ V38: num 6 6 6 6 4 5 6 4 6 6 ...
## $ V39: num 6 6 3 6 4 4 6 4 6 6 ...
## $ V40: num 6 6 1 5 5 4 5 6 6 6 ...
## $ V41: num 33 33 24 38 39 40 31 39 39 36 ...
## $ V42: num 13 14 15 15 11 14 15 10 18 17 ...
## $ V43: num 4 6 2 9 9 6 7 4 6 6 ...
## $ V44: num 4 7 5 9 9 6 9 4 9 6 ...
## $ V45: num 6 8 7 8 8 8 7 7 9 9 ...
## $ V46: num 9 6 10 9 8 8 9 5 10 9 ...
```

```
dim(CFA)
```

```
## [1] 265 46
```

```
head(CFA)
```

```
## V1 V2 V3 V4 V5 V6 V7 V8 V9 V10 V11 V12 V13 V14 V15 V16 V17 V18 V19 V20
## 1 3 4 3 3 3 3 3 4 1 3 3 4 2 2 3 3 2 3 3
## 2 4 4 4 4 4 4 4 4 4 4 4 4 4 4 4 4 4 4 4
## 3 1 4 4 4 4 1 3 4 1 4 4 1 1 1 1 4 1 4 4
## 4 3 3 3 2 3 3 3 4 3 3 3 3 3 1 4 3 4 3 4
## 5 3 4 4 4 3 4 4 3 2 4 3 3 3 4 3 4 3 1 3
## 6 2 3 3 2 3 2 3 3 2 3 3 2 3 3 1 1 3 3 2 3
## V21 V22 V23 V24 V25 V26 V27 V28 V29 V30 V31 V32 V33 V34 V35 V36 V37 V38
## 1 3 3 3 3 6 5 4 6 3 4 4 6 2 6 1 5 6 6
## 2 4 4 4 4 6 6 6 6 6 6 6 6 5 6 6 6 6
## 3 4 4 4 1 4 6 6 2 6 4 6 3 6 5 4 5 6 6
## 4 3 4 3 3 5 5 5 6 5 6 5 6 5 6 3 5 6 6
## 5 3 3 3 2 6 5 5 4 3 4 4 4 4 6 5 6 3 4
## 6 1 1 2 2 5 5 5 3 3 2 4 4 4 4 5 6 4 5
## V39 V40 V41 V42 V43 V44 V45 V46
## 1 6 6 33 13 4 4 6 9
## 2 6 6 33 14 6 7 8 6
## 3 3 1 24 15 2 5 7 10
## 4 6 5 38 15 9 9 8 9
## 5 4 5 39 11 9 9 8 8
## 6 4 4 40 14 6 6 8 8
```

- Creating names for all the variables

```
names(CFA) = c("SPPCN08", "SPPCN18", "SPPCN28", "SPPCN38", "SPPCN48", "SPPCN58", "SPPCN01", "SPPCN11", "SPPCN21", "SPPCN31", "SPPCN41", "SPPCN51", "SDQ2N01", "SDQ2N13", "SDQ2N25", "SDQ2N37", "SDQ2N04", "SDQ2N16", "SDQ2N28", "SDQ2N40", "SDQ2N10", "SDQ2N22", "SDQ2N34", "SDQ2N46", "MASTENG1", "MASTMAT1", "TENG1", "TMAT1", "SENG1", "SMAT1")
```

```
names(CFA)
```

```
## [1] "SPPCN08" "SPPCN18" "SPPCN28" "SPPCN38" "SPPCN48" "SPPCN58"
## [7] "SPPCN01" "SPPCN11" "SPPCN21" "SPPCN31" "SPPCN41" "SPPCN51"
## [13] "SPPCN06" "SPPCN16" "SPPCN26" "SPPCN36" "SPPCN46" "SPPCN56"
## [19] "SPPCN03" "SPPCN13" "SPPCN23" "SPPCN33" "SPPCN43" "SPPCN53"
## [25] "SDQ2N01" "SDQ2N13" "SDQ2N25" "SDQ2N37" "SDQ2N04" "SDQ2N16"
## [31] "SDQ2N28" "SDQ2N40" "SDQ2N10" "SDQ2N22" "SDQ2N34" "SDQ2N46"
```

```
## [37] "SDQ2N07" "SDQ2N19" "SDQ2N31" "SDQ2N43" "MASTENG1" "MASTMAT1"
## [43] "TENG1"    "TMAT1"    "SENG1"    "SMAT1"
```

- Specify the 4-factor model

```
library(lavaan)
model <- '
F1 =~ SDQ2N01 + SDQ2N13 + SDQ2N25 + SDQ2N37
F2 =~ SDQ2N04 + SDQ2N16 + SDQ2N28 + SDQ2N40
F3 =~ SDQ2N10 + SDQ2N22 + SDQ2N34 + SDQ2N46
F4 =~ SDQ2N07 + SDQ2N19 + SDQ2N31 + SDQ2N43
'
```

- Fitting the model

```
fit <- cfa(model, data=CFA, control=list(iter.max=1000))
```

- Display summary output

```
summary(fit, fit.measures=TRUE)
```

```
## lavaan 0.6-3 ended normally after 49 iterations
##
## Optimization method          NLMINB
## Number of free parameters    38
##
## Number of observations       265
##
## Estimator                    ML
## Model Fit Test Statistic     159.112
## Degrees of freedom          98
## P-value (Chi-square)        0.000
##
## Model test baseline model:
##
## Minimum Function Test Statistic 1703.155
## Degrees of freedom            120
## P-value                      0.000
##
## User model versus baseline model:
##
## Comparative Fit Index (CFI)    0.961
## Tucker-Lewis Index (TLI)     0.953
##
## Loglikelihood and Information Criteria:
##
## Loglikelihood user model (H0)  -6562.678
## Loglikelihood unrestricted model (H1) -6483.122
##
## Number of free parameters      38
## Akaike (AIC)                  13201.356
## Bayesian (BIC)                13337.386
## Sample-size adjusted Bayesian (BIC) 13216.905
##
## Root Mean Square Error of Approximation:
##
## RMSEA                        0.049
```

```

## 90 Percent Confidence Interval          0.034  0.062
## P-value RMSEA <= 0.05                  0.556
##
## Standardized Root Mean Square Residual:
##
## SRMR                                    0.048
##
## Parameter Estimates:
##
## Information                               Expected
## Information saturated (h1) model         Structured
## Standard Errors                          Standard
##
## Latent Variables:
##      Estimate Std.Err z-value P(>|z|)
## F1 =~
##   SDQ2N01      1.000
##   SDQ2N13      1.083    0.154    7.044    0.000
##   SDQ2N25      0.851    0.132    6.455    0.000
##   SDQ2N37      0.934    0.131    7.131    0.000
## F2 =~
##   SDQ2N04      1.000
##   SDQ2N16      1.279    0.150    8.520    0.000
##   SDQ2N28      1.247    0.154    8.097    0.000
##   SDQ2N40      1.259    0.156    8.048    0.000
## F3 =~
##   SDQ2N10      1.000
##   SDQ2N22      0.889    0.103    8.658    0.000
##   SDQ2N34      0.670    0.148    4.539    0.000
##   SDQ2N46      0.843    0.117    7.225    0.000
## F4 =~
##   SDQ2N07      1.000
##   SDQ2N19      0.841    0.058   14.495    0.000
##   SDQ2N31      0.952    0.049   19.516    0.000
##   SDQ2N43      0.655    0.049   13.298    0.000
##
## Covariances:
##      Estimate Std.Err z-value P(>|z|)
## F1 ~~
##   F2          0.415    0.078    5.292    0.000
##   F3          0.355    0.072    4.947    0.000
##   F4          0.635    0.118    5.387    0.000
## F2 ~~
##   F3          0.464    0.078    5.921    0.000
##   F4          0.873    0.134    6.519    0.000
## F3 ~~
##   F4          0.331    0.100    3.309    0.001
##
## Variances:
##      Estimate Std.Err z-value P(>|z|)
##   .SDQ2N01      1.198    0.126    9.537    0.000
##   .SDQ2N13      1.119    0.124    9.019    0.000
##   .SDQ2N25      1.056    0.107    9.897    0.000
##   .SDQ2N37      0.771    0.087    8.821    0.000

```

##	.SDQ2N04	1.394	0.128	10.900	0.000
##	.SDQ2N16	0.616	0.068	9.020	0.000
##	.SDQ2N28	0.896	0.090	9.959	0.000
##	.SDQ2N40	0.952	0.095	10.029	0.000
##	.SDQ2N10	0.653	0.082	7.941	0.000
##	.SDQ2N22	0.657	0.075	8.735	0.000
##	.SDQ2N34	2.590	0.233	11.128	0.000
##	.SDQ2N46	1.201	0.118	10.183	0.000
##	.SDQ2N07	0.854	0.100	8.551	0.000
##	.SDQ2N19	1.228	0.121	10.153	0.000
##	.SDQ2N31	0.365	0.065	5.649	0.000
##	.SDQ2N43	0.964	0.092	10.473	0.000
##	F1	0.613	0.137	4.464	0.000
##	F2	0.561	0.126	4.453	0.000
##	F3	0.668	0.116	5.749	0.000
##	F4	2.307	0.273	8.460	0.000

- The estimator used is ML, the model seems to be converged normally, the number of observations is equal to the number of rows in the data.
- Chi-Square Test of Model Fit : Assess overall fit and the discrepancy between the sample and fitted covariance matrices. Here the χ^2 is 159.112, with 98 degrees of freedom (ideal value $>2df$). The p-value should be more than >0.05 to have a good model fit and here, the p-value is 0.000.
- Comparative fit index (CFI): The index tells whether the model fits the data better than a more baseline model. The higher the index, the better it is. The CFI (0.961) with 4-factor model seems to be fit okay i.e. $> .9$.
- TLI (Tucker-Lewis index): The index is similar to CFI but more conservative one. It also tells whether the model fits the data better than a more baseline model. The higher the index, the better it is. The TLI (0.953) appears to be fit okay i.e. $> .9$.
- The difference between AIC and BIC seems to be low. The lower the difference, the better it is.
- RMSEA (Root mean square error of approximation): It indicates residuals and measures covariance among indicators. The lower, the better. Here, the RMSEA (0.049) is less than 0.05 (ideal value) with a 90%CI from .03 to .06.
- SRMR (Standardized Root Mean Square Residual) : The square-root of the difference between the residuals of the covariance matrix and the hypothesized model. The cut-off of good fit is <0.08 . Here, the SRMR is 0.048.
- Obtaining confidence intervals for the estimated coefficients

```
parameterEstimates(fit, ci = TRUE, level = 0.95)
```

##	lhs op	rhs	est	se	z	pvalue	ci.lower	ci.upper
## 1	F1 =~	SDQ2N01	1.000	0.000	NA	NA	1.000	1.000
## 2	F1 =~	SDQ2N13	1.083	0.154	7.044	0.000	0.782	1.384
## 3	F1 =~	SDQ2N25	0.851	0.132	6.455	0.000	0.592	1.109
## 4	F1 =~	SDQ2N37	0.934	0.131	7.131	0.000	0.677	1.190
## 5	F2 =~	SDQ2N04	1.000	0.000	NA	NA	1.000	1.000
## 6	F2 =~	SDQ2N16	1.279	0.150	8.520	0.000	0.985	1.573
## 7	F2 =~	SDQ2N28	1.247	0.154	8.097	0.000	0.945	1.549
## 8	F2 =~	SDQ2N40	1.259	0.156	8.048	0.000	0.952	1.565
## 9	F3 =~	SDQ2N10	1.000	0.000	NA	NA	1.000	1.000
## 10	F3 =~	SDQ2N22	0.889	0.103	8.658	0.000	0.688	1.091
## 11	F3 =~	SDQ2N34	0.670	0.148	4.539	0.000	0.381	0.960
## 12	F3 =~	SDQ2N46	0.843	0.117	7.225	0.000	0.614	1.071


```
## 13      F4 =~ SDQ2N07 1.000 0.000      NA      NA      1.000      1.000
## 14      F4 =~ SDQ2N19 0.841 0.058 14.495 0.000      0.727      0.955
## 15      F4 =~ SDQ2N31 0.952 0.049 19.516 0.000      0.857      1.048
## 16      F4 =~ SDQ2N43 0.655 0.049 13.298 0.000      0.559      0.752
## 17 SDQ2N01 ~~ SDQ2N01 1.198 0.126  9.537 0.000      0.952      1.444
## 18 SDQ2N13 ~~ SDQ2N13 1.119 0.124  9.019 0.000      0.876      1.362
## 19 SDQ2N25 ~~ SDQ2N25 1.056 0.107  9.897 0.000      0.847      1.265
## 20 SDQ2N37 ~~ SDQ2N37 0.771 0.087  8.821 0.000      0.600      0.943
## 21 SDQ2N04 ~~ SDQ2N04 1.394 0.128 10.900 0.000      1.144      1.645
## 22 SDQ2N16 ~~ SDQ2N16 0.616 0.068  9.020 0.000      0.482      0.750
## 23 SDQ2N28 ~~ SDQ2N28 0.896 0.090  9.959 0.000      0.719      1.072
## 24 SDQ2N40 ~~ SDQ2N40 0.952 0.095 10.029 0.000      0.766      1.138
## 25 SDQ2N10 ~~ SDQ2N10 0.653 0.082  7.941 0.000      0.492      0.815
## 26 SDQ2N22 ~~ SDQ2N22 0.657 0.075  8.735 0.000      0.510      0.805
## 27 SDQ2N34 ~~ SDQ2N34 2.590 0.233 11.128 0.000      2.134      3.046
## 28 SDQ2N46 ~~ SDQ2N46 1.201 0.118 10.183 0.000      0.970      1.432
## 29 SDQ2N07 ~~ SDQ2N07 0.854 0.100  8.551 0.000      0.658      1.050
## 30 SDQ2N19 ~~ SDQ2N19 1.228 0.121 10.153 0.000      0.991      1.465
## 31 SDQ2N31 ~~ SDQ2N31 0.365 0.065  5.649 0.000      0.238      0.491
## 32 SDQ2N43 ~~ SDQ2N43 0.964 0.092 10.473 0.000      0.783      1.144
## 33      F1 ~~      F1 0.613 0.137  4.464 0.000      0.344      0.883
## 34      F2 ~~      F2 0.561 0.126  4.453 0.000      0.314      0.808
## 35      F3 ~~      F3 0.668 0.116  5.749 0.000      0.440      0.896
## 36      F4 ~~      F4 2.307 0.273  8.460 0.000      1.773      2.842
## 37      F1 ~~      F2 0.415 0.078  5.292 0.000      0.261      0.568
## 38      F1 ~~      F3 0.355 0.072  4.947 0.000      0.214      0.496
## 39      F1 ~~      F4 0.635 0.118  5.387 0.000      0.404      0.867
## 40      F2 ~~      F3 0.464 0.078  5.921 0.000      0.310      0.617
## 41      F2 ~~      F4 0.873 0.134  6.519 0.000      0.610      1.135
## 42      F3 ~~      F4 0.331 0.100  3.309 0.001      0.135      0.527
```

- Obtaining goodness of fit indicators of the model

```
fitMeasures(fit, c("chisq", "rmsea", "srmr", "gfi", "ecvi"))
```

```
##   chisq  rmsea   srmr    gfi   ecvi
## 159.112  0.049  0.048  0.933  0.887
```

- The GFI should be > 0.95 . Here, it is 0.93.
- Obtaining reliability

```
reliability(fit)
```

```
##           F1           F2           F3           F4      total
## alpha  0.6925568 0.7594267 0.6075534 0.8847428 0.8646270
## omega  0.6888167 0.7690608 0.6025494 0.8894519 0.9011247
## omega2 0.6888167 0.7690608 0.6025494 0.8894519 0.9011247
## omega3 0.6829250 0.7789836 0.5952326 0.8848980 0.9178356
## avevar 0.3580256 0.4565463 0.2787087 0.6731031 0.4683085
```

- Inspecting the model

```
inspect(fit)
```

```
## $lambda
##           F1 F2 F3 F4
## SDQ2N01   0  0  0  0
```

```

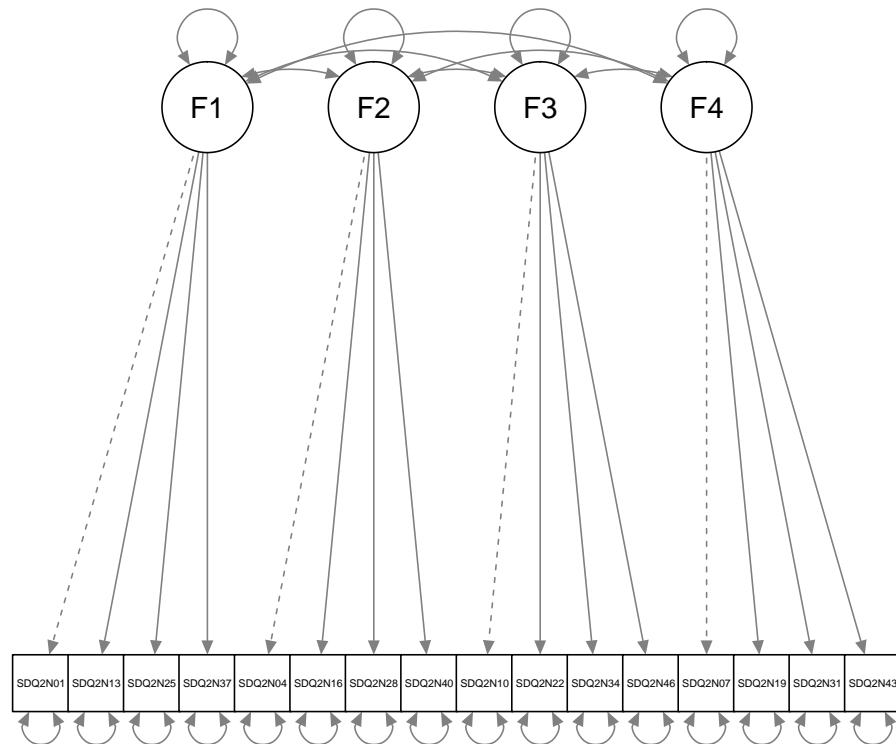
## SDQ2N13  1  0  0  0
## SDQ2N25  2  0  0  0
## SDQ2N37  3  0  0  0
## SDQ2N04  0  0  0  0
## SDQ2N16  0  4  0  0
## SDQ2N28  0  5  0  0
## SDQ2N40  0  6  0  0
## SDQ2N10  0  0  0  0
## SDQ2N22  0  0  7  0
## SDQ2N34  0  0  8  0
## SDQ2N46  0  0  9  0
## SDQ2N07  0  0  0  0
## SDQ2N19  0  0  0 10
## SDQ2N31  0  0  0 11
## SDQ2N43  0  0  0 12
##
## $theta
##      SDQ2N01 SDQ2N13 SDQ2N25 SDQ2N37 SDQ2N04 SDQ2N16 SDQ2N28 SDQ2N40
## SDQ2N01 13
## SDQ2N13  0      14
## SDQ2N25  0      0      15
## SDQ2N37  0      0      0      16
## SDQ2N04  0      0      0      0      17
## SDQ2N16  0      0      0      0      0      18
## SDQ2N28  0      0      0      0      0      0      19
## SDQ2N40  0      0      0      0      0      0      0      20
## SDQ2N10  0      0      0      0      0      0      0      0
## SDQ2N22  0      0      0      0      0      0      0      0
## SDQ2N34  0      0      0      0      0      0      0      0
## SDQ2N46  0      0      0      0      0      0      0      0
## SDQ2N07  0      0      0      0      0      0      0      0
## SDQ2N19  0      0      0      0      0      0      0      0
## SDQ2N31  0      0      0      0      0      0      0      0
## SDQ2N43  0      0      0      0      0      0      0      0
##      SDQ2N10 SDQ2N22 SDQ2N34 SDQ2N46 SDQ2N07 SDQ2N19 SDQ2N31 SDQ2N43
## SDQ2N01
## SDQ2N13
## SDQ2N25
## SDQ2N37
## SDQ2N04
## SDQ2N16
## SDQ2N28
## SDQ2N40
## SDQ2N10 21
## SDQ2N22  0      22
## SDQ2N34  0      0      23
## SDQ2N46  0      0      0      24
## SDQ2N07  0      0      0      0      25
## SDQ2N19  0      0      0      0      0      26
## SDQ2N31  0      0      0      0      0      0      27
## SDQ2N43  0      0      0      0      0      0      0      28
##
## $psi
##      F1 F2 F3 F4

```

```
## F1 29
## F2 33 30
## F3 34 36 31
## F4 35 37 38 32
```

- Creating diagram

```
semPaths(fit)
```



Exercise 2.2

Draw the graphs, specify and test these two additional hypotheses (again draw conclusions based on the χ^2 statistic and the CFI, TLI and RMSEA indices):

1. Hypothesis 2: SC is a two-factor structure consisting of GSC and ASC (so that the four GSC measures load onto the GSC and all other onto the ASC).

- Specify the 2-factor model

```
model11 <- '
GSC =~ SDQ2N01 + SDQ2N13 + SDQ2N25 + SDQ2N37
ASC =~ SDQ2N04 + SDQ2N16 + SDQ2N28 + SDQ2N40 + SDQ2N10 + SDQ2N22 + SDQ2N34 + SDQ2N46 +
SDQ 2N07 + SDQ2N19 + SDQ2N31 + SDQ2N43
'
```

- Fitting the model

```
fit1 <- cfa(model1, data=CFA, control=list(iter.max=1000))
```

- Displaying summary output

```
summary(fit1, fit.measures=TRUE)
```

```
## lavaan 0.6-3 ended normally after 38 iterations
##
##      Optimization method          NLMINB
##      Number of free parameters      33
##
##      Number of observations          265
##
##      Estimator                      ML
##      Model Fit Test Statistic        457.653
##      Degrees of freedom              103
##      P-value (Chi-square)            0.000
##
## Model test baseline model:
##
##      Minimum Function Test Statistic 1703.155
##      Degrees of freedom              120
##      P-value                        0.000
##
## User model versus baseline model:
##
##      Comparative Fit Index (CFI)      0.776
##      Tucker-Lewis Index (TLI)        0.739
##
## Loglikelihood and Information Criteria:
##
##      Loglikelihood user model (H0)      -6711.949
##      Loglikelihood unrestricted model (H1) -6483.122
##
##      Number of free parameters          33
##      Akaike (AIC)                      13489.897
##      Bayesian (BIC)                    13608.028
##      Sample-size adjusted Bayesian (BIC) 13503.401
##
## Root Mean Square Error of Approximation:
##
##      RMSEA                          0.114
##      90 Percent Confidence Interval    0.103 0.125
##      P-value RMSEA <= 0.05            0.000
##
## Standardized Root Mean Square Residual:
##
##      SRMR                          0.101
##
## Parameter Estimates:
##
##      Information                      Expected
##      Information saturated (h1) model  Structured
##      Standard Errors                  Standard
```

```

##
## Latent Variables:
##      Estimate   Std.Err   z-value   P(>|z|)
##      GSC =~
##      SDQ2N01      1.000
##      SDQ2N13      1.048    0.151    6.930    0.000
##      SDQ2N25      0.860    0.131    6.542    0.000
##      SDQ2N37      0.890    0.128    6.957    0.000
##      ASC =~
##      SDQ2N04      1.000
##      SDQ2N16      1.263    0.170    7.440    0.000
##      SDQ2N28      1.276    0.177    7.221    0.000
##      SDQ2N40      1.235    0.176    7.026    0.000
##      SDQ2N10      0.581    0.123    4.736    0.000
##      SDQ2N22      0.558    0.117    4.786    0.000
##      SDQ2N34      0.065    0.161    0.406    0.685
##      SDQ2N46      0.514    0.132    3.885    0.000
##      SDQ2N07      2.069    0.262    7.885    0.000
##      SDQ2N19      1.871    0.242    7.721    0.000
##      SDQ2N31      2.021    0.247    8.192    0.000
##      SDQ2N43      1.442    0.193    7.481    0.000
##
## Covariances:
##      Estimate   Std.Err   z-value   P(>|z|)
##      GSC ~~
##      ASC          0.340    0.068    4.975    0.000
##
## Variances:
##      Estimate   Std.Err   z-value   P(>|z|)
##      .SDQ2N01      1.170    0.127    9.216    0.000
##      .SDQ2N13      1.134    0.127    8.906    0.000
##      .SDQ2N25      1.026    0.107    9.582    0.000
##      .SDQ2N37      0.799    0.090    8.842    0.000
##      .SDQ2N04      1.495    0.134   11.171    0.000
##      .SDQ2N16      0.799    0.076   10.490    0.000
##      .SDQ2N28      1.018    0.095   10.695    0.000
##      .SDQ2N40      1.138    0.105   10.828    0.000
##      .SDQ2N10      1.166    0.103   11.364    0.000
##      .SDQ2N22      1.043    0.092   11.360    0.000
##      .SDQ2N34      2.888    0.251   11.510    0.000
##      .SDQ2N46      1.554    0.136   11.425    0.000
##      .SDQ2N07      1.191    0.123    9.654    0.000
##      .SDQ2N19      1.247    0.124   10.067    0.000
##      .SDQ2N31      0.575    0.073    7.852    0.000
##      .SDQ2N43      0.996    0.095   10.442    0.000
##      GSC          0.641    0.142    4.508    0.000
##      ASC          0.461    0.114    4.034    0.000

```

- The model seems to be converged normally, the number of observations is equal to the number of rows in the data.
- Chi-Square Test of Model Fit : Here the χ^2 is 457.65, with 103 degrees of freedom (ideal value $>2df$). The p-value should be more than >0.05 to have a good model fit and here, the p-value is 0.000.
- Comparative fit index (CFI): The higher the index, the better it is. The CFI (0.776) value suggests

2-factor model seems to be not a good fit as it should be $>.9$.

- TLI (Tucker-Lewis index): The higher the index, the better it is. The TLI again should be more than $>.9$ and here, it is 0.739.
- The difference between AIC and BIC seems to be okay. The lower the difference, the better it is.
- RMSEA (Root mean square error of approximation): Here, the RMSEA (0.114) is more than 0.05 (ideal value) with a 90%CI from 0.103 to 0.125.
- SRMR (Standardized Root Mean Square Residual) : The cut-off of good fit is <0.08 . Here, the SRMR is 0.101.
- Obtaining confidence intervals for the estimated coefficients

```
parameterEstimates(fit1, ci = TRUE, level = 0.95)
```

##	lhs	op	rhs	est	se	z	pvalue	ci.lower	ci.upper
## 1	GSC	=~	SDQ2N01	1.000	0.000	NA	NA	1.000	1.000
## 2	GSC	=~	SDQ2N13	1.048	0.151	6.930	0.000	0.751	1.344
## 3	GSC	=~	SDQ2N25	0.860	0.131	6.542	0.000	0.602	1.117
## 4	GSC	=~	SDQ2N37	0.890	0.128	6.957	0.000	0.639	1.140
## 5	ASC	=~	SDQ2N04	1.000	0.000	NA	NA	1.000	1.000
## 6	ASC	=~	SDQ2N16	1.263	0.170	7.440	0.000	0.930	1.596
## 7	ASC	=~	SDQ2N28	1.276	0.177	7.221	0.000	0.930	1.623
## 8	ASC	=~	SDQ2N40	1.235	0.176	7.026	0.000	0.891	1.580
## 9	ASC	=~	SDQ2N10	0.581	0.123	4.736	0.000	0.340	0.821
## 10	ASC	=~	SDQ2N22	0.558	0.117	4.786	0.000	0.329	0.786
## 11	ASC	=~	SDQ2N34	0.065	0.161	0.406	0.685	-0.250	0.381
## 12	ASC	=~	SDQ2N46	0.514	0.132	3.885	0.000	0.255	0.774
## 13	ASC	=~	SDQ2N07	2.069	0.262	7.885	0.000	1.554	2.583
## 14	ASC	=~	SDQ2N19	1.871	0.242	7.721	0.000	1.396	2.346
## 15	ASC	=~	SDQ2N31	2.021	0.247	8.192	0.000	1.538	2.505
## 16	ASC	=~	SDQ2N43	1.442	0.193	7.481	0.000	1.065	1.820
## 17	SDQ2N01	~~	SDQ2N01	1.170	0.127	9.216	0.000	0.921	1.419
## 18	SDQ2N13	~~	SDQ2N13	1.134	0.127	8.906	0.000	0.885	1.384
## 19	SDQ2N25	~~	SDQ2N25	1.026	0.107	9.582	0.000	0.816	1.236
## 20	SDQ2N37	~~	SDQ2N37	0.799	0.090	8.842	0.000	0.622	0.976
## 21	SDQ2N04	~~	SDQ2N04	1.495	0.134	11.171	0.000	1.232	1.757
## 22	SDQ2N16	~~	SDQ2N16	0.799	0.076	10.490	0.000	0.650	0.948
## 23	SDQ2N28	~~	SDQ2N28	1.018	0.095	10.695	0.000	0.832	1.205
## 24	SDQ2N40	~~	SDQ2N40	1.138	0.105	10.828	0.000	0.932	1.344
## 25	SDQ2N10	~~	SDQ2N10	1.166	0.103	11.364	0.000	0.965	1.368
## 26	SDQ2N22	~~	SDQ2N22	1.043	0.092	11.360	0.000	0.863	1.223
## 27	SDQ2N34	~~	SDQ2N34	2.888	0.251	11.510	0.000	2.396	3.380
## 28	SDQ2N46	~~	SDQ2N46	1.554	0.136	11.425	0.000	1.287	1.820
## 29	SDQ2N07	~~	SDQ2N07	1.191	0.123	9.654	0.000	0.949	1.432
## 30	SDQ2N19	~~	SDQ2N19	1.247	0.124	10.067	0.000	1.004	1.489
## 31	SDQ2N31	~~	SDQ2N31	0.575	0.073	7.852	0.000	0.431	0.718
## 32	SDQ2N43	~~	SDQ2N43	0.996	0.095	10.442	0.000	0.809	1.183
## 33	GSC	~~	GSC	0.641	0.142	4.508	0.000	0.362	0.920
## 34	ASC	~~	ASC	0.461	0.114	4.034	0.000	0.237	0.684
## 35	GSC	~~	ASC	0.340	0.068	4.975	0.000	0.206	0.474

- Obtaining goodness of fit indicators of the model

```
fitMeasures(fit1, c("chisq", "rmsea", "srmr", "gfi", "ecvi"))
```

```
##      chisq    rmsea      srmr      gfi      ecvi
## 457.653    0.114    0.101    0.754    1.976
```

- The GFI should be > 0.95 . Here, it is 0.75.

*Obtaining reliability

```
reliability(fit1)
```

```
##              GSC      ASC      total
## alpha  0.6925568 0.8448618 0.8646270
## omega  0.6911301 0.8547893 0.8745261
## omega2 0.6911301 0.8547893 0.8745261
## omega3 0.6879643 0.8153354 0.8177602
## avevar 0.3602449 0.3858905 0.3805607
```

```
inspect(fit1)
```

```
## $lambda
##              GSC  ASC
## SDQ2N01      0    0
## SDQ2N13      1    0
## SDQ2N25      2    0
## SDQ2N37      3    0
## SDQ2N04      0    0
## SDQ2N16      0    4
## SDQ2N28      0    5
## SDQ2N40      0    6
## SDQ2N10      0    7
## SDQ2N22      0    8
## SDQ2N34      0    9
## SDQ2N46      0   10
## SDQ2N07      0   11
## SDQ2N19      0   12
## SDQ2N31      0   13
## SDQ2N43      0   14
##
## $theta
##              SDQ2N01 SDQ2N13 SDQ2N25 SDQ2N37 SDQ2N04 SDQ2N16 SDQ2N28 SDQ2N40
## SDQ2N01 15
## SDQ2N13  0      16
## SDQ2N25  0      0      17
## SDQ2N37  0      0      0      18
## SDQ2N04  0      0      0      0      19
## SDQ2N16  0      0      0      0      0      20
## SDQ2N28  0      0      0      0      0      0      21
## SDQ2N40  0      0      0      0      0      0      0      22
## SDQ2N10  0      0      0      0      0      0      0      0
## SDQ2N22  0      0      0      0      0      0      0      0
## SDQ2N34  0      0      0      0      0      0      0      0
## SDQ2N46  0      0      0      0      0      0      0      0
## SDQ2N07  0      0      0      0      0      0      0      0
## SDQ2N19  0      0      0      0      0      0      0      0
## SDQ2N31  0      0      0      0      0      0      0      0
## SDQ2N43  0      0      0      0      0      0      0      0
##              SDQ2N10 SDQ2N22 SDQ2N34 SDQ2N46 SDQ2N07 SDQ2N19 SDQ2N31 SDQ2N43
```

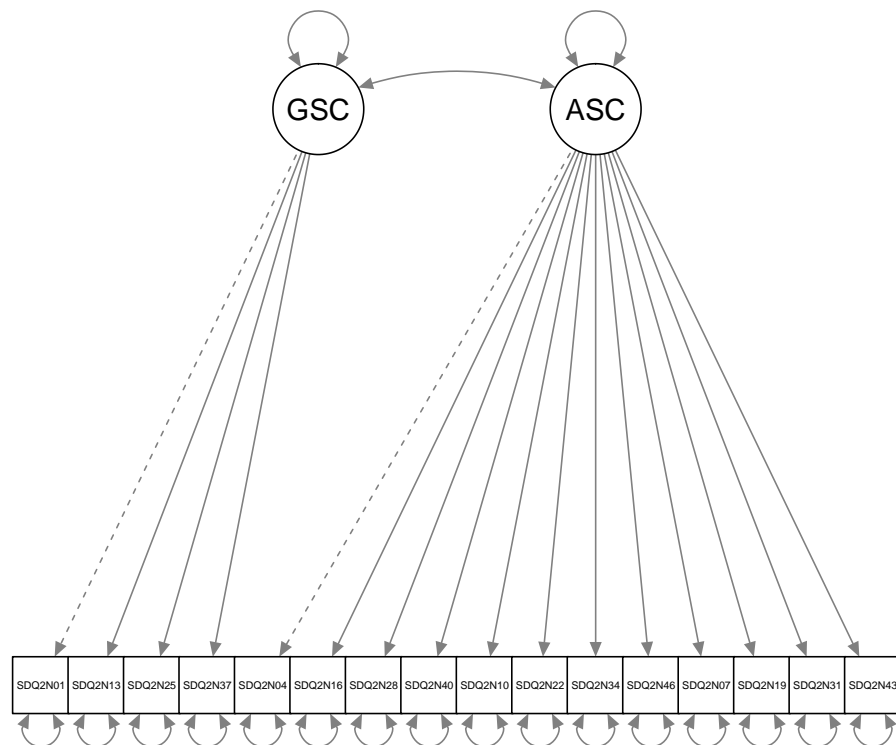
```

## SDQ2N01
## SDQ2N13
## SDQ2N25
## SDQ2N37
## SDQ2N04
## SDQ2N16
## SDQ2N28
## SDQ2N40
## SDQ2N10 23
## SDQ2N22 0      24
## SDQ2N34 0      0      25
## SDQ2N46 0      0      0      26
## SDQ2N07 0      0      0      0      27
## SDQ2N19 0      0      0      0      0      28
## SDQ2N31 0      0      0      0      0      0      29
## SDQ2N43 0      0      0      0      0      0      0      30
##
## $psi
##      GSC ASC
## GSC 31
## ASC 33 32

```

*Creating diagram

```
semPaths(fit1)
```



2. Hypothesis 3: SC is a one-factor structure. Compare the models with the four-factor model.

*Specify the 1 factor model

```
model2 <- '
f1 =~ SDQ2N01 + SDQ2N13 + SDQ2N25 + SDQ2N37 + SDQ2N04 +
SDQ2N16 + SDQ2N28 + SDQ2N40 +SDQ2 N10 + SDQ2N22 +
SDQ2N34 + SDQ2N46 + SDQ2N07 + SDQ2N19 + SDQ2N31 + SDQ2N43
'
```

*Fitting the model

```
fit2 <- cfa(model2, data=CFA, control=list(iter.max=1000))
```

*Displaying summary output

```
summary(fit2, fit.measures=TRUE)
```

```
## lavaan 0.6-3 ended normally after 43 iterations
##
##      Optimization method          NLMINB
##      Number of free parameters      32
##
##      Number of observations          265
##
##      Estimator                      ML
##      Model Fit Test Statistic        531.918
##      Degrees of freedom              104
##      P-value (Chi-square)            0.000
##
## Model test baseline model:
##
##      Minimum Function Test Statistic  1703.155
##      Degrees of freedom               120
##      P-value                          0.000
##
## User model versus baseline model:
##
##      Comparative Fit Index (CFI)      0.730
##      Tucker-Lewis Index (TLI)        0.688
##
## Loglikelihood and Information Criteria:
##
##      Loglikelihood user model (H0)      -6749.081
##      Loglikelihood unrestricted model (H1) -6483.122
##
##      Number of free parameters          32
##      Akaike (AIC)                      13562.162
##      Bayesian (BIC)                    13676.713
##      Sample-size adjusted Bayesian (BIC) 13575.256
##
## Root Mean Square Error of Approximation:
##
##      RMSEA                          0.125
##      90 Percent Confidence Interval    0.114  0.135
##      P-value RMSEA <= 0.05            0.000
##
## Standardized Root Mean Square Residual:
```

```

##
##   SRMR                                0.104
##
## Parameter Estimates:
##
##   Information                                Expected
##   Information saturated (h1) model          Structured
##   Standard Errors                          Standard
##
## Latent Variables:
##           Estimate   Std.Err   z-value   P(>|z|)
##   f1 =~
##     SDQ2N01           1.000
##     SDQ2N13           1.158     0.247     4.690     0.000
##     SDQ2N25           0.903     0.209     4.330     0.000
##     SDQ2N37           1.126     0.224     5.018     0.000
##     SDQ2N04           1.407     0.278     5.063     0.000
##     SDQ2N16           1.772     0.310     5.716     0.000
##     SDQ2N28           1.775     0.317     5.605     0.000
##     SDQ2N40           1.744     0.315     5.541     0.000
##     SDQ2N10           0.859     0.197     4.362     0.000
##     SDQ2N22           0.816     0.187     4.371     0.000
##     SDQ2N34           0.181     0.222     0.815     0.415
##     SDQ2N46           0.756     0.202     3.732     0.000
##     SDQ2N07           2.743     0.471     5.826     0.000
##     SDQ2N19           2.505     0.434     5.768     0.000
##     SDQ2N31           2.711     0.454     5.970     0.000
##     SDQ2N43           1.929     0.341     5.659     0.000
##
## Variances:
##           Estimate   Std.Err   z-value   P(>|z|)
##     .SDQ2N01           1.565     0.138    11.335     0.000
##     .SDQ2N13           1.508     0.134    11.266     0.000
##     .SDQ2N25           1.299     0.115    11.338     0.000
##     .SDQ2N37           0.994     0.089    11.160     0.000
##     .SDQ2N04           1.469     0.132    11.140     0.000
##     .SDQ2N16           0.762     0.073    10.368     0.000
##     .SDQ2N28           0.994     0.093    10.633     0.000
##     .SDQ2N40           1.093     0.102    10.742     0.000
##     .SDQ2N10           1.140     0.101    11.333     0.000
##     .SDQ2N22           1.022     0.090    11.332     0.000
##     .SDQ2N34           2.882     0.250    11.508     0.000
##     .SDQ2N46           1.535     0.135    11.409     0.000
##     .SDQ2N07           1.311     0.132     9.913     0.000
##     .SDQ2N19           1.316     0.129    10.186     0.000
##     .SDQ2N31           0.650     0.078     8.367     0.000
##     .SDQ2N43           1.040     0.099    10.520     0.000
##     f1                 0.246     0.083     2.972     0.003

```

- The model seems to be converged normally, the number of observations is equal to the number of rows in the data.
- Chi-Square Test of Model Fit : Here the χ^2 is 1703.155, with 104 degrees of freedom (ideal value $>2df$). The p-value should be more than >0.05 to have a good model fit and here, the p-value is 0.000.

- Comparative fit index (CFI): The higher the index, the better it is. 1-factor model seems to be not a good fit as the CFI value is 0.730 and it should be $>.9$.
- TLI (Tucker-Lewis index): The higher the index, the better it is. The TLI again should be more than $>.9$ and here, it is 0.688.
- The difference between AIC and BIC seems to be okay. The lower the difference, the better it is.
- RMSEA (Root mean square error of approximation): Here, the RMSEA (0.125) is more than 0.05 (ideal value) with a 90%CI from 0.114 to 0.135.
- SRMR (Standardized Root Mean Square Residual) : The cut-off of good fit is <0.08 . Here, the SRMR is 0.104.

*Obtaining confidence intervals for the estimated coefficients

```
parameterEstimates(fit2, ci = TRUE, level = 0.95)
```

##	lhs op	rhs	est	se	z	pvalue	ci.lower	ci.upper
## 1	f1 ==	SDQ2N01	1.000	0.000	NA	NA	1.000	1.000
## 2	f1 ==	SDQ2N13	1.158	0.247	4.690	0.000	0.674	1.642
## 3	f1 ==	SDQ2N25	0.903	0.209	4.330	0.000	0.494	1.312
## 4	f1 ==	SDQ2N37	1.126	0.224	5.018	0.000	0.686	1.566
## 5	f1 ==	SDQ2N04	1.407	0.278	5.063	0.000	0.862	1.952
## 6	f1 ==	SDQ2N16	1.772	0.310	5.716	0.000	1.164	2.379
## 7	f1 ==	SDQ2N28	1.775	0.317	5.605	0.000	1.154	2.396
## 8	f1 ==	SDQ2N40	1.744	0.315	5.541	0.000	1.127	2.361
## 9	f1 ==	SDQ2N10	0.859	0.197	4.362	0.000	0.473	1.245
## 10	f1 ==	SDQ2N22	0.816	0.187	4.371	0.000	0.450	1.182
## 11	f1 ==	SDQ2N34	0.181	0.222	0.815	0.415	-0.254	0.617
## 12	f1 ==	SDQ2N46	0.756	0.202	3.732	0.000	0.359	1.152
## 13	f1 ==	SDQ2N07	2.743	0.471	5.826	0.000	1.820	3.666
## 14	f1 ==	SDQ2N19	2.505	0.434	5.768	0.000	1.654	3.357
## 15	f1 ==	SDQ2N31	2.711	0.454	5.970	0.000	1.821	3.601
## 16	f1 ==	SDQ2N43	1.929	0.341	5.659	0.000	1.261	2.597
## 17	SDQ2N01 ==	SDQ2N01	1.565	0.138	11.335	0.000	1.295	1.836
## 18	SDQ2N13 ==	SDQ2N13	1.508	0.134	11.266	0.000	1.246	1.771
## 19	SDQ2N25 ==	SDQ2N25	1.299	0.115	11.338	0.000	1.075	1.524
## 20	SDQ2N37 ==	SDQ2N37	0.994	0.089	11.160	0.000	0.820	1.169
## 21	SDQ2N04 ==	SDQ2N04	1.469	0.132	11.140	0.000	1.210	1.727
## 22	SDQ2N16 ==	SDQ2N16	0.762	0.073	10.368	0.000	0.618	0.906
## 23	SDQ2N28 ==	SDQ2N28	0.994	0.093	10.633	0.000	0.811	1.177
## 24	SDQ2N40 ==	SDQ2N40	1.093	0.102	10.742	0.000	0.894	1.293
## 25	SDQ2N10 ==	SDQ2N10	1.140	0.101	11.333	0.000	0.943	1.338
## 26	SDQ2N22 ==	SDQ2N22	1.022	0.090	11.332	0.000	0.845	1.199
## 27	SDQ2N34 ==	SDQ2N34	2.882	0.250	11.508	0.000	2.391	3.373
## 28	SDQ2N46 ==	SDQ2N46	1.535	0.135	11.409	0.000	1.271	1.799
## 29	SDQ2N07 ==	SDQ2N07	1.311	0.132	9.913	0.000	1.052	1.571
## 30	SDQ2N19 ==	SDQ2N19	1.316	0.129	10.186	0.000	1.063	1.570
## 31	SDQ2N31 ==	SDQ2N31	0.650	0.078	8.367	0.000	0.498	0.803
## 32	SDQ2N43 ==	SDQ2N43	1.040	0.099	10.520	0.000	0.846	1.233
## 33	f1 ==	f1	0.246	0.083	2.972	0.003	0.084	0.408

*Obtaining goodness of fit indicators of the model

```
fitMeasures(fit2, c("chisq", "rmsea", "srmr", "gfi", "ecvi"))
```

##	chisq	rmsea	srmr	gfi	ecvi
----	-------	-------	------	-----	------

```
## 531.918    0.125    0.104    0.724    2.249
```

- – The GFI should be >0.95. Here, it is 0.72.

*Obtaining reliability

```
reliability(fit2)
```

```
##          f1      total
## alpha  0.8646270 0.8646270
## omega  0.8672223 0.8672223
## omega2 0.8672223 0.8672223
## omega3 0.8198549 0.8198549
## avevar 0.3372906 0.3372906
```

```
inspect(fit2)
```

```
## $lambda
##          f1
## SDQ2N01  0
## SDQ2N13  1
## SDQ2N25  2
## SDQ2N37  3
## SDQ2N04  4
## SDQ2N16  5
## SDQ2N28  6
## SDQ2N40  7
## SDQ2N10  8
## SDQ2N22  9
## SDQ2N34 10
## SDQ2N46 11
## SDQ2N07 12
## SDQ2N19 13
## SDQ2N31 14
## SDQ2N43 15
##
## $theta
##          SDQ2N01 SDQ2N13 SDQ2N25 SDQ2N37 SDQ2N04 SDQ2N16 SDQ2N28 SDQ2N40
## SDQ2N01 16
## SDQ2N13  0      17
## SDQ2N25  0      0      18
## SDQ2N37  0      0      0      19
## SDQ2N04  0      0      0      0      20
## SDQ2N16  0      0      0      0      0      21
## SDQ2N28  0      0      0      0      0      0      22
## SDQ2N40  0      0      0      0      0      0      0      23
## SDQ2N10  0      0      0      0      0      0      0      0
## SDQ2N22  0      0      0      0      0      0      0      0
## SDQ2N34  0      0      0      0      0      0      0      0
## SDQ2N46  0      0      0      0      0      0      0      0
## SDQ2N07  0      0      0      0      0      0      0      0
## SDQ2N19  0      0      0      0      0      0      0      0
## SDQ2N31  0      0      0      0      0      0      0      0
## SDQ2N43  0      0      0      0      0      0      0      0
##          SDQ2N10 SDQ2N22 SDQ2N34 SDQ2N46 SDQ2N07 SDQ2N19 SDQ2N31 SDQ2N43
## SDQ2N01
```

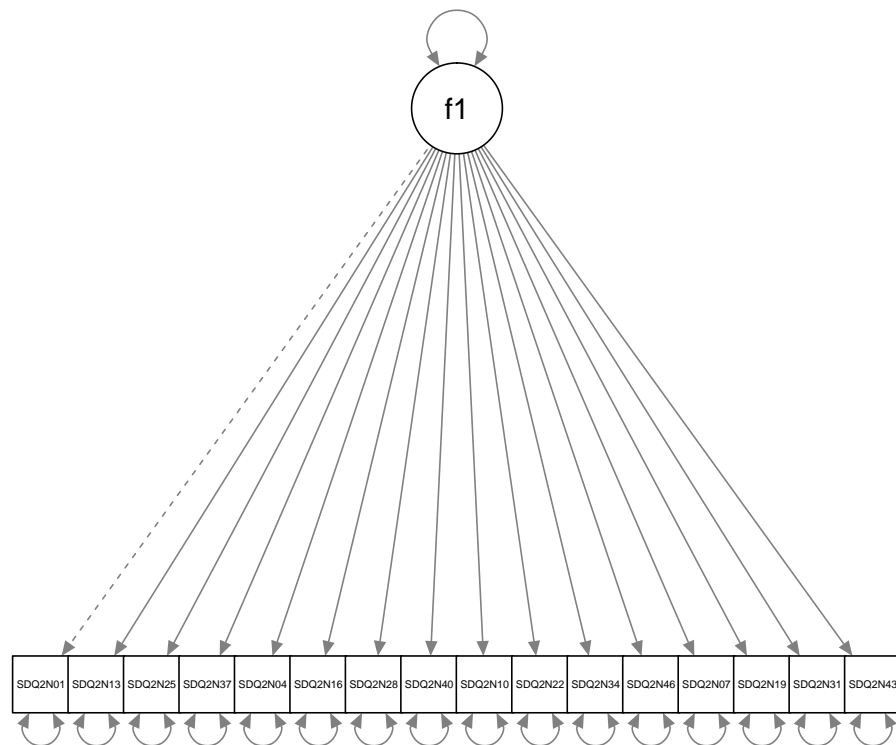
```

## SDQ2N13
## SDQ2N25
## SDQ2N37
## SDQ2N04
## SDQ2N16
## SDQ2N28
## SDQ2N40
## SDQ2N10 24
## SDQ2N22 0      25
## SDQ2N34 0      0      26
## SDQ2N46 0      0      0      27
## SDQ2N07 0      0      0      0      28
## SDQ2N19 0      0      0      0      0      29
## SDQ2N31 0      0      0      0      0      0      30
## SDQ2N43 0      0      0      0      0      0      0      31
##
## $psi
##      f1
## f1 32

```

*Creating diagram

```
semPaths(fit2)
```



*Model Comparison

```
anova(fit, fit1, fit2)
```

```
## Chi Square Difference Test
##
##      Df    AIC    BIC  Chisq Chisq diff Df diff Pr(>Chisq)
## fit   98 13201 13337 159.11
## fit1 103 13490 13608 457.65    298.541      5 < 2.2e-16 ***
## fit2 104 13562 13677 531.92     74.265      1 < 2.2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Final Interpretation

The p-value is significant in all the 3 models. The other values of good model fit will be considered. As seen from the results above, four factor model is acceptable but not excellent as compared to the other two models with CFI and TLI of .961 and .953 resp and RMSEA of .049 90%CI(.03 to .06). The Standardized Root Mean Square Residual (0.048) is below the cut off value suggesting good model fit. The other two models (2-factor and 1-factor) seems to have low CFI, TLI values and high RMSEA and SRMR as compared to their ideal cut-offs.

References

- Week 2 SEM materials
- https://www.cscu.cornell.edu/news/Handouts/SEM_fit.pdf
- <http://www.understandingdata.net/2017/03/22/cfa-in-lavaan/>

Week 3 SEM Assignment

Shweta Goswami

04-02-2019

Exercise 3.1

TITLE: CFA of MBI for Male Elementary Teachers (Calibration Group), Initial Model - ML Estimation, (Byrne 2012, p. 102)

Reading the data

```
CFA <- read.fortran("ELEM1.DAT", format=c("22F1.0"))
glimpse(CFA)
```

```
## Observations: 372
## Variables: 22
## $ V1 <dbl> 4, 2, 6, 7, 6, 2, 6, 4, 6, 4, 6, 2, 4, 6, 6, 2, 7, 6, 4, 4...
## $ V2 <dbl> 4, 2, 6, 7, 6, 2, 6, 6, 5, 6, 6, 2, 6, 6, 6, 2, 7, 6, 6, 4...
## $ V3 <dbl> 5, 1, 7, 7, 6, 2, 6, 3, 5, 2, 3, 2, 2, 4, 3, 1, 6, 3, 4, 2...
## $ V4 <dbl> 4, 7, 7, 7, 6, 7, 7, 7, 7, 4, 6, 7, 7, 6, 4, 7, 7, 4, 7, 7...
## $ V5 <dbl> 4, 2, 3, 1, 4, 6, 2, 2, 4, 2, 1, 1, 2, 6, 2, 1, 1, 6, 1, 1...
## $ V6 <dbl> 2, 1, 5, 1, 2, 2, 7, 3, 3, 2, 3, 1, 1, 2, 3, 1, 4, 6, 2, 2...
## $ V7 <dbl> 7, 7, 6, 7, 6, 7, 7, 7, 7, 6, 6, 7, 7, 7, 5, 7, 6, 6, 7, 7...
## $ V8 <dbl> 2, 2, 6, 7, 2, 1, 7, 3, 4, 1, 6, 1, 1, 4, 4, 2, 5, 6, 4, 2...
## $ V9 <dbl> 7, 7, 5, 7, 7, 7, 4, 7, 6, 7, 6, 7, 6, 7, 7, 7, 6, 6, 7, 7...
## $ V10 <dbl> 2, 1, 4, 1, 6, 1, 1, 3, 4, 2, 4, 1, 2, 2, 3, 2, 1, 6, 2, 1...
## $ V11 <dbl> 2, 1, 5, 1, 6, 1, 1, 3, 4, 2, 1, 1, 2, 1, 7, 1, 1, 6, 1, 1...
## $ V12 <dbl> 6, 4, 4, 1, 7, 7, 1, 6, 6, 6, 6, 7, 5, 6, 6, 7, 6, 4, 6, 7...
## $ V13 <dbl> 3, 2, 4, 1, 4, 3, 6, 3, 3, 3, 6, 1, 3, 4, 4, 2, 5, 5, 4, 1...
## $ V14 <dbl> 4, 2, 4, 4, 7, 2, 6, 3, 6, 5, 4, 1, 7, 3, 5, 2, 3, 4, 6, 1...
## $ V15 <dbl> 1, 1, 2, 1, 5, 1, 1, 3, 4, 1, 1, 1, 2, 4, 1, 1, 1, 1, 1, 1...
## $ V16 <dbl> 1, 1, 5, 1, 2, 2, 7, 3, 4, 2, 2, 1, 1, 2, 4, 1, 2, 6, 1, 1...
## $ V17 <dbl> 7, 7, 5, 7, 7, 7, 6, 7, 6, 6, 6, 7, 7, 6, 5, 7, 7, 6, 7, 7...
## $ V18 <dbl> 6, 4, 6, 5, 7, 6, 2, 6, 6, 6, 4, 7, 5, 6, 7, 6, 6, 7, 6, 7...
## $ V19 <dbl> 6, 6, 6, 7, 7, 5, 4, 6, 7, 6, 5, 7, 5, 6, 6, 7, 6, 7, 6, 7...
## $ V20 <dbl> 2, 1, 2, 4, 3, 2, 2, 2, 3, 2, 5, 1, 1, 1, 2, 2, 6, 1, 1, 1...
## $ V21 <dbl> 6, 6, 4, 7, 5, 6, 6, 6, 6, 2, 5, 7, 6, 6, 2, 7, 6, 6, 7, 7...
## $ V22 <dbl> 2, 1, 3, 1, 2, 2, 1, 6, 3, 2, 1, 1, 4, 1, 2, 1, 6, 2, 1, 4...
```

The dataset has 372 observations (male elementary teachers) of 22 variables (7-point Likert scales).

Creating names for all the variables

```
names(CFA) = c("ITEM1", "ITEM2", "ITEM3", "ITEM4", "ITEM5", "ITEM6", "ITEM7", "ITEM8", "ITEM9", "ITEM10",
               "ITEM11", "ITEM12", "ITEM13", "ITEM14", "ITEM15", "ITEM16", "ITEM17", "ITEM18", "ITEM19", "ITEM20",
               "ITEM21", "ITEM22")
str(CFA)
```

```
## 'data.frame': 372 obs. of 22 variables:
## $ ITEM1 : num 4 2 6 7 6 2 6 4 6 4 ...
## $ ITEM2 : num 4 2 6 7 6 2 6 6 5 6 ...
## $ ITEM3 : num 5 1 7 7 6 2 6 3 5 2 ...
## $ ITEM4 : num 4 7 7 7 6 7 7 7 7 4 ...
## $ ITEM5 : num 4 2 3 1 4 6 2 2 4 2 ...
## $ ITEM6 : num 2 1 5 1 2 2 7 3 3 2 ...
```

```
## $ ITEM7 : num 7 7 6 7 6 7 7 7 7 6 ...
## $ ITEM8 : num 2 2 6 7 2 1 7 3 4 1 ...
## $ ITEM9 : num 7 7 5 7 7 7 4 7 6 7 ...
## $ ITEM10: num 2 1 4 1 6 1 1 3 4 2 ...
## $ ITEM11: num 2 1 5 1 6 1 1 3 4 2 ...
## $ ITEM12: num 6 4 4 1 7 7 1 6 6 6 ...
## $ ITEM13: num 3 2 4 1 4 3 6 3 3 3 ...
## $ ITEM14: num 4 2 4 4 7 2 6 3 6 5 ...
## $ ITEM15: num 1 1 2 1 5 1 1 3 4 1 ...
## $ ITEM16: num 1 1 5 1 2 2 7 3 4 2 ...
## $ ITEM17: num 7 7 5 7 7 7 6 7 6 6 ...
## $ ITEM18: num 6 4 6 5 7 6 2 6 6 6 ...
## $ ITEM19: num 6 6 6 7 7 5 4 6 7 6 ...
## $ ITEM20: num 2 1 2 4 3 2 2 2 3 2 ...
## $ ITEM21: num 6 6 4 7 5 6 6 6 6 2 ...
## $ ITEM22: num 2 1 3 1 2 2 1 6 3 2 ...
```

The aim of this analysis is to test the factorial validity for a widely used measuring instrument called MBI (Maslach Burnout Inventory) which combines Emotional Exhaustion (EE), Depersonalization (DP) and Personal Accomplishment (PA).

According to the lecture materials, the hypothesized model includes MBI responses that can be explained by EE, DP and PA factors, each item has a nonzero loading on the appropriate factor and zero loadings on all other factors, the three factors are correlated, residuals of the items are uncorrelated

Exploratory data analysis to understand data properties

```
#Data type
df_status(CFA)
```

##	variable	q_zeros	p_zeros	q_na	p_na	q_inf	p_inf	type	unique
## 1	ITEM1	0	0	0	0	0	0	numeric	7
## 2	ITEM2	0	0	0	0	0	0	numeric	7
## 3	ITEM3	0	0	0	0	0	0	numeric	7
## 4	ITEM4	0	0	0	0	0	0	numeric	6
## 5	ITEM5	0	0	0	0	0	0	numeric	7
## 6	ITEM6	0	0	0	0	0	0	numeric	7
## 7	ITEM7	0	0	0	0	0	0	numeric	6
## 8	ITEM8	0	0	0	0	0	0	numeric	7
## 9	ITEM9	0	0	0	0	0	0	numeric	7
## 10	ITEM10	0	0	0	0	0	0	numeric	7
## 11	ITEM11	0	0	0	0	0	0	numeric	7
## 12	ITEM12	0	0	0	0	0	0	numeric	7
## 13	ITEM13	0	0	0	0	0	0	numeric	7
## 14	ITEM14	0	0	0	0	0	0	numeric	7
## 15	ITEM15	0	0	0	0	0	0	numeric	7
## 16	ITEM16	0	0	0	0	0	0	numeric	7
## 17	ITEM17	0	0	0	0	0	0	numeric	6
## 18	ITEM18	0	0	0	0	0	0	numeric	7
## 19	ITEM19	0	0	0	0	0	0	numeric	7
## 20	ITEM20	0	0	0	0	0	0	numeric	7
## 21	ITEM21	0	0	0	0	0	0	numeric	6
## 22	ITEM22	0	0	0	0	0	0	numeric	7

```
#Analyzing quantitatively
data_prof=profiling_num(CFA)
```


##	variable	mean	std_dev	variation_coef	p_01	p_05	p_25	p_50	p_75	p_95	p_99
## 1	ITEM1	4.4	1.66	0.38	1.7	2	3	4.0	6	7.0	7
## 2	ITEM2	4.9	1.55	0.32	1.7	2	4	5.0	6	7.0	7
## 3	ITEM3	3.5	1.73	0.49	1.0	1	2	3.0	5	6.0	7
## 4	ITEM4	6.3	1.00	0.16	2.7	4	6	7.0	7	7.0	7
## 5	ITEM5	2.2	1.49	0.68	1.0	1	1	2.0	3	6.0	6
## 6	ITEM6	2.7	1.58	0.59	1.0	1	2	2.0	4	6.0	7
## 7	ITEM7	6.3	0.84	0.13	3.0	5	6	6.0	7	7.0	7
## 8	ITEM8	3.0	1.73	0.57	1.0	1	2	2.0	4	6.0	7
## 9	ITEM9	6.0	1.32	0.22	2.0	3	6	7.0	7	7.0	7
## 10	ITEM10	2.2	1.45	0.66	1.0	1	1	2.0	3	5.4	6
## 11	ITEM11	2.2	1.53	0.68	1.0	1	1	2.0	3	5.4	7
## 12	ITEM12	5.7	1.19	0.21	2.0	3	5	6.0	6	7.0	7
## 13	ITEM13	3.6	1.68	0.47	1.0	1	2	3.5	5	7.0	7
## 14	ITEM14	4.0	1.73	0.43	1.0	1	3	4.0	5	7.0	7
## 15	ITEM15	1.8	1.30	0.73	1.0	1	1	1.0	2	5.0	7
## 16	ITEM16	2.5	1.44	0.58	1.0	1	1	2.0	3	5.0	6
## 17	ITEM17	6.4	0.85	0.13	3.7	5	6	7.0	7	7.0	7
## 18	ITEM18	5.7	1.27	0.22	2.0	3	5	6.0	7	7.0	7
## 19	ITEM19	5.9	1.19	0.20	2.0	4	6	6.0	7	7.0	7
## 20	ITEM20	2.2	1.41	0.63	1.0	1	1	2.0	3	5.0	7
## 21	ITEM21	5.9	1.27	0.22	2.0	3	5	6.0	7	7.0	7
## 22	ITEM22	2.6	1.58	0.61	1.0	1	1	2.0	3	6.0	7

##	skewness	kurtosis	iqr	range_98	range_80
## 1	-0.115	1.8	3	[1.71, 7]	[2, 6]
## 2	-0.507	2.3	2	[1.71, 7]	[2, 7]
## 3	0.317	1.9	3	[1, 7]	[2, 6]
## 4	-1.811	6.7	1	[2.71, 7]	[5, 7]
## 5	1.328	3.9	2	[1, 6]	[1, 4]
## 6	0.924	3.0	2	[1, 7]	[1, 5]
## 7	-1.649	6.8	1	[3, 7]	[5, 7]
## 8	0.741	2.4	2	[1, 7]	[1, 6]
## 9	-1.542	4.9	1	[2, 7]	[4, 7]
## 10	1.202	3.6	2	[1, 6]	[1, 4]
## 11	1.273	3.8	2	[1, 7]	[1, 5]
## 12	-1.320	4.9	1	[2, 7]	[4, 7]
## 13	0.347	2.2	3	[1, 7]	[2, 6]
## 14	0.031	2.1	2	[1, 7]	[2, 6]
## 15	2.096	7.3	1	[1, 7]	[1, 3]
## 16	0.971	3.2	2	[1, 6]	[1, 5]
## 17	-1.978	8.1	1	[3.71, 7]	[6, 7]
## 18	-1.231	4.4	2	[2, 7]	[4, 7]
## 19	-1.484	5.2	1	[2, 7]	[4, 7]
## 20	1.300	4.2	2	[1, 7]	[1, 4]
## 21	-1.300	4.2	2	[2, 7]	[4, 7]
## 22	1.066	3.2	2	[1, 7]	[1, 5]

All the numeric variables have bunch of statistics. The kurtosis seems to be high than the acceptable values in most of the variables suggesting data is not normally distributed.

Three factor CFA model using estimation method (ML)

Specifying model

```
model <- '
F1 =~ ITEM1 + ITEM2+ ITEM3 + ITEM6 + ITEM8 + ITEM13 + ITEM14 + ITEM16 + ITEM20
```

```
F2 =~ ITEM5 + ITEM10 + ITEM11 + ITEM15 + ITEM22
F3 =~ ITEM4 + ITEM7 + ITEM9 + ITEM12 + ITEM17 + ITEM18 + ITEM19 + ITEM21
'
```

Fitting the model

```
fit <- cfa(model, data=CFA)
```

Display summary output

```
summary(fit, fit.measures=TRUE)
```

```
## lavaan 0.6-3 ended normally after 46 iterations
##
##      Optimization method          NLMINB
##      Number of free parameters      47
##
##      Number of observations          372
##
##      Estimator                      ML
##      Model Fit Test Statistic        695.719
##      Degrees of freedom              206
##      P-value (Chi-square)            0.000
##
## Model test baseline model:
##
##      Minimum Function Test Statistic  3452.269
##      Degrees of freedom              231
##      P-value                        0.000
##
## User model versus baseline model:
##
##      Comparative Fit Index (CFI)      0.848
##      Tucker-Lewis Index (TLI)        0.830
##
## Loglikelihood and Information Criteria:
##
##      Loglikelihood user model (H0)    -12811.043
##      Loglikelihood unrestricted model (H1) -12463.184
##
##      Number of free parameters          47
##      Akaike (AIC)                      25716.087
##      Bayesian (BIC)                    25900.275
##      Sample-size adjusted Bayesian (BIC) 25751.158
##
## Root Mean Square Error of Approximation:
##
##      RMSEA                          0.080
##      90 Percent Confidence Interval    0.073 0.087
##      P-value RMSEA <= 0.05            0.000
##
## Standardized Root Mean Square Residual:
##
##      SRMR                          0.073
##
```

```

## Parameter Estimates:
##
## Information Expected
## Information saturated (h1) model Structured
## Standard Errors Standard
##
## Latent Variables:
## Estimate Std.Err z-value P(>|z|)
## F1 =~
## ITEM1 1.000
## ITEM2 0.887 0.061 14.621 0.000
## ITEM3 1.021 0.068 15.085 0.000
## ITEM6 0.764 0.064 12.013 0.000
## ITEM8 1.143 0.066 17.299 0.000
## ITEM13 1.017 0.065 15.544 0.000
## ITEM14 0.848 0.069 12.251 0.000
## ITEM16 0.715 0.058 12.410 0.000
## ITEM20 0.753 0.056 13.410 0.000
## F2 =~
## ITEM5 1.000
## ITEM10 1.142 0.127 8.986 0.000
## ITEM11 1.353 0.142 9.511 0.000
## ITEM15 0.905 0.109 8.318 0.000
## ITEM22 0.768 0.121 6.361 0.000
## F3 =~
## ITEM4 1.000
## ITEM7 0.970 0.150 6.482 0.000
## ITEM9 1.780 0.254 7.007 0.000
## ITEM12 1.499 0.221 6.769 0.000
## ITEM17 1.348 0.181 7.463 0.000
## ITEM18 1.918 0.262 7.329 0.000
## ITEM19 1.716 0.238 7.205 0.000
## ITEM21 1.356 0.218 6.219 0.000
##
## Covariances:
## Estimate Std.Err z-value P(>|z|)
## F1 ~~
## F2 0.701 0.099 7.061 0.000
## F3 -0.192 0.042 -4.537 0.000
## F2 ~~
## F3 -0.172 0.035 -4.850 0.000
##
## Variances:
## Estimate Std.Err z-value P(>|z|)
## .ITEM1 1.128 0.095 11.861 0.000
## .ITEM2 1.105 0.090 12.214 0.000
## .ITEM3 1.301 0.108 12.031 0.000
## .ITEM6 1.553 0.121 12.888 0.000
## .ITEM8 0.852 0.081 10.553 0.000
## .ITEM13 1.142 0.097 11.821 0.000
## .ITEM14 1.804 0.140 12.844 0.000
## .ITEM16 1.235 0.096 12.812 0.000
## .ITEM20 1.075 0.085 12.585 0.000
## .ITEM5 1.503 0.125 12.026 0.000

```

##	.ITEM10	1.169	0.107	10.901	0.000
##	.ITEM11	1.044	0.112	9.330	0.000
##	.ITEM15	1.106	0.093	11.838	0.000
##	.ITEM22	2.076	0.160	12.958	0.000
##	.ITEM4	0.802	0.062	12.901	0.000
##	.ITEM7	0.523	0.042	12.572	0.000
##	.ITEM9	1.117	0.093	11.952	0.000
##	.ITEM12	0.987	0.080	12.287	0.000
##	.ITEM17	0.375	0.035	10.739	0.000
##	.ITEM18	0.909	0.081	11.224	0.000
##	.ITEM19	0.844	0.073	11.557	0.000
##	.ITEM21	1.245	0.098	12.764	0.000
##	F1	1.625	0.190	8.551	0.000
##	F2	0.705	0.132	5.321	0.000
##	F3	0.193	0.048	4.047	0.000

The χ^2 is 695.719, with 206 degrees of freedom. The p-value should be more than >0.05 to have a good model fit and here, the p-value is 0.000. The CFI and TLI is 0.848 and 0.830 respectively and both values are less than the acceptable value (> 0.9). The value of RMSEA and SRMR is 0.080 with a 90%CI from 0.073 to 0.087 and 0.073 respectively and it should be <0.08 .

Three factor CFA model using estimation method (MLM)

Specifying model

```
model1 <- '
F1 =~ ITEM1 + ITEM2+ ITEM3 + ITEM6 + ITEM8 + ITEM13 + ITEM14 + ITEM16 + ITEM20
F2 =~ ITEM5 + ITEM10 + ITEM11 + ITEM15 + ITEM22
F3 =~ ITEM4 + ITEM7 + ITEM9 + ITEM12 + ITEM17 + ITEM18 + ITEM19 + ITEM21
'
```

Fitting the model

```
fit1 <- cfa(model1, data=CFA, estimator = "MLM")
```

Display summary output

```
summary(fit1, fit.measures=TRUE)
```

```
## lavaan 0.6-3 ended normally after 46 iterations
##
## Optimization method          NLMINB
## Number of free parameters    47
##
## Number of observations       372
##
## Estimator                    ML      Robust
## Model Fit Test Statistic     695.719  567.753
## Degrees of freedom           206      206
## P-value (Chi-square)         0.000    0.000
## Scaling correction factor    1.225
##   for the Satorra-Bentler correction
##
## Model test baseline model:
##
## Minimum Function Test Statistic  3452.269  2911.466
## Degrees of freedom              231      231
## P-value                        0.000    0.000
```

```

##
## User model versus baseline model:
##
##   Comparative Fit Index (CFI)                0.848        0.865
##   Tucker-Lewis Index (TLI)                  0.830        0.849
##
##   Robust Comparative Fit Index (CFI)          0.861
##   Robust Tucker-Lewis Index (TLI)            0.844
##
## Loglikelihood and Information Criteria:
##
##   Loglikelihood user model (H0)              -12811.043   -12811.043
##   Loglikelihood unrestricted model (H1)       -12463.184   -12463.184
##
##   Number of free parameters                   47          47
##   Akaike (AIC)                               25716.087   25716.087
##   Bayesian (BIC)                             25900.275   25900.275
##   Sample-size adjusted Bayesian (BIC)        25751.158   25751.158
##
## Root Mean Square Error of Approximation:
##
##   RMSEA                                     0.080        0.069
##   90 Percent Confidence Interval             0.073   0.087        0.063   0.075
##   P-value RMSEA <= 0.05                     0.000        0.000
##
##   Robust RMSEA                               0.076
##   90 Percent Confidence Interval             0.069   0.084
##
## Standardized Root Mean Square Residual:
##
##   SRMR                                     0.073        0.073
##
## Parameter Estimates:
##
##   Information                               Expected
##   Information saturated (h1) model          Structured
##   Standard Errors                          Robust.sem
##
## Latent Variables:
##
##           Estimate  Std.Err  z-value  P(>|z|)
## F1 =~
##   ITEM1           1.000
##   ITEM2           0.887    0.040   22.391    0.000
##   ITEM3           1.021    0.053   19.310    0.000
##   ITEM6           0.764    0.070   10.974    0.000
##   ITEM8           1.143    0.059   19.366    0.000
##   ITEM13          1.017    0.062   16.340    0.000
##   ITEM14          0.848    0.058   14.584    0.000
##   ITEM16          0.715    0.066   10.826    0.000
##   ITEM20          0.753    0.061   12.303    0.000
## F2 =~
##   ITEM5           1.000
##   ITEM10          1.142    0.152    7.509    0.000
##   ITEM11          1.353    0.162    8.368    0.000

```

```

##      ITEM15          0.905    0.123    7.366    0.000
##      ITEM22          0.768    0.122    6.284    0.000
##      F3 =~
##      ITEM4           1.000
##      ITEM7           0.970    0.128    7.563    0.000
##      ITEM9           1.780    0.322    5.529    0.000
##      ITEM12          1.499    0.241    6.232    0.000
##      ITEM17          1.348    0.200    6.757    0.000
##      ITEM18          1.918    0.298    6.435    0.000
##      ITEM19          1.716    0.287    5.978    0.000
##      ITEM21          1.356    0.227    5.984    0.000
##
## Covariances:
##              Estimate Std.Err z-value P(>|z|)
##      F1 ~~
##      F2          0.701    0.106    6.608    0.000
##      F3         -0.192    0.040   -4.796    0.000
##      F2 ~~
##      F3         -0.172    0.036   -4.777    0.000
##
## Variances:
##              Estimate Std.Err z-value P(>|z|)
##      .ITEM1        1.128    0.093   12.177    0.000
##      .ITEM2        1.105    0.088   12.506    0.000
##      .ITEM3        1.301    0.106   12.317    0.000
##      .ITEM6        1.553    0.134   11.550    0.000
##      .ITEM8        0.852    0.082   10.450    0.000
##      .ITEM13       1.142    0.124    9.173    0.000
##      .ITEM14       1.804    0.142   12.730    0.000
##      .ITEM16       1.235    0.110   11.278    0.000
##      .ITEM20       1.075    0.137    7.860    0.000
##      .ITEM5        1.503    0.179    8.381    0.000
##      .ITEM10       1.169    0.147    7.959    0.000
##      .ITEM11       1.044    0.141    7.398    0.000
##      .ITEM15       1.106    0.153    7.220    0.000
##      .ITEM22       2.076    0.184   11.266    0.000
##      .ITEM4        0.802    0.113    7.124    0.000
##      .ITEM7        0.523    0.075    7.010    0.000
##      .ITEM9        1.117    0.149    7.487    0.000
##      .ITEM12       0.987    0.126    7.852    0.000
##      .ITEM17       0.375    0.056    6.635    0.000
##      .ITEM18       0.909    0.143    6.376    0.000
##      .ITEM19       0.844    0.111    7.622    0.000
##      .ITEM21       1.245    0.133    9.338    0.000
##      F1           1.625    0.148   11.004    0.000
##      F2           0.705    0.158    4.452    0.000
##      F3           0.193    0.050    3.839    0.000

```

The MLM estimator is used here to provide robust standard errors and a scaled test statistic. The Satorra-Bentler correction accounts for non-normality or when distributional assumptions are violated. In the current dataset, this approach seems to be better to incorporate scaling corrections of the non-normal data.

The indices seems to improve a bit in this model. The χ^2 is 567.753, with 206 degrees of freedom. The p-value is 0.000. The CFI and TLI is 0.865 and 0.849 respectively and both values are still less than the acceptable value (> 0.9). The value of RMSEA and SRMR is 0.069 with a 90%CI from 0.063 to 0.075 and

0.073 respectively and it should be <0.08 .

Final Interpretation

```
fitMeasures(fit, c("chisq", "rmsea", "srmr", "cfi", "tli"))
```

```
##   chisq   rmsea   srmr    cfi    tli
## 695.719  0.080   0.073  0.848  0.830
```

```
fitMeasures(fit1, c("chisq", "rmsea", "srmr", "cfi", "tli"))
```

```
##   chisq   rmsea   srmr    cfi    tli
## 695.719  0.080   0.073  0.848  0.830
```

The second model has improved indices

The values of CFI and TLI improved in the second model but still not above the acceptable value

The value of RMSEA has lowered down to 0.069 and SRMR is same in both the models. RMSEA and SRMR values are under the acceptable range (<0.08) in the second model

The chi-square statistic shows considerable difference as compared to the first model

The Satorra-Bentler correction is 1.225 in the second model indicating normality assumptions are violated.

The hypothesized model cannot be accepted.

Exercise 3.2

Continuing with post hoc model fitting (exploratory approach).

Aim: to modify the model in a sound and responsible manner (step by step)

Model 2

Model Modification indices for model 2

```
modindices(fit1, minimum = 30)
```

```
##      lhs op    rhs mi    epc sepc.lv sepc.all sepc.nox
## 59      F1 =~ ITEM12 42 -0.31  -0.40  -0.34  -0.34
## 95    ITEM1 ~~  ITEM2 82  0.61   0.61   0.55   0.55
## 158  ITEM6 ~~  ITEM16 91  0.73   0.73   0.53   0.53
## 260 ITEM10 ~~  ITEM11 38  0.58   0.58   0.52   0.52
## 298  ITEM4 ~~  ITEM7  33  0.21   0.21   0.32   0.32
## 310  ITEM7 ~~  ITEM21 34  0.26   0.26   0.33   0.33
```

The largest modification indices for the covariances is addressed. Item 6 and Item 16 seems to have the largest modification and is included in the model.

Also, Item12 on the F1 has higher modification and could have more appropriate loading on F1 (Emotional Exhaustion) than F3 (Personal Accomplishment).

Specifying model

```
model12 <- '
F1 =~  ITEM1 + ITEM2+ ITEM3 + ITEM6 + ITEM8 + ITEM13 + ITEM14 + ITEM16 + ITEM20
F2 =~  ITEM5 + ITEM10 + ITEM11 + ITEM15 + ITEM22
F3 =~  ITEM4 + ITEM7 + ITEM9 + ITEM12 + ITEM17 + ITEM18 + ITEM19 + ITEM21
#Residual covariance
ITEM6~~ITEM16
'
```

Fitting the model

```
fit2 <- cfa(model2, data=CFA, estimator = "MLM")
```

Display summary output

```
summary(fit2, fit.measures=TRUE)
```

```
## lavaan 0.6-3 ended normally after 48 iterations
##
##      Optimization method          NLMINB
##      Number of free parameters      48
##
##      Number of observations          372
##
##      Estimator              ML      Robust
##      Model Fit Test Statistic    597.731    493.398
##      Degrees of freedom           205      205
##      P-value (Chi-square)         0.000      0.000
##      Scaling correction factor      1.211
##      for the Satorra-Bentler correction
##
## Model test baseline model:
##
##      Minimum Function Test Statistic    3452.269    2911.466
##      Degrees of freedom                 231      231
##      P-value                           0.000      0.000
##
## User model versus baseline model:
##
##      Comparative Fit Index (CFI)         0.878      0.892
##      Tucker-Lewis Index (TLI)           0.863      0.879
##
##      Robust Comparative Fit Index (CFI)      0.890
##      Robust Tucker-Lewis Index (TLI)         0.876
##
## Loglikelihood and Information Criteria:
##
##      Loglikelihood user model (H0)          -12762.049    -12762.049
##      Loglikelihood unrestricted model (H1)    -12463.184    -12463.184
##
##      Number of free parameters              48      48
##      Akaike (AIC)                          25620.098    25620.098
##      Bayesian (BIC)                        25808.205    25808.205
##      Sample-size adjusted Bayesian (BIC)     25655.916    25655.916
##
## Root Mean Square Error of Approximation:
##
##      RMSEA                                0.072      0.061
##      90 Percent Confidence Interval          0.065    0.078      0.055    0.068
##      P-value RMSEA <= 0.05                 0.000      0.002
##
##      Robust RMSEA                          0.068
##      90 Percent Confidence Interval          0.060    0.075
```



```

## Standardized Root Mean Square Residual:
##
##   SRMR                      0.071      0.071
##
## Parameter Estimates:
##
##   Information                      Expected
##   Information saturated (h1) model      Structured
##   Standard Errors                      Robust.sem
##
## Latent Variables:
##
##           Estimate  Std.Err  z-value  P(>|z|)
## F1 =~
##   ITEM1           1.000
##   ITEM2           0.887    0.040   22.303    0.000
##   ITEM3           1.015    0.052   19.632    0.000
##   ITEM6           0.715    0.069   10.369    0.000
##   ITEM8           1.133    0.058   19.698    0.000
##   ITEM13          1.002    0.062   16.227    0.000
##   ITEM14          0.847    0.058   14.692    0.000
##   ITEM16          0.672    0.065   10.294    0.000
##   ITEM20          0.746    0.061   12.288    0.000
## F2 =~
##   ITEM5           1.000
##   ITEM10          1.151    0.154    7.473    0.000
##   ITEM11          1.363    0.164    8.329    0.000
##   ITEM15          0.909    0.124    7.351    0.000
##   ITEM22          0.771    0.123    6.252    0.000
## F3 =~
##   ITEM4           1.000
##   ITEM7           0.969    0.128    7.564    0.000
##   ITEM9           1.779    0.322    5.529    0.000
##   ITEM12          1.496    0.240    6.232    0.000
##   ITEM17          1.347    0.199    6.756    0.000
##   ITEM18          1.917    0.298    6.441    0.000
##   ITEM19          1.714    0.287    5.979    0.000
##   ITEM21          1.356    0.227    5.985    0.000
##
## Covariances:
##
##           Estimate  Std.Err  z-value  P(>|z|)
## .ITEM6 ~~
##   .ITEM16          0.733    0.121    6.069    0.000
## F1 ~~
##   F2              0.697    0.106    6.605    0.000
##   F3             -0.188    0.040   -4.670    0.000
## F2 ~~
##   F3             -0.171    0.036   -4.768    0.000
##
## Variances:
##
##           Estimate  Std.Err  z-value  P(>|z|)
## .ITEM1           1.091    0.092   11.824    0.000
## .ITEM2           1.076    0.088   12.219    0.000
## .ITEM3           1.283    0.105   12.211    0.000
## .ITEM6           1.654    0.141   11.710    0.000

```

##	.ITEM8	0.844	0.080	10.559	0.000
##	.ITEM13	1.156	0.129	8.945	0.000
##	.ITEM14	1.780	0.141	12.655	0.000
##	.ITEM16	1.317	0.115	11.413	0.000
##	.ITEM20	1.071	0.136	7.863	0.000
##	.ITEM5	1.511	0.180	8.414	0.000
##	.ITEM10	1.164	0.147	7.927	0.000
##	.ITEM11	1.038	0.141	7.364	0.000
##	.ITEM15	1.108	0.153	7.225	0.000
##	.ITEM22	2.077	0.184	11.269	0.000
##	.ITEM4	0.801	0.112	7.124	0.000
##	.ITEM7	0.523	0.075	7.011	0.000
##	.ITEM9	1.116	0.149	7.484	0.000
##	.ITEM12	0.988	0.126	7.855	0.000
##	.ITEM17	0.375	0.056	6.636	0.000
##	.ITEM18	0.909	0.143	6.376	0.000
##	.ITEM19	0.844	0.111	7.626	0.000
##	.ITEM21	1.244	0.133	9.339	0.000
##	F1	1.662	0.148	11.216	0.000
##	F2	0.697	0.158	4.424	0.000
##	F3	0.193	0.050	3.842	0.000

There seems to be a considerable improvement in fit measures. The x2 statistics showing drop (493.398) using estimator MLM as compared to fit1 (567.753). The p-value is still 0.000. CFI (0.892) and TLI(0.879) values have increased and RMSEA(0.061) and SRMR (0.071) values have lowered down suggesting effective inclusion of parameters.

Model 3

Model Modification indices for model 3

```
modindices(fit2, minimum = 30)
```

##	lhs op	rhs mi	epc	sepc.lv	sepc.all	sepc.nox
## 60	F1 =~	ITEM12 42	-0.31	-0.40	-0.34	-0.34
## 96	ITEM1 ~~	ITEM2 78	0.59	0.59	0.54	0.54
## 260	ITEM10 ~~	ITEM11 37	0.58	0.58	0.53	0.53
## 298	ITEM4 ~~	ITEM7 33	0.21	0.21	0.32	0.32
## 310	ITEM7 ~~	ITEM21 33	0.26	0.26	0.33	0.33

The residual covariance Item 1 and 2 has higher modification and is included in the model.

Specifying model

```
model3 <- '
F1 =~ ITEM1 + ITEM2+ ITEM3 + ITEM6 + ITEM8 + ITEM13 + ITEM14 + ITEM16 + ITEM20
F2 =~ ITEM5 + ITEM10 + ITEM11 + ITEM15 + ITEM22
F3 =~ ITEM4 + ITEM7 + ITEM9 + ITEM12 + ITEM17 + ITEM18 + ITEM19 + ITEM21
#Residual covariance
ITEM6~~ITEM16
ITEM1~~ITEM2
'
```

Fitting the model

```
fit3 <- cfa(model3, data=CFA, estimator = "MLM")
```

Display summary output

```
summary(fit3, fit.measures=TRUE)
```

```
## lavaan 0.6-3 ended normally after 46 iterations
##
##      Optimization method          NLMINB
##      Number of free parameters      49
##
##      Number of observations          372
##
##      Estimator                      ML      Robust
##      Model Fit Test Statistic        520.481  431.496
##      Degrees of freedom              204      204
##      P-value (Chi-square)            0.000      0.000
##      Scaling correction factor
##      for the Satorra-Bentler correction
##
## Model test baseline model:
##
##      Minimum Function Test Statistic    3452.269  2911.466
##      Degrees of freedom                231      231
##      P-value                          0.000      0.000
##
## User model versus baseline model:
##
##      Comparative Fit Index (CFI)        0.902      0.915
##      Tucker-Lewis Index (TLI)          0.889      0.904
##
##      Robust Comparative Fit Index (CFI)      0.914
##      Robust Tucker-Lewis Index (TLI)        0.902
##
## Loglikelihood and Information Criteria:
##
##      Loglikelihood user model (H0)        -12723.424 -12723.424
##      Loglikelihood unrestricted model (H1) -12463.184 -12463.184
##
##      Number of free parameters            49      49
##      Akaike (AIC)                        25544.849  25544.849
##      Bayesian (BIC)                      25736.875  25736.875
##      Sample-size adjusted Bayesian (BIC)  25581.413  25581.413
##
## Root Mean Square Error of Approximation:
##
##      RMSEA                                0.065      0.055
##      90 Percent Confidence Interval        0.058  0.071      0.048  0.061
##      P-value RMSEA <= 0.05                0.000      0.114
##
##      Robust RMSEA                        0.060
##      90 Percent Confidence Interval        0.052  0.068
##
## Standardized Root Mean Square Residual:
##
##      SRMR                                0.069      0.069
##
## Parameter Estimates:
```

```

##
## Information Expected
## Information saturated (h1) model Structured
## Standard Errors Robust.sem
##
## Latent Variables:
## Estimate Std.Err z-value P(>|z|)
## F1 =~
## ITEM1 1.000
## ITEM2 0.877 0.041 21.156 0.000
## ITEM3 1.068 0.059 18.221 0.000
## ITEM6 0.767 0.077 10.025 0.000
## ITEM8 1.216 0.067 18.238 0.000
## ITEM13 1.086 0.069 15.688 0.000
## ITEM14 0.884 0.063 14.109 0.000
## ITEM16 0.727 0.072 10.053 0.000
## ITEM20 0.811 0.067 12.137 0.000
## F2 =~
## ITEM5 1.000
## ITEM10 1.151 0.154 7.478 0.000
## ITEM11 1.363 0.163 8.346 0.000
## ITEM15 0.910 0.124 7.363 0.000
## ITEM22 0.769 0.123 6.264 0.000
## F3 =~
## ITEM4 1.000
## ITEM7 0.969 0.128 7.566 0.000
## ITEM9 1.782 0.323 5.524 0.000
## ITEM12 1.505 0.241 6.239 0.000
## ITEM17 1.349 0.200 6.759 0.000
## ITEM18 1.919 0.298 6.431 0.000
## ITEM19 1.718 0.287 5.979 0.000
## ITEM21 1.356 0.227 5.977 0.000
##
## Covariances:
## Estimate Std.Err z-value P(>|z|)
## .ITEM6 ~~
## .ITEM16 0.708 0.122 5.804 0.000
## .ITEM1 ~~
## .ITEM2 0.596 0.087 6.891 0.000
## F1 ~~
## F2 0.672 0.103 6.524 0.000
## F3 -0.193 0.039 -4.914 0.000
## F2 ~~
## F3 -0.171 0.036 -4.764 0.000
##
## Variances:
## Estimate Std.Err z-value P(>|z|)
## .ITEM1 1.276 0.105 12.210 0.000
## .ITEM2 1.246 0.098 12.669 0.000
## .ITEM3 1.312 0.110 11.931 0.000
## .ITEM6 1.633 0.143 11.444 0.000
## .ITEM8 0.793 0.083 9.559 0.000
## .ITEM13 1.081 0.124 8.712 0.000
## .ITEM14 1.819 0.145 12.567 0.000

```

##	.ITEM16	1.287	0.117	11.021	0.000
##	.ITEM20	1.024	0.136	7.506	0.000
##	.ITEM5	1.511	0.179	8.429	0.000
##	.ITEM10	1.165	0.147	7.912	0.000
##	.ITEM11	1.037	0.140	7.392	0.000
##	.ITEM15	1.106	0.153	7.238	0.000
##	.ITEM22	2.079	0.184	11.292	0.000
##	.ITEM4	0.802	0.113	7.126	0.000
##	.ITEM7	0.523	0.075	7.018	0.000
##	.ITEM9	1.116	0.149	7.495	0.000
##	.ITEM12	0.985	0.125	7.853	0.000
##	.ITEM17	0.375	0.056	6.643	0.000
##	.ITEM18	0.909	0.143	6.374	0.000
##	.ITEM19	0.844	0.110	7.636	0.000
##	.ITEM21	1.245	0.133	9.334	0.000
##	F1	1.477	0.150	9.869	0.000
##	F2	0.697	0.157	4.428	0.000
##	F3	0.192	0.050	3.836	0.000

The improvement can be seen in fit measures. The x2 statistics showing drop (431.496) using estimator MLM as compared to fit2 (493.398). The p-value is still 0.000. CFI (0.915) and TLI (0.904) values have increased and RMSEA(0.055) and SRMR (0.069) values have lowered down suggesting effective inclusion of mispecified parameter.

Model 4

Model Modification indices for model 4

```
modindices(fit3, minimum = 30)
```

##	lhs op	rhs mi	epc	sepc.lv	sepc.all	sepc.nox
## 61	F1 =~	ITEM12 41	-0.33	-0.40	-0.34	-0.34
## 260	ITEM10 ~~	ITEM11 37	0.57	0.57	0.52	0.52
## 298	ITEM4 ~~	ITEM7 34	0.21	0.21	0.32	0.32
## 310	ITEM7 ~~	ITEM21 34	0.26	0.26	0.33	0.33

The Modification Indices suggest links to change in the model structure. The greatest modification relates to the misspecified factor loading i.e.item 12 as mentioned previously. Therefore, cross-loading of Item 12 on both F1 and F3 is included in the model.

Specifying model

```
model4 <- '
F1 =~ ITEM1 + ITEM2+ ITEM3 + ITEM6 + ITEM8 + ITEM12 + ITEM13 + ITEM14 + ITEM16 + ITEM20
F2 =~ ITEM5 + ITEM10 + ITEM11 + ITEM15 + ITEM22
F3 =~ ITEM4 + ITEM7 + ITEM9 + ITEM12 + ITEM17 + ITEM18 + ITEM19 + ITEM21
#Residual covariance
ITEM6~~ITEM16
ITEM1~~ITEM2
'
```

Fitting the model

```
fit4 <- cfa(model4, data=CFA, estimator = "MLM")
```

Display summary output

```
summary(fit4, fit.measures=TRUE)
```

```

## lavaan 0.6-3 ended normally after 46 iterations
##
## Optimization method NLMINB
## Number of free parameters 50
##
## Number of observations 372
##
## Estimator ML Robust
## Model Fit Test Statistic 478.584 398.090
## Degrees of freedom 203 203
## P-value (Chi-square) 0.000 0.000
## Scaling correction factor 1.202
## for the Satorra-Bentler correction
##
## Model test baseline model:
##
## Minimum Function Test Statistic 3452.269 2911.466
## Degrees of freedom 231 231
## P-value 0.000 0.000
##
## User model versus baseline model:
##
## Comparative Fit Index (CFI) 0.914 0.927
## Tucker-Lewis Index (TLI) 0.903 0.917
##
## Robust Comparative Fit Index (CFI) 0.926
## Robust Tucker-Lewis Index (TLI) 0.916
##
## Loglikelihood and Information Criteria:
##
## Loglikelihood user model (H0) -12702.476 -12702.476
## Loglikelihood unrestricted model (H1) -12463.184 -12463.184
##
## Number of free parameters 50 50
## Akaike (AIC) 25504.952 25504.952
## Bayesian (BIC) 25700.897 25700.897
## Sample-size adjusted Bayesian (BIC) 25542.262 25542.262
##
## Root Mean Square Error of Approximation:
##
## RMSEA 0.060 0.051
## 90 Percent Confidence Interval 0.053 0.067 0.044 0.058
## P-value RMSEA <= 0.05 0.008 0.411
##
## Robust RMSEA 0.056
## 90 Percent Confidence Interval 0.048 0.064
##
## Standardized Root Mean Square Residual:
##
## SRMR 0.058 0.058
##
## Parameter Estimates:
##
## Information Expected

```

```

## Information saturated (h1) model      Structured
## Standard Errors                      Robust.sem
##
## Latent Variables:
##      Estimate  Std.Err  z-value  P(>|z|)
## F1 =~
##   ITEM1      1.000
##   ITEM2      0.877    0.041   21.316    0.000
##   ITEM3      1.074    0.058   18.409    0.000
##   ITEM6      0.761    0.076    9.948    0.000
##   ITEM8      1.217    0.066   18.437    0.000
##   ITEM12     -0.317    0.054   -5.902    0.000
##   ITEM13      1.072    0.070   15.421    0.000
##   ITEM14      0.879    0.062   14.089    0.000
##   ITEM16      0.726    0.073   10.015    0.000
##   ITEM20      0.806    0.066   12.138    0.000
## F2 =~
##   ITEM5      1.000
##   ITEM10     1.155    0.155    7.450    0.000
##   ITEM11     1.368    0.165    8.318    0.000
##   ITEM15     0.912    0.124    7.329    0.000
##   ITEM22     0.769    0.123    6.246    0.000
## F3 =~
##   ITEM4      1.000
##   ITEM7      0.967    0.127    7.587    0.000
##   ITEM9      1.762    0.316    5.581    0.000
##   ITEM12     1.135    0.202    5.610    0.000
##   ITEM17     1.328    0.198    6.704    0.000
##   ITEM18     1.892    0.291    6.498    0.000
##   ITEM19     1.689    0.284    5.940    0.000
##   ITEM21     1.342    0.223    6.023    0.000
##
## Covariances:
##      Estimate  Std.Err  z-value  P(>|z|)
## .ITEM6 ~~
## .ITEM16      0.710    0.122    5.807    0.000
## .ITEM1 ~~
## .ITEM2      0.589    0.086    6.859    0.000
## F1 ~~
## F2          0.669    0.103    6.491    0.000
## F3         -0.167    0.038   -4.353    0.000
## F2 ~~
## F3         -0.162    0.035   -4.669    0.000
##
## Variances:
##      Estimate  Std.Err  z-value  P(>|z|)
## .ITEM1      1.268    0.103   12.293    0.000
## .ITEM2      1.239    0.098   12.607    0.000
## .ITEM3      1.284    0.107   11.967    0.000
## .ITEM6      1.642    0.143   11.485    0.000
## .ITEM8      0.777    0.080    9.745    0.000
## .ITEM12     0.894    0.105    8.520    0.000
## .ITEM13     1.116    0.128    8.701    0.000
## .ITEM14     1.825    0.144   12.637    0.000

```

##	.ITEM16	1.283	0.116	11.053	0.000
##	.ITEM20	1.031	0.137	7.516	0.000
##	.ITEM5	1.514	0.180	8.425	0.000
##	.ITEM10	1.162	0.147	7.884	0.000
##	.ITEM11	1.034	0.141	7.353	0.000
##	.ITEM15	1.107	0.153	7.235	0.000
##	.ITEM22	2.081	0.184	11.296	0.000
##	.ITEM4	0.795	0.112	7.109	0.000
##	.ITEM7	0.517	0.074	7.008	0.000
##	.ITEM9	1.108	0.149	7.411	0.000
##	.ITEM17	0.373	0.056	6.693	0.000
##	.ITEM18	0.903	0.143	6.323	0.000
##	.ITEM19	0.842	0.113	7.464	0.000
##	.ITEM21	1.240	0.132	9.367	0.000
##	F1	1.486	0.150	9.933	0.000
##	F2	0.693	0.157	4.408	0.000
##	F3	0.200	0.051	3.904	0.000

The results are progressive towards good model fit. The x2 statistics showing drop (398.090) using estimator MLM as compared to fit3 (431.496). The p-value is still 0.000. CFI (0.927) and TLI (0.917) values have increased and RMSEA (0.051) and SRMR (0.058) values have lowered down suggesting effective loading of item 12 on both F1 and F3.

Model 5

Model Modification indices for model 5

```
modindices(fit4, minimum = 30)
```

##	lhs	op	rhs	mi	epc	sepc.lv	sepc.all	sepc.nox
## 271	ITEM10	~~	ITEM11	37	0.57	0.57	0.52	0.52
## 305	ITEM4	~~	ITEM7	32	0.20	0.20	0.32	0.32
## 315	ITEM7	~~	ITEM21	33	0.26	0.26	0.32	0.32

The highest MI as seen above relates to items 11 and 10 and thus included in the model.

Specifying model

```
model5 <- '
F1 =~ ITEM1 + ITEM2+ ITEM3 + ITEM6 + ITEM8 + ITEM12 + ITEM13 + ITEM14 + ITEM16 + ITEM20
F2 =~ ITEM5 + ITEM10 + ITEM11 + ITEM15 + ITEM22
F3 =~ ITEM4 + ITEM7 + ITEM9 + ITEM12 + ITEM17 + ITEM18 + ITEM19 + ITEM21
#Residual covariance
ITEM6~~ITEM16
ITEM1~~ITEM2
ITEM10~~ITEM11
'
```

Fitting the model

```
fit5 <- cfa(model5, data=CFA, estimator = "MLM")
standardizedSolution(fit)
```

##	lhs	op	rhs	est.std	se	z	pvalue	ci.lower	ci.upper
## 1	F1	==	ITEM1	0.77	0.024	32.1	0	0.72	0.81
## 2	F1	==	ITEM2	0.73	0.027	27.5	0	0.68	0.78
## 3	F1	==	ITEM3	0.75	0.025	29.9	0	0.70	0.80
## 4	F1	==	ITEM6	0.62	0.035	17.8	0	0.55	0.68

## 5	F1 =~	ITEM8	0.84	0.018	47.0	0	0.81	0.88
## 6	F1 =~	ITEM13	0.77	0.024	32.6	0	0.72	0.82
## 7	F1 =~	ITEM14	0.63	0.034	18.5	0	0.56	0.69
## 8	F1 =~	ITEM16	0.63	0.033	19.0	0	0.57	0.70
## 9	F1 =~	ITEM20	0.68	0.030	22.3	0	0.62	0.74
## 10	F2 =~	ITEM5	0.56	0.042	13.3	0	0.48	0.65
## 11	F2 =~	ITEM10	0.66	0.037	17.8	0	0.59	0.74
## 12	F2 =~	ITEM11	0.74	0.033	22.5	0	0.68	0.81
## 13	F2 =~	ITEM15	0.59	0.041	14.1	0	0.50	0.67
## 14	F2 =~	ITEM22	0.41	0.050	8.2	0	0.31	0.51
## 15	F3 =~	ITEM4	0.44	0.048	9.2	0	0.35	0.53
## 16	F3 =~	ITEM7	0.51	0.045	11.4	0	0.42	0.59
## 17	F3 =~	ITEM9	0.59	0.040	14.8	0	0.52	0.67
## 18	F3 =~	ITEM12	0.55	0.042	13.0	0	0.47	0.64
## 19	F3 =~	ITEM17	0.69	0.034	20.3	0	0.63	0.76
## 20	F3 =~	ITEM18	0.66	0.036	18.3	0	0.59	0.73
## 21	F3 =~	ITEM19	0.63	0.038	16.8	0	0.56	0.71
## 22	F3 =~	ITEM21	0.47	0.046	10.2	0	0.38	0.56
## 23	ITEM1 =~	ITEM1	0.41	0.037	11.1	0	0.34	0.48
## 24	ITEM2 =~	ITEM2	0.46	0.039	11.9	0	0.39	0.54
## 25	ITEM3 =~	ITEM3	0.43	0.038	11.5	0	0.36	0.51
## 26	ITEM6 =~	ITEM6	0.62	0.043	14.5	0	0.54	0.70
## 27	ITEM8 =~	ITEM8	0.29	0.030	9.4	0	0.23	0.35
## 28	ITEM13 =~	ITEM13	0.40	0.037	11.1	0	0.33	0.48
## 29	ITEM14 =~	ITEM14	0.61	0.043	14.3	0	0.52	0.69
## 30	ITEM16 =~	ITEM16	0.60	0.042	14.1	0	0.52	0.68
## 31	ITEM20 =~	ITEM20	0.54	0.041	13.0	0	0.46	0.62
## 32	ITEM5 =~	ITEM5	0.68	0.048	14.2	0	0.59	0.78
## 33	ITEM10 =~	ITEM10	0.56	0.049	11.3	0	0.46	0.66
## 34	ITEM11 =~	ITEM11	0.45	0.049	9.1	0	0.35	0.54
## 35	ITEM15 =~	ITEM15	0.66	0.048	13.5	0	0.56	0.75
## 36	ITEM22 =~	ITEM22	0.83	0.041	20.5	0	0.75	0.91
## 37	ITEM4 =~	ITEM4	0.81	0.042	19.2	0	0.72	0.89
## 38	ITEM7 =~	ITEM7	0.74	0.045	16.4	0	0.65	0.83
## 39	ITEM9 =~	ITEM9	0.65	0.048	13.6	0	0.55	0.74
## 40	ITEM12 =~	ITEM12	0.69	0.047	14.9	0	0.60	0.79
## 41	ITEM17 =~	ITEM17	0.52	0.048	10.9	0	0.42	0.61
## 42	ITEM18 =~	ITEM18	0.56	0.048	11.7	0	0.47	0.66
## 43	ITEM19 =~	ITEM19	0.60	0.048	12.5	0	0.50	0.69
## 44	ITEM21 =~	ITEM21	0.78	0.044	17.8	0	0.69	0.86
## 45	F1 =~	F1	1.00	0.000	NA	NA	1.00	1.00
## 46	F2 =~	F2	1.00	0.000	NA	NA	1.00	1.00
## 47	F3 =~	F3	1.00	0.000	NA	NA	1.00	1.00
## 48	F1 =~	F2	0.66	0.041	16.1	0	0.57	0.73
## 49	F1 =~	F3	-0.34	0.054	-6.3	0	-0.45	-0.24
## 50	F2 =~	F3	-0.47	0.055	-8.4	0	-0.57	-0.36

Display summary output

```
summary(fit5, fit.measures=TRUE)
```

```
## lavaan 0.6-3 ended normally after 52 iterations
```

```
##
```

```
## Optimization method NLMINB
```

```
## Number of free parameters 51
```

```

##
##   Number of observations                372
##
##   Estimator                           ML      Robust
##   Model Fit Test Statistic             446.419  369.998
##   Degrees of freedom                   202      202
##   P-value (Chi-square)                 0.000    0.000
##   Scaling correction factor             1.207
##   for the Satorra-Bentler correction
##
## Model test baseline model:
##
##   Minimum Function Test Statistic      3452.269  2911.466
##   Degrees of freedom                   231      231
##   P-value                             0.000    0.000
##
## User model versus baseline model:
##
##   Comparative Fit Index (CFI)           0.924    0.937
##   Tucker-Lewis Index (TLI)            0.913    0.928
##
##   Robust Comparative Fit Index (CFI)    0.936
##   Robust Tucker-Lewis Index (TLI)      0.927
##
## Loglikelihood and Information Criteria:
##
##   Loglikelihood user model (H0)         -12686.394 -12686.394
##   Loglikelihood unrestricted model (H1) -12463.184 -12463.184
##
##   Number of free parameters             51      51
##   Akaike (AIC)                         25474.787  25474.787
##   Bayesian (BIC)                       25674.651  25674.651
##   Sample-size adjusted Bayesian (BIC)   25512.844  25512.844
##
## Root Mean Square Error of Approximation:
##
##   RMSEA                                0.057    0.047
##   90 Percent Confidence Interval         0.050  0.064    0.040  0.054
##   P-value RMSEA <= 0.05                0.052    0.735
##
##   Robust RMSEA                          0.052
##   90 Percent Confidence Interval         0.044  0.060
##
## Standardized Root Mean Square Residual:
##
##   SRMR                                0.057    0.057
##
## Parameter Estimates:
##
##   Information                          Expected
##   Information saturated (h1) model      Structured
##   Standard Errors                       Robust.sem
##
## Latent Variables:

```

```

##               Estimate Std.Err z-value P(>|z|)
## F1 =~
##   ITEM1          1.000
##   ITEM2          0.878    0.041   21.316    0.000
##   ITEM3          1.073    0.058   18.460    0.000
##   ITEM6          0.764    0.076    9.992    0.000
##   ITEM8          1.215    0.066   18.382    0.000
##   ITEM12         -0.316    0.054   -5.890    0.000
##   ITEM13          1.072    0.070   15.415    0.000
##   ITEM14          0.880    0.063   14.071    0.000
##   ITEM16          0.727    0.072   10.032    0.000
##   ITEM20          0.806    0.066   12.127    0.000
## F2 =~
##   ITEM5          1.000
##   ITEM10          0.889    0.124    7.178    0.000
##   ITEM11          1.105    0.130    8.530    0.000
##   ITEM15          0.921    0.120    7.671    0.000
##   ITEM22          0.776    0.116    6.668    0.000
## F3 =~
##   ITEM4          1.000
##   ITEM7          0.973    0.128    7.602    0.000
##   ITEM9          1.763    0.317    5.561    0.000
##   ITEM12          1.131    0.202    5.607    0.000
##   ITEM17          1.327    0.198    6.717    0.000
##   ITEM18          1.890    0.291    6.497    0.000
##   ITEM19          1.695    0.286    5.933    0.000
##   ITEM21          1.342    0.224    5.993    0.000
##
## Covariances:
##               Estimate Std.Err z-value P(>|z|)
## .ITEM6 ~~
## .ITEM16          0.706    0.122    5.773    0.000
## .ITEM1 ~~
## .ITEM2          0.588    0.086    6.870    0.000
## .ITEM10 ~~
## .ITEM11          0.517    0.110    4.719    0.000
## F1 ~~
## F2          0.747    0.106    7.038    0.000
## F3         -0.167    0.038   -4.355    0.000
## F2 ~~
## F3         -0.181    0.038   -4.788    0.000
##
## Variances:
##               Estimate Std.Err z-value P(>|z|)
## .ITEM1          1.268    0.103   12.268    0.000
## .ITEM2          1.238    0.098   12.631    0.000
## .ITEM3          1.285    0.108   11.939    0.000
## .ITEM6          1.636    0.143   11.474    0.000
## .ITEM8          0.783    0.080    9.828    0.000
## .ITEM12          0.898    0.105    8.557    0.000
## .ITEM13          1.115    0.128    8.693    0.000
## .ITEM14          1.822    0.144   12.651    0.000
## .ITEM16          1.281    0.116   11.047    0.000
## .ITEM20          1.031    0.137    7.519    0.000

```

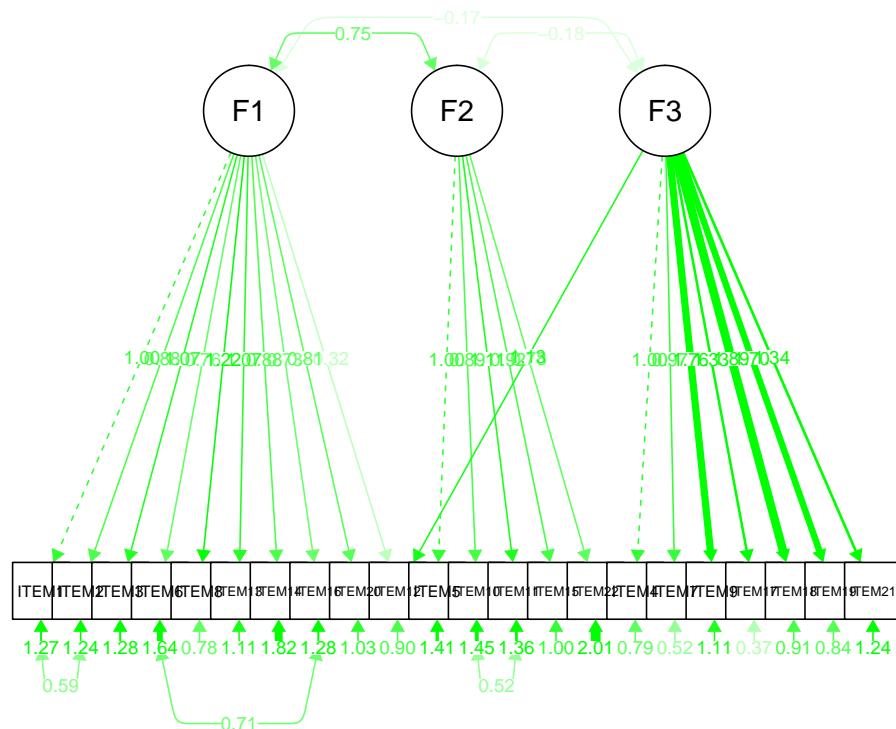
##	.ITEM5	1.407	0.181	7.771	0.000
##	.ITEM10	1.455	0.150	9.710	0.000
##	.ITEM11	1.355	0.159	8.504	0.000
##	.ITEM15	1.004	0.142	7.094	0.000
##	.ITEM22	2.008	0.182	11.021	0.000
##	.ITEM4	0.795	0.112	7.108	0.000
##	.ITEM7	0.515	0.074	6.997	0.000
##	.ITEM9	1.108	0.150	7.407	0.000
##	.ITEM17	0.374	0.056	6.694	0.000
##	.ITEM18	0.906	0.143	6.335	0.000
##	.ITEM19	0.838	0.113	7.436	0.000
##	.ITEM21	1.240	0.132	9.366	0.000
##	F1	1.486	0.150	9.933	0.000
##	F2	0.800	0.171	4.684	0.000
##	F3	0.199	0.051	3.896	0.000

The results are progressive towards good model fit. The x2 statistics showing drop (369.998) using estimator MLM as compared to the previous model (398.090). The p-value is still 0.000. CFI (0.937) and TLI (0.928) values have increased and RMSEA (0.047) and SRMR (0.057) values have lowered down suggesting effective inclusion of items 10 and 11.

Creating diagram

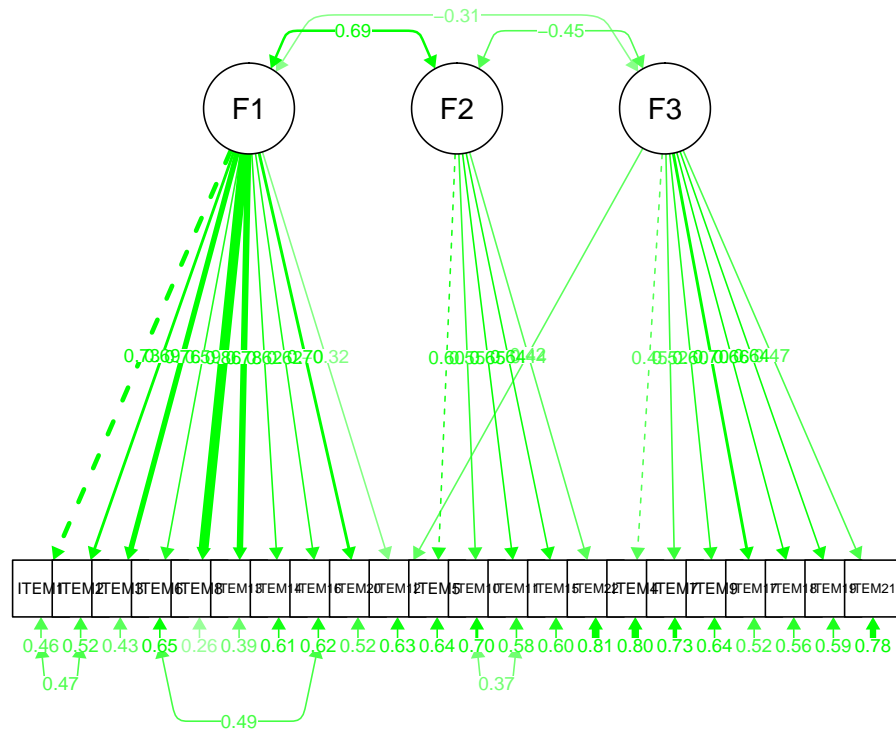
- Unstandardized plot

```
semPaths(fit5, "estimates", curvePivot = TRUE, style = "lisrel", edge.label.cex=0.75, edge.color="green")
```



- Standardized plot

```
semPaths(fit5, "standardized", curvePivot = TRUE, style = "lisrel", edge.label.cex=0.75, edge.color="green")
```



Model 6

With the remaining misspecified parameters

Model Modification indices for model 5

```
modindices(fit5, minimum = 30)
```

```
##      lhs op   rhs mi   epc sepc.lv sepc.all sepc.nox
## 305 ITEM4 ~~ ITEM7 32 0.20    0.20    0.32    0.32
## 315 ITEM7 ~~ ITEM21 33 0.26    0.26    0.32    0.32
```

Specifying model 6

```
model6 <- '
F1 =~  ITEM1 + ITEM2+ ITEM3 + ITEM6 + ITEM8 + ITEM12 + ITEM13 + ITEM14 + ITEM16 + ITEM20
F2 =~  ITEM5 + ITEM10 + ITEM11 + ITEM15 + ITEM22
F3 =~  ITEM4 + ITEM7 + ITEM9 + ITEM17 + ITEM18 + ITEM19 + ITEM21
#Residual covariance
ITEM6~~ITEM16
ITEM1~~ITEM2
ITEM10~~ITEM11
ITEM7~~ITEM21
'
```

Fitting the model

```
fit6 <- cfa(model6, data=CFA, estimator = "MLM")
```

Display summary output

```
summary(fit6, fit.measures=TRUE, standardized=TRUE)
```

```
## lavaan 0.6-3 ended normally after 50 iterations
##
##      Optimization method          NLMINB
##      Number of free parameters          51
##
##      Number of observations          372
##
##      Estimator              ML      Robust
##      Model Fit Test Statistic    477.384    398.637
##      Degrees of freedom          202      202
##      P-value (Chi-square)        0.000      0.000
##      Scaling correction factor          1.198
##      for the Satorra-Bentler correction
##
## Model test baseline model:
##
##      Minimum Function Test Statistic    3452.269    2911.466
##      Degrees of freedom          231      231
##      P-value          0.000      0.000
##
## User model versus baseline model:
##
##      Comparative Fit Index (CFI)          0.915      0.927
##      Tucker-Lewis Index (TLI)          0.902      0.916
##
##      Robust Comparative Fit Index (CFI)          0.926
##      Robust Tucker-Lewis Index (TLI)          0.915
##
## Loglikelihood and Information Criteria:
##
##      Loglikelihood user model (H0)          -12701.876    -12701.876
##      Loglikelihood unrestricted model (H1)    -12463.184    -12463.184
##
##      Number of free parameters          51      51
##      Akaike (AIC)          25505.752    25505.752
##      Bayesian (BIC)          25705.616    25705.616
##      Sample-size adjusted Bayesian (BIC)    25543.808    25543.808
##
## Root Mean Square Error of Approximation:
##
##      RMSEA          0.061      0.051
##      90 Percent Confidence Interval    0.054    0.068      0.044    0.058
##      P-value RMSEA <= 0.05          0.007      0.380
##
##      Robust RMSEA          0.056
##      90 Percent Confidence Interval    0.048    0.064
##
## Standardized Root Mean Square Residual:
```

```

##
##      SRMR                      0.066      0.066
##
## Parameter Estimates:
##
##      Information                      Expected
##      Information saturated (h1) model      Structured
##      Standard Errors                      Robust.sem
##
## Latent Variables:
##      Estimate  Std.Err  z-value  P(>|z|)  Std.lv  Std.all
##      F1 =~
##      ITEM1      1.000
##      ITEM2      0.879    0.042   21.116   0.000    1.062    0.688
##      ITEM3      1.081    0.059   18.344   0.000    1.306    0.754
##      ITEM6      0.774    0.077   10.005   0.000    0.935    0.591
##      ITEM8      1.227    0.067   18.330   0.000    1.482    0.859
##      ITEM12     -0.460    0.058   -7.887   0.000   -0.556   -0.466
##      ITEM13      1.085    0.070   15.461   0.000    1.311    0.780
##      ITEM14      0.882    0.063   13.943   0.000    1.066    0.618
##      ITEM16      0.737    0.073   10.051   0.000    0.891    0.620
##      ITEM20      0.814    0.067   12.093   0.000    0.984    0.696
##      F2 =~
##      ITEM5      1.000
##      ITEM10     0.886    0.123    7.202   0.000    0.794    0.550
##      ITEM11     1.100    0.129    8.544   0.000    0.986    0.646
##      ITEM15     0.919    0.119    7.717   0.000    0.824    0.635
##      ITEM22     0.776    0.116    6.657   0.000    0.695    0.441
##      F3 =~
##      ITEM4      1.000
##      ITEM7      0.975    0.137    7.106   0.000    0.406    0.484
##      ITEM9      1.894    0.359    5.280   0.000    0.789    0.600
##      ITEM17     1.419    0.226    6.271   0.000    0.591    0.694
##      ITEM18     2.054    0.338    6.082   0.000    0.855    0.672
##      ITEM19     1.901    0.341    5.575   0.000    0.792    0.666
##      ITEM21     1.289    0.231    5.584   0.000    0.537    0.424
##
## Covariances:
##      Estimate  Std.Err  z-value  P(>|z|)  Std.lv  Std.all
##      .ITEM6 ~~
##      .ITEM16     0.699    0.122    5.708   0.000    0.699    0.485
##      .ITEM1 ~~
##      .ITEM2     0.610    0.087    7.035   0.000    0.610    0.478
##      .ITEM10 ~~
##      .ITEM11     0.520    0.110    4.721   0.000    0.520    0.369
##      .ITEM7 ~~
##      .ITEM21     0.258    0.063    4.127   0.000    0.258    0.307
##      F1 ~~
##      F2      0.749    0.106    7.084   0.000    0.691    0.691
##      F3     -0.169    0.038   -4.436   0.000   -0.336   -0.336
##      F2 ~~
##      F3     -0.173    0.037   -4.732   0.000   -0.463   -0.463
##
## Variances:

```

##		Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
##	.ITEM1	1.295	0.104	12.421	0.000	1.295	0.470
##	.ITEM2	1.255	0.099	12.721	0.000	1.255	0.527
##	.ITEM3	1.292	0.107	12.082	0.000	1.292	0.431
##	.ITEM6	1.629	0.143	11.433	0.000	1.629	0.651
##	.ITEM8	0.781	0.078	9.948	0.000	0.781	0.262
##	.ITEM12	1.111	0.110	10.115	0.000	1.111	0.783
##	.ITEM13	1.105	0.126	8.754	0.000	1.105	0.391
##	.ITEM14	1.837	0.145	12.686	0.000	1.837	0.618
##	.ITEM16	1.273	0.116	10.977	0.000	1.273	0.616
##	.ITEM20	1.029	0.137	7.486	0.000	1.029	0.516
##	.ITEM5	1.404	0.181	7.776	0.000	1.404	0.636
##	.ITEM10	1.457	0.150	9.701	0.000	1.457	0.698
##	.ITEM11	1.360	0.160	8.520	0.000	1.360	0.583
##	.ITEM15	1.004	0.141	7.093	0.000	1.004	0.596
##	.ITEM22	2.007	0.182	11.021	0.000	2.007	0.806
##	.ITEM4	0.821	0.113	7.240	0.000	0.821	0.826
##	.ITEM7	0.539	0.077	6.956	0.000	0.539	0.766
##	.ITEM9	1.105	0.150	7.367	0.000	1.105	0.640
##	.ITEM17	0.376	0.057	6.578	0.000	0.376	0.518
##	.ITEM18	0.887	0.145	6.126	0.000	0.887	0.548
##	.ITEM19	0.785	0.107	7.339	0.000	0.785	0.556
##	.ITEM21	1.311	0.136	9.623	0.000	1.311	0.820
##	F1	1.459	0.149	9.775	0.000	1.000	1.000
##	F2	0.804	0.171	4.705	0.000	1.000	1.000
##	F3	0.173	0.048	3.618	0.000	1.000	1.000

There seems to have slightly higher χ^2 values (398.637) than the final model (369.998). The p-value is still 0.000. CFI (0.927) and TLI (0.916) values have lowered down and RMSEA (0.051) and SRMR (0.066) values have increased suggesting ineffective inclusion of items 7 and 21.

According to the results, model 5 has a better model fit and seems to somewhat accept the hypothesized model that includes MBI responses explained by EE, DP and PA factors, each item has a nonzero loading on the appropriate factor and zero loadings on all other factors (except one item 12) and the three factors are correlated.

Week 4 SEM Assignment

Shweta Goswami

12-02-2019

TITLE: Full SEM Model of Burnout for Secondary Teachers, Hypothesized Model (Byrne 2012, p. 154)

Exercise 4.1

Reading the data

```
alsec <- read.delim("~/sem2019/allsecondary.DAT", header=FALSE)
glimpse(alsec)
```

```
## Observations: 1,430
## Variables: 32
## $ V1 <dbl> 1.33, 2.33, 3.33, 2.00, 3.00, 2.67, 1.67, 2.00, 4.00, 2.67...
## $ V2 <dbl> 1.5, 2.0, 4.5, 2.0, 1.0, 3.0, 1.5, 3.5, 3.5, 3.5, 2.5, 1.5...
## $ V3 <dbl> 3.33, 2.67, 4.00, 3.00, 5.00, 4.33, 2.33, 2.67, 3.00, 3.67...
## $ V4 <dbl> 3.0, 3.0, 5.0, 3.0, 5.0, 3.0, 2.5, 1.5, 3.0, 2.0, 4.0, 1.5...
## $ V5 <dbl> 2.33, 4.00, 5.33, 3.67, 3.00, 3.33, 3.00, 2.00, 4.00, 3.33...
## $ V6 <dbl> 2.0, 2.5, 5.0, 3.0, 1.5, 4.5, 3.0, 1.5, 3.0, 2.0, 2.5, 1.0...
## $ V7 <dbl> 3.33, 3.00, 3.33, 3.33, 2.67, 3.67, 2.67, 3.00, 2.67, 4.00...
## $ V8 <dbl> 3.67, 3.33, 2.67, 3.33, 2.67, 2.67, 3.33, 2.67, 2.53, 3.00...
## $ V9 <dbl> 4.00, 3.33, 3.00, 3.33, 3.33, 3.67, 3.33, 3.33, 2.97, 3.00...
## $ V10 <dbl> 4.00, 2.50, 2.50, 3.00, 4.00, 3.50, 3.50, 4.00, 3.35, 2.50...
## $ V11 <dbl> 5.33, 4.67, 3.67, 4.67, 4.33, 3.67, 5.33, 3.67, 3.00, 4.67...
## $ V12 <dbl> 5.0, 5.0, 3.5, 5.0, 3.0, 1.5, 5.0, 3.0, 3.5, 5.5, 5.5, 5.0...
## $ V13 <dbl> 5.67, 2.33, 3.00, 4.67, 4.00, 2.67, 5.67, 5.00, 5.33, 4.67...
## $ V14 <dbl> 5.5, 3.5, 4.5, 5.0, 1.5, 1.0, 6.0, 5.0, 4.5, 4.5, 5.0, 5.5...
## $ V15 <dbl> 5.67, 5.00, 3.67, 4.67, 5.33, 3.33, 5.00, 4.00, 4.67, 5.33...
## $ V16 <dbl> 5.5, 5.0, 3.5, 4.5, 5.5, 5.5, 5.0, 3.5, 5.0, 4.5, 4.5, 5.0...
## $ V17 <dbl> 3.33, 4.00, 3.67, 3.67, 4.00, 3.67, 4.00, 4.00, 4.00, 4.00...
## $ V18 <dbl> 3.00, 4.00, 3.75, 3.50, 3.75, 4.00, 4.00, 3.25, 3.75, 4.00...
## $ V19 <dbl> 3.00, 4.00, 3.67, 4.00, 3.00, 3.00, 3.67, 3.33, 3.67, 4.00...
## $ V20 <dbl> 3.2, 2.6, 2.6, 2.8, 4.0, 1.8, 2.8, 2.4, 2.4, 2.4, 2.0, 3.4...
## $ V21 <dbl> 3.50, 2.00, 2.75, 3.25, 4.25, 3.25, 2.25, 4.00, 2.75, 2.25...
## $ V22 <dbl> 2.6, 2.8, 2.4, 3.4, 4.0, 2.4, 2.2, 2.6, 2.6, 2.4, 2.8, 2.4...
## $ V23 <dbl> 3.25, 1.75, 2.50, 2.75, 3.75, 1.75, 2.00, 2.50, 2.00, 1.75...
## $ V24 <dbl> 2.60, 2.00, 2.80, 2.60, 3.00, 2.20, 1.60, 2.80, 1.80, 1.80...
## $ V25 <dbl> 3.67, 3.33, 5.67, 5.00, 2.67, 2.33, 4.67, 2.00, 4.33, 3.00...
## $ V26 <dbl> 3.67, 4.00, 4.67, 3.67, 3.00, 3.33, 3.33, 2.67, 4.67, 3.33...
## $ V27 <dbl> 1.67, 3.00, 5.67, 3.00, 2.00, 2.00, 2.33, 2.67, 3.67, 2.33...
## $ V28 <dbl> 2.00, 2.33, 1.67, 2.00, 3.00, 2.67, 1.67, 2.33, 2.00, 1.00...
## $ V29 <dbl> 1.5, 3.0, 1.5, 1.5, 1.5, 3.5, 1.5, 1.5, 1.5, 2.0, 1.5, 1.0...
## $ V30 <dbl> 6.33, 6.00, 5.67, 5.33, 5.33, 6.00, 6.33, 5.67, 4.67, 7.00...
## $ V31 <dbl> 6.5, 5.0, 5.5, 5.5, 5.5, 6.0, 6.5, 6.0, 5.5, 6.5, 6.5, 7.0...
## $ V32 <dbl> 6.33, 5.33, 5.33, 5.33, 5.33, 5.33, 7.00, 6.00, 5.00, 5.00...
```

The dataset has 1,430 observations (sample of secondary teachers) of 32 unidimensional indicator variables and is carefully grouped according to content.

Creating names for all the variables

```
names(alsec) <- c("ROLEA1", "ROLEA2", "ROLEC1", "ROLEC2", "WORK1", "WORK2", "CCLIM1", "CCLIM2", "CCLIM3", "CCLIM4", "DEC1", "DEC2", "SSUP1", "SSUP2", "PSUP1", "PSUP2", "SELF1", "SELF2", "SELF3", "ELC1", "ELC2", "ELC3", "ELC4", "ELC5", "EE1", "EE2", "EE3", "DP1", "DP2", "PA1", "PA2", "PA3")
str(alsec)
```

```
## 'data.frame': 1430 obs. of 32 variables:
## $ ROLEA1: num 1.33 2.33 3.33 2 3 2.67 1.67 2 4 2.67 ...
## $ ROLEA2: num 1.5 2 4.5 2 1 3 1.5 3.5 3.5 3.5 ...
## $ ROLEC1: num 3.33 2.67 4 3 5 4.33 2.33 2.67 3 3.67 ...
## $ ROLEC2: num 3 3 5 3 5 3 2.5 1.5 3 2 ...
## $ WORK1 : num 2.33 4 5.33 3.67 3 3.33 3 2 4 3.33 ...
## $ WORK2 : num 2 2.5 5 3 1.5 4.5 3 1.5 3 2 ...
## $ CCLIM1: num 3.33 3 3.33 3.33 2.67 3.67 2.67 3 2.67 4 ...
## $ CCLIM2: num 3.67 3.33 2.67 3.33 2.67 2.67 3.33 2.67 2.53 3 ...
## $ CCLIM3: num 4 3.33 3 3.33 3.33 3.67 3.33 3.33 2.97 3 ...
## $ CCLIM4: num 4 2.5 2.5 3 4 3.5 3.5 4 3.35 2.5 ...
## $ DEC1 : num 5.33 4.67 3.67 4.67 4.33 3.67 5.33 3.67 3 4.67 ...
## $ DEC2 : num 5 5 3.5 5 3 1.5 5 3 3.5 5.5 ...
## $ SSUP1 : num 5.67 2.33 3 4.67 4 2.67 5.67 5 5.33 4.67 ...
## $ SSUP2 : num 5.5 3.5 4.5 5 1.5 1 6 5 4.5 4.5 ...
## $ PSUP1 : num 5.67 5 3.67 4.67 5.33 3.33 5 4 4.67 5.33 ...
## $ PSUP2 : num 5.5 5 3.5 4.5 5.5 5.5 5 3.5 5 4.5 ...
## $ SELF1 : num 3.33 4 3.67 3.67 4 3.67 4 4 4 4 ...
## $ SELF2 : num 3 4 3.75 3.5 3.75 4 4 3.25 3.75 4 ...
## $ SELF3 : num 3 4 3.67 4 3 3 3.67 3.33 3.67 4 ...
## $ ELC1 : num 3.2 2.6 2.6 2.8 4 1.8 2.8 2.4 2.4 2.4 ...
## $ ELC2 : num 3.5 2 2.75 3.25 4.25 3.25 2.25 4 2.75 2.25 ...
## $ ELC3 : num 2.6 2.8 2.4 3.4 4 2.4 2.2 2.6 2.6 2.4 ...
## $ ELC4 : num 3.25 1.75 2.5 2.75 3.75 1.75 2 2.5 2 1.75 ...
## $ ELC5 : num 2.6 2 2.8 2.6 3 2.2 1.6 2.8 1.8 1.8 ...
## $ EE1 : num 3.67 3.33 5.67 5 2.67 2.33 4.67 2 4.33 3 ...
## $ EE2 : num 3.67 4 4.67 3.67 3 3.33 3.33 2.67 4.67 3.33 ...
## $ EE3 : num 1.67 3 5.67 3 2 2 2.33 2.67 3.67 2.33 ...
## $ DP1 : num 2 2.33 1.67 2 3 2.67 1.67 2.33 2 1 ...
## $ DP2 : num 1.5 3 1.5 1.5 1.5 3.5 1.5 1.5 1.5 2 ...
## $ PA1 : num 6.33 6 5.67 5.33 5.33 6 6.33 5.67 4.67 7 ...
## $ PA2 : num 6.5 5 5.5 5.5 5.5 6 6.5 6 5.5 6.5 ...
## $ PA3 : num 6.33 5.33 5.33 5.33 5.33 5.33 5.33 7 6 5 5 ...
```

As mentioned in the lecture material and proposed structural model of teacher burnout:

The Teacher Stress Scale has six subscales designed to measure Role Ambiguity, Role Conflict, Work Overload, Decision Making, Superior Support, and Peer Support. The MBI consists of three subscales designed to measure three facets of burnout : Emotional Exhaustion, Depersonalization and Personal Accomplishment.

The aim of this analysis is to test the validity of a causal structure. The subject is the impact of organizational and personality variables on three conceptually distinct factors of burnout i.e. Emotional Exhaustion (EE), Depersonalization (DP), Personal Accomplishment (PA). This is a single-group analyses of SEM.

EE is the central facet to different stressor in the teacher's work environment. As shown in the model paths, EE hypothesized to positively impact DP but negatively impact PA. DP hypothesized to have negative impact on PA.

The independent latent variables are F1 - F7 and the dependent latent variables are F8 - F12.

Specifying model 1

```

model1 <- '
F1 =~ ROLEA1 + ROLEA2 + DEC2
F2 =~ ROLEC1 + ROLEC2
F3 =~ WORK1 + WORK2
F4 =~ CCLIM1 + CCLIM2 + CCLIM3 + CCLIM4
F5 =~ DEC1 + DEC2
F6 =~ SSUP1 + SSUP2 + DEC2
F7 =~ PSUP1 + PSUP2
F8 =~ SELF1 + SELF2 + SELF3
F9 =~ ELC1 + ELC2 + ELC3 + ELC4 + ELC5
F10 =~ EE1 + EE2 + EE3
F11 =~ DP1 + DP2
F12 =~ PA1 + PA2 + PA3

F8 ~ F5 + F6 + F7
F9 ~ F5
F10 ~ F2 + F3 + F4
F11 ~ F2 + F10
F12 ~ F1 + F8 + F9 + F10 + F11
'

```

Fitting the model

```
fit1 <- sem(model1, data=alsec, estimator = "MLM")
```

```
## Warning in lav_object_post_check(object): lavaan WARNING: some estimated lv
## variances are negative
```

Display summary output

```
summary(fit1, fit.measures=FALSE)
```

```

## lavaan 0.6-3 ended normally after 199 iterations
##
##      Optimization method          NLMINB
##      Number of free parameters      101
##
##      Number of observations          1430
##
##      Estimator                      ML      Robust
##      Model Fit Test Statistic        1737.090  1541.844
##      Degrees of freedom              427      427
##      P-value (Chi-square)            0.000      0.000
##      Scaling correction factor        1.127
##      for the Satorra-Bentler correction
##
## Parameter Estimates:
##
##      Information                    Expected
##      Information saturated (h1) model  Structured
##      Standard Errors                  Robust.sem
##
## Latent Variables:
##      Estimate Std.Err z-value P(>|z|)
##      F1 =~
##      ROLEA1          1.000

```

##	ROLEA2	1.238	0.058	21.499	0.000
##	DEC2	0.229	0.089	2.579	0.010
##	F2 =~				
##	ROLEC1	1.000			
##	ROLEC2	1.308	0.053	24.767	0.000
##	F3 =~				
##	WORK1	1.000			
##	WORK2	0.749	0.032	23.203	0.000
##	F4 =~				
##	CCLIM1	1.000			
##	CCLIM2	1.478	0.077	19.254	0.000
##	CCLIM3	0.958	0.056	17.114	0.000
##	CCLIM4	1.334	0.080	16.764	0.000
##	F5 =~				
##	DEC1	1.000			
##	DEC2	0.407	0.106	3.852	0.000
##	F6 =~				
##	SSUP1	1.000			
##	SSUP2	1.098	0.026	42.261	0.000
##	DEC2	0.859	0.049	17.574	0.000
##	F7 =~				
##	PSUP1	1.000			
##	PSUP2	1.079	0.046	23.684	0.000
##	F8 =~				
##	SELF1	1.000			
##	SELF2	1.278	0.045	28.157	0.000
##	SELF3	1.357	0.057	23.744	0.000
##	F9 =~				
##	ELC1	1.000			
##	ELC2	0.848	0.042	20.398	0.000
##	ELC3	0.944	0.041	23.153	0.000
##	ELC4	0.904	0.047	19.274	0.000
##	ELC5	1.110	0.050	22.388	0.000
##	F10 =~				
##	EE1	1.000			
##	EE2	1.020	0.019	53.503	0.000
##	EE3	0.973	0.023	43.048	0.000
##	F11 =~				
##	DP1	1.000			
##	DP2	0.918	0.046	20.022	0.000
##	F12 =~				
##	PA1	1.000			
##	PA2	1.039	0.038	27.420	0.000
##	PA3	0.963	0.040	23.869	0.000
##					
##	Regressions:				
##		Estimate	Std.Err	z-value	P(> z)
##	F8 ~				
##	F5	0.475	0.054	8.784	0.000
##	F6	-0.155	0.026	-5.890	0.000
##	F7	-0.066	0.030	-2.223	0.026
##	F9 ~				
##	F5	-0.288	0.023	-12.787	0.000
##	F10 ~				

```

##      F2      -8.707    6.705   -1.298    0.194
##      F3      8.082    5.647    1.431    0.152
##      F4     -0.930    0.740   -1.257    0.209
##    F11 ~
##      F2      0.258    0.054    4.789    0.000
##     F10      0.373    0.036   10.242    0.000
##    F12 ~
##      F1     -0.071    0.048   -1.474    0.140
##      F8      0.472    0.090    5.245    0.000
##      F9     -0.208    0.052   -3.975    0.000
##     F10     -0.064    0.026   -2.416    0.016
##     F11     -0.218    0.033   -6.556    0.000
##
## Covariances:
##              Estimate  Std.Err  z-value  P(>|z|)
##    F1 ~~
##      F2      0.360    0.025   14.389    0.000
##      F3      0.419    0.027   15.239    0.000
##      F4     -0.065    0.008   -7.755    0.000
##      F5     -0.373    0.026  -14.497    0.000
##      F6     -0.386    0.030  -12.736    0.000
##      F7     -0.242    0.022  -10.976    0.000
##    F2 ~~
##      F3      0.666    0.035   19.038    0.000
##      F4     -0.086    0.011   -8.092    0.000
##      F5     -0.407    0.028  -14.530    0.000
##      F6     -0.429    0.032  -13.235    0.000
##      F7     -0.234    0.023  -10.351    0.000
##    F3 ~~
##      F4     -0.097    0.013   -7.504    0.000
##      F5     -0.491    0.030  -16.117    0.000
##      F6     -0.501    0.035  -14.309    0.000
##      F7     -0.277    0.026  -10.790    0.000
##    F4 ~~
##      F5      0.100    0.011    9.329    0.000
##      F6      0.120    0.014    8.728    0.000
##      F7      0.055    0.009    5.897    0.000
##    F5 ~~
##      F6      0.616    0.038   16.239    0.000
##      F7      0.385    0.028   13.835    0.000
##    F6 ~~
##      F7      0.394    0.032   12.431    0.000
##
## Variances:
##              Estimate  Std.Err  z-value  P(>|z|)
##    .ROLEA1      0.422    0.024   17.386    0.000
##    .ROLEA2      0.313    0.027   11.556    0.000
##    .DEC2        0.598    0.033   18.016    0.000
##    .ROLEC1      0.642    0.029   22.304    0.000
##    .ROLEC2      0.546    0.037   14.798    0.000
##    .WORK1       0.646    0.030   21.317    0.000
##    .WORK2       0.739    0.035   20.903    0.000
##    .CCLIM1      0.180    0.008   22.588    0.000
##    .CCLIM2      0.151    0.010   14.874    0.000

```

```
## .CCLIM3      0.141    0.007   19.356    0.000
## .CCLIM4      0.337    0.015   21.843    0.000
## .DEC1        0.515    0.027   19.233    0.000
## .SSUP1       0.398    0.026   15.205    0.000
## .SSUP2       0.200    0.022    8.898    0.000
## .PSUP1       0.336    0.027   12.238    0.000
## .PSUP2       0.164    0.026    6.287    0.000
## .SELF1       0.082    0.005   16.563    0.000
## .SELF2       0.065    0.005   13.033    0.000
## .SELF3       0.083    0.006   13.021    0.000
## .ELC1        0.204    0.010   20.506    0.000
## .ELC2        0.259    0.011   23.326    0.000
## .ELC3        0.135    0.007   18.174    0.000
## .ELC4        0.215    0.010   21.720    0.000
## .ELC5        0.187    0.010   18.595    0.000
## .EE1         0.413    0.024   17.250    0.000
## .EE2         0.225    0.019   11.753    0.000
## .EE3         0.449    0.025   17.799    0.000
## .DP1         0.278    0.045    6.144    0.000
## .DP2         0.622    0.049   12.655    0.000
## .PA1         0.270    0.022   12.414    0.000
## .PA2         0.319    0.025   12.783    0.000
## .PA3         0.407    0.024   17.000    0.000
## F1          0.413    0.033   12.434    0.000
## F2          0.571    0.041   13.843    0.000
## F3          0.797    0.047   16.926    0.000
## F4          0.112    0.010   10.732    0.000
## F5          0.504    0.038   13.435    0.000
## F6          1.151    0.061   18.983    0.000
## F7          0.595    0.043   13.894    0.000
## .F8          0.079    0.008    9.693    0.000
## .F9          0.143    0.012   12.447    0.000
## .F10         -0.432    0.816   -0.530    0.596
## .F11         0.605    0.053   11.482    0.000
## .F12         0.383    0.025   15.337    0.000
```

```
fitMeasures(fit1, c("chisq.scaled", "df.scaled", "pvalue.scaled", "cfi.robust", "tli.robust", "rmsea.robust"))
```

```
##  chisq.scaled    df.scaled pvalue.scaled    cfi.robust    tli.robust
##    1541.844      427.000         0.000         0.945         0.936
##  rmsea.robust      srmr
##         0.045         0.053
```

The non-significant parameters are F10 (Emotional Exhaustion) on F2 (Role Conflict), F10 (Emotional Exhaustion) on F3 (Work Overload), F10 (Emotional Exhaustion) on F4 (Classroom Climate) and F12 (Personal Accomplishment) on F1 (Role Ambiguity). In the final model, all parameters should be statistically significant.

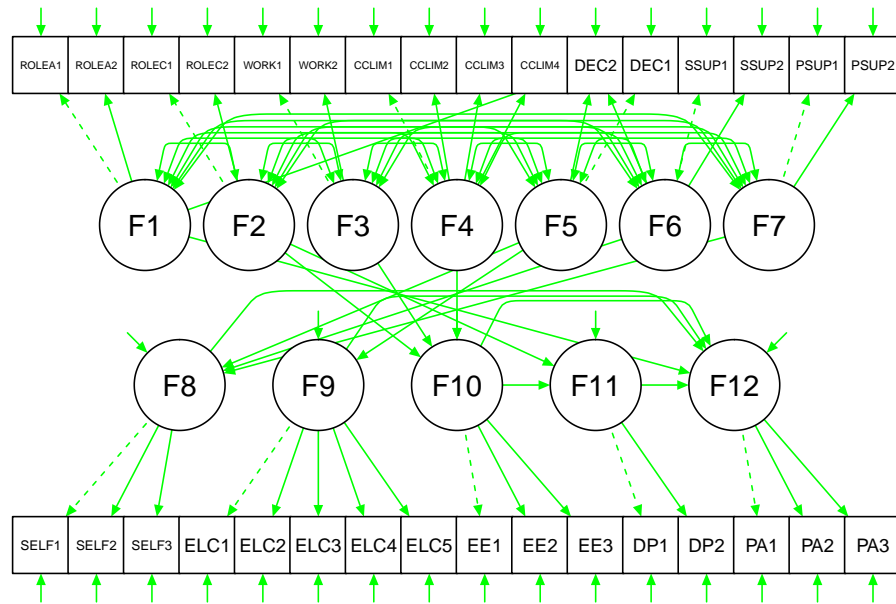
The MLM estimator is used to have robust standard errors and a scaled test statistic. The Satorra-Bentler correction is 1.127. The χ^2 is 1541.844, with 427 degrees of freedom. The p-value is 0.000. The CFI (0.940) and TLI (0.930) values are more than the acceptable value (> 0.9). The value of RMSEA and SRMR is 0.043 (90%CI from 0.041 to 0.045) and 0.053 respectively and it should be < 0.08 . The model seems to have sound fit.

Creating graph

```

labels = list(F1 = "Role Ambiguity", F2 = " Role Conflict", F3 = " Work Overload", F4 = " Classroom Climate", F5 = " Teacher Efficacy", F6 = " Student Engagement", F7 = " Student Achievement", F8 = " Teacher Self-Efficacy", F9 = " Student Self-Efficacy", F10 = " Teacher Efficacy", F11 = " Student Engagement", F12 = " Student Achievement")
# standardized path
semPaths(fit1, curvePivot = TRUE, style = "lisrel", edge.label.cex=0.75, edge.color="green")

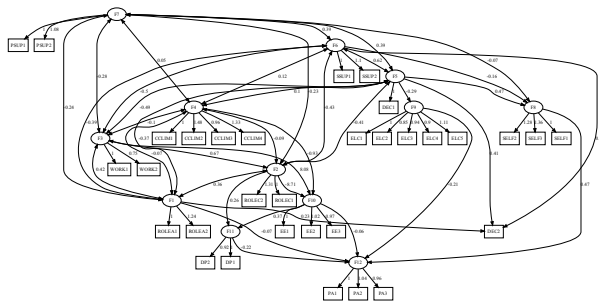
```



```

lavaanPlot(model = fit1, coefs = TRUE, covs = TRUE, stars = TRUE)

```



```
# unstandardized path
lavaanPlot(model = fit1, coefs = TRUE, stand = FALSE)
```



Exercise 4.2 & 4.3

Aim: to modify the model in a sound and responsible manner (step by step)

Model Modification

Model 2

Model Modification indices for model 2

```
mi <- modindices(fit1, minimum.value = 60, sort. = TRUE)
mi[mi$op == "~",]
```

```
##      lhs op rhs      mi      epc sepc.lv sepc.all sepc.nox
## 1038 F11 ~  F4 112.597 -0.974 -0.339 -0.339 -0.339
## 1104  F4 ~ F11  90.818 -0.141 -0.404 -0.404 -0.404
## 1037 F11 ~  F3  85.322 -4.799 -4.467 -4.467 -4.467
```

The largest MI (113) for the regression associates with F11 on F4 (Depersonalization on Classroom Climate) and hence, included in the model. The EPC is -0.974.

Re-specifying model

```
model2 <- '
  F1 =~ ROLEA1 + ROLEA2 + DEC2
  F2 =~ ROLEC1 + ROLEC2
  F3 =~ WORK1 + WORK2
  F4 =~ CCLIM1 + CCLIM2 + CCLIM3 + CCLIM4
  F5 =~ DEC1 + DEC2
  F6 =~ SSUP1 + SSUP2 + DEC2
  F7 =~ PSUP1 + PSUP2
  F8 =~ SELF1 + SELF2 + SELF3
  F9 =~ ELC1 + ELC2 + ELC3 + ELC4 + ELC5
  F10 =~ EE1 + EE2 + EE3
  F11 =~ DP1 + DP2
  F12 =~ PA1 + PA2 + PA3

  F8 ~ F5 + F6 + F7
  F9 ~ F5
  F10 ~ F2 + F3 + F4
  F11 ~ F2 + F4 + F10
  F12 ~ F1 + F8 + F9 + F10 + F11
'
```

Fitting the model

```
fit2 <- sem(model2, data=alsec, estimator = "MLM")
```

```
## Warning in lav_object_post_check(object): lavaan WARNING: some estimated lv
## variances are negative
```

Display summary output

```
fitMeasures(fit2, c("chisq.scaled", "df.scaled", "pvalue.scaled", "cfi.robust", "tli.robust", "rmsea.robust", "srmr"))
```

```
##  chisq.scaled    df.scaled pvalue.scaled    cfi.robust    tli.robust
##      1440.864      426.000         0.000         0.950         0.942
##  rmsea.robust      srmr
##      0.043      0.048
```

The χ^2 is 1440.86, with 426 degrees of freedom. The p-value is 0.000. The CFI and TLI values are 0.950 and 0.942 respectively. The value of RMSEA and SRMR indices are 0.043 and 0.048 respectively.

Comparison of model 1 and 2

```
options(scipen=999)
compareFit(fit1,fit2, nested = FALSE)
```

```
## ##### Model Fit Indices #####
##      chisq.scaled df.scaled pvalue.scaled cfi.robust tli.robust      aic
## fit2    1440.864†      426          .000      .950†      .942† 94567.591†
## fit1    1541.844      427          .000      .945      .936 94682.256
##      bic rmsea.robust srmr
## fit2 95104.665†      .043† .048†
## fit1 95214.064      .045 .053
```

```
anova(fit1,fit2)
```

```
## Scaled Chi Square Difference Test (method = "satorra.bentler.2001")
##
##      Df    AIC    BIC  Chisq Chisq diff Df diff      Pr(>Chisq)
## fit2 426 94568 95105 1620.4
## fit1 427 94682 95214 1737.1      58.818      1 0.00000000000001729 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

The model has improved as compared to the previous model. The chi-square difference test is statistically significant with 1 df indicating the addition of non-significant parameters appropriate.

Model 3

The warning message (negative variance) is still there in the previous model and to determine the best fitting model which includes only significant structural paths and remove all insignificant paths, post hoc analysis will be continued with model 3.

Model Modification indices for model 3

```
mi1 <- modindices(fit2, minimum.value = 40, sort. = TRUE)
mi1[mi1$op == "~",]
```

```
##      lhs op rhs      mi      epc sepc.lv sepc.all sepc.nox
## 1009  F8 ~ F12 49.856 0.330 0.720 0.720 0.720
## 1058  F6 ~ F9 48.895 0.530 0.213 0.213 0.213
## 1040 F12 ~ F5 47.087 0.480 0.458 0.458 0.458
## 1024 F10 ~ F8 42.769 -1.029 -0.306 -0.306 -0.306
## 1014  F9 ~ F8 42.452 -0.295 -0.234 -0.234 -0.234
```

The largest MI (50) for the regression associates with F8 on F12. But according to Byrne, F12 ON F5 with MI (47) is the most appropriate both substantially and statistically and is included in model 3. It makes sense as participation of teachers in decision making (F5) raise the sense of personal accomplishment (F12)

Re-specifying model 3

```
model3 <- '
F1 =~ ROLEA1 + ROLEA2 + DEC2
F2 =~ ROLEC1 + ROLEC2
F3 =~ WORK1 + WORK2
F4 =~ CCLIM1 + CCLIM2 + CCLIM3 + CCLIM4
F5 =~ DEC1 + DEC2
F6 =~ SSUP1 + SSUP2 + DEC2
F7 =~ PSUP1 + PSUP2
F8 =~ SELF1 + SELF2 + SELF3
F9 =~ ELC1 + ELC2 + ELC3 + ELC4 + ELC5
```

```

F10 =~ EE1 + EE2 + EE3
F11 =~ DP1 + DP2
F12 =~ PA1 + PA2 + PA3

F8 ~ F5 + F6 + F7
F9 ~ F5
F10 ~ F2 + F3 + F4
F11 ~ F2 + F4 + F10
F12 ~ F1 + F5 + F8 + F9 + F10 + F11

```

Fitting the model

```
fit3 <- sem(model3, data=alsec, estimator = "MLM")
```

```
## Warning in lav_object_post_check(object): lavaan WARNING: some estimated lv
## variances are negative
```

Display summary output

```
fitMeasures(fit3, c("chisq.scaled", "df.scaled", "pvalue.scaled", "cfi.robust", "tli.robust", "rmsea.robust", "srmr"))
```

```
##  chisq.scaled    df.scaled pvalue.scaled    cfi.robust    tli.robust
##      1396.527      425.000         0.000         0.952         0.944
##  rmsea.robust      srmr
##      0.042         0.045
```

The x2 is 1396.527, with 425 degrees of freedom. The p-value is 0.000. The CFI and TLI values are 0.952 and 0.944 respectively. The value of RMSEA and SRMR indices are 0.042 and 0.045 respectively.

Comparison of model 1, 2 and 3

```
options(scipen=999)
```

```
compareFit(fit1, fit2, fit3, nested = FALSE)
```

```
## ##### Model Fit Indices #####
##      chisq.scaled df.scaled pvalue.scaled cfi.robust tli.robust      aic
## fit3   1396.527†    425         .000       .952†    .944† 94520.133†
## fit2   1440.864     426         .000       .950     .942 94567.591
## fit1   1541.844     427         .000       .945     .936 94682.256
##      bic rmsea.robust srmr
## fit3 95062.473†    .042† .045†
## fit2 95104.665     .043  .048
## fit1 95214.064     .045  .053
```

```
anova(fit2, fit3)
```

```
## Scaled Chi Square Difference Test (method = "satorra.bentler.2001")
##
##      Df   AIC   BIC  Chisq Chisq diff Df diff      Pr(>Chisq)
## fit3 425 94520 95062 1571.0
## fit2 426 94568 95105 1620.4      49.398      1 0.00000000002089 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

The chi-square difference test is statistically significant with 1 df indicating the addition of non-significant parameters appropriate.

Model 4

The warning message (negative variance) is still there in the model 3.

Model Modification indices for model 4

```
mi2 <- modindices(fit3, minimum.value = 30, sort. = TRUE)
mi2[mi2$op == "~",]
```

##	lhs	op	rhs	mi	epc	sepc.lv	sepc.all	sepc.nox
## 1058	F6	~	F9	48.571	0.523	0.210	0.210	0.210
## 1025	F10	~	F8	43.412	-1.021	-0.304	-0.304	-0.304
## 1021	F9	~	F2	41.343	0.191	0.336	0.336	0.336
## 1015	F9	~	F8	39.841	-0.284	-0.225	-0.225	-0.225
## 1010	F8	~	F12	39.568	0.295	0.647	0.647	0.647
## 1090	F3	~	F8	38.645	-0.172	-0.065	-0.065	-0.065
## 1022	F9	~	F3	36.061	0.154	0.321	0.321	0.321
## 1079	F2	~	F8	35.047	0.134	0.060	0.060	0.060
## 1008	F8	~	F10	34.969	-0.116	-0.389	-0.389	-0.389
## 1019	F9	~	F6	33.752	0.130	0.323	0.323	0.323

F9 ON F2 is the most appropriate to include in model 4. F10 ON F8 and F9 ON F8 seems to have incorrect ???ow of causal direction according to the lecture material.

Re-specifying model 4

```
model4 <- '
  F1 =~ ROLEA1 + ROLEA2 + DEC2
  F2 =~ ROLEC1 + ROLEC2
  F3 =~ WORK1 + WORK2
  F4 =~ CCLIM1 + CCLIM2 + CCLIM3 + CCLIM4
  F5 =~ DEC1 + DEC2
  F6 =~ SSUP1 + SSUP2 + DEC2
  F7 =~ PSUP1 + PSUP2
  F8 =~ SELF1 + SELF2 + SELF3
  F9 =~ ELC1 + ELC2 + ELC3 + ELC4 + ELC5
  F10 =~ EE1 + EE2 + EE3
  F11 =~ DP1 + DP2
  F12 =~ PA1 + PA2 + PA3

  F8 ~ F5 + F6 + F7
  F9 ~ F2 + F5
  F10 ~ F2 + F3 + F4
  F11 ~ F2 + F4 + F10
  F12 ~ F1 + F5 + F8 + F9 + F10 + F11
'
```

Fitting the model

```
fit4 <- sem(model4, data=alsec, estimator = "MLM")
```

```
## Warning in lav_object_post_check(object): lavaan WARNING: some estimated lv
## variances are negative
```

Display summary output

```
fitMeasures(fit4, c("chisq.scaled", "df.scaled", "pvalue.scaled", "cfi.robust", "tli.robust", "rmsea.robust"))
```

##	chisq.scaled	df.scaled	pvalue.scaled	cfi.robust	tli.robust
##	1356.810	424.000	0.000	0.954	0.946

```
## rmsea.robust      srmr
##          0.042      0.042
```

The χ^2 is 1356.810, with 424 degrees of freedom. The p-value is 0.000. The CFI and TLI values are 0.954 and 0.946 respectively. The value of RMSEA and SRMR indices are 0.042 and 0.042 respectively.

Comparison of model 1, 2, 3 and 4

```
options(scipen=999)
compareFit(fit1, fit2, fit3, fit4, nested = FALSE)

## ##### Model Fit Indices #####
##      chisq.scaled df.scaled pvalue.scaled cfi.robust tli.robust      aic
## fit4    1356.810†    424          .000      .954†    .946† 94477.933†
## fit3    1396.527    425          .000      .952    .944 94520.133
## fit2    1440.864    426          .000      .950    .942 94567.591
## fit1    1541.844    427          .000      .945    .936 94682.256
##      bic rmsea.robust srmr
## fit4 95025.537†    .042† .042†
## fit3 95062.473    .042 .045
## fit2 95104.665    .043 .048
## fit1 95214.064    .045 .053

anova(fit3, fit4)
```

```
## Scaled Chi Square Difference Test (method = "satorra.bentler.2001")
##
##      Df  AIC  BIC  Chisq Chisq diff Df diff      Pr(>Chisq)
## fit4 424 94478 95026 1526.8
## fit3 425 94520 95062 1571.0      45.294      1 0.00000000001696 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

The difference in fit between model 3 and model 4 is statistically significant.

Model 5

The warning message (negative variance) is still there in the model 4.

Model Modification indices for model 5

```
mi3 <- modindices(fit4, minimum.value = 30, sort. = TRUE)
mi3[mi3$op == "~",]
```

```
##      lhs op rhs      mi      epc sepc.lv sepc.all sepc.nox
## 1016  F9 ~  F8 38.685 -0.261 -0.208 -0.208 -0.208
## 1068  F7 ~  F8 38.309  3.764  1.659  1.659  1.659
## 1011  F8 ~ F12 37.408  0.302  0.662  0.662  0.662
## 1058  F6 ~  F9 33.241  0.418  0.166  0.166  0.166
## 1019  F9 ~ F12 30.392 -0.265 -0.464 -0.464 -0.464
```

F9 (External Locus of Control) ON F8 (Self-Esteem) is the most appropriate to include in model 5.

Re-specifying model 5

```
model5 <- '
  F1 =~ ROLEA1 + ROLEA2 + DEC2
  F2 =~ ROLEC1 + ROLEC2
  F3 =~ WORK1 + WORK2
  F4 =~ CCLIM1 + CCLIM2 + CCLIM3 + CCLIM4
```

```

F5 =~ DEC1 + DEC2
F6 =~ SSUP1 + SSUP2 + DEC2
F7 =~ PSUP1 + PSUP2
F8 =~ SELF1 + SELF2 + SELF3
F9 =~ ELC1 + ELC2 + ELC3 + ELC4 + ELC5
F10 =~ EE1 + EE2 + EE3
F11 =~ DP1 + DP2
F12 =~ PA1 + PA2 + PA3

F8 ~ F5 + F6 + F7
F9 ~ F2 + F5 + F8
F10 ~ F2 + F3 + F4
F11 ~ F2 + F4 + F10
F12 ~ F1 + F5 + F8 + F9 + F10 + F11

```

Fitting the model

```
fit5 <- sem(model5, data=alsec, estimator = "MLM")
```

```
## Warning in lav_object_post_check(object): lavaan WARNING: some estimated lv
## variances are negative
```

Display summary output

```
fitMeasures(fit5, c("chisq.scaled", "df.scaled", "pvalue.scaled", "cfi.robust", "tli.robust", "rmsea.robust", "srmr"))
```

```
##  chisq.scaled    df.scaled pvalue.scaled    cfi.robust    tli.robust
##      1323.061      423.000         0.000         0.956         0.948
##  rmsea.robust      srmr
##      0.041         0.040
```

The χ^2 is 1323.061, with 423 degrees of freedom. The p-value is 0.000. The CFI and TLI values are 0.956 and 0.948 respectively. The value of RMSEA and SRMR indices are 0.041 and 0.040 respectively.

Comparison of model 1, 2, 3, 4 and 5

```
options(scipen=999)
```

```
compareFit(fit1, fit2, fit3, fit4, fit5, nested = FALSE)
```

```
## ##### Model Fit Indices #####
##      chisq.scaled df.scaled pvalue.scaled cfi.robust tli.robust      aic
## fit5      1323.061†      423          .000      .956†      .948† 94440.776†
## fit4      1356.810      424          .000      .954      .946 94477.933
## fit3      1396.527      425          .000      .952      .944 94520.133
## fit2      1440.864      426          .000      .950      .942 94567.591
## fit1      1541.844      427          .000      .945      .936 94682.256
##      bic rmsea.robust  srmr
## fit5 94993.646†      .041† .040†
## fit4 95025.537      .042  .042
## fit3 95062.473      .042  .045
## fit2 95104.665      .043  .048
## fit1 95214.064      .045  .053
```

```
anova(fit4, fit5)
```

```
## Scaled Chi Square Difference Test (method = "satorra.bentler.2001")
##
```

```
##           Df    AIC    BIC  Chisq Chisq diff Df diff    Pr(>Chisq)
## fit5 423 94441 94994 1487.6
## fit4 424 94478 95026 1526.8      26.059      1 0.0000003312 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

The difference in fit between Model 5 and Model 4 is found to be statistically significant

Model 6

The warning message (negative variance) is still there in the model 5.

Model Modification indices for model 6

```
mi4 <- modindices(fit5, minimum.value = 20, sort. = TRUE)
mi4[mi4$op == "~",]
```

##	lhs	op	rhs	mi	epc	sepc.lv	sepc.all	sepc.nox
## 1068	F7	~	F8	44.064	4.164	1.829	1.829	1.829
## 1057	F6	~	F8	31.635	2.552	0.808	0.808	0.808
## 1025	F10	~	F8	30.096	-1.068	-0.318	-0.318	-0.318
## 1011	F8	~	F11	25.670	-0.066	-0.188	-0.188	-0.188
## 1090	F3	~	F8	25.621	-0.175	-0.066	-0.066	-0.066
## 1016	F8	~	F1	25.474	0.261	0.491	0.491	0.491
## 1033	F11	~	F8	21.980	-0.404	-0.142	-0.142	-0.142
## 1079	F2	~	F8	21.296	0.129	0.058	0.058	0.058
## 1012	F8	~	F12	20.836	0.239	0.526	0.526	0.526
## 1010	F8	~	F10	20.767	-0.121	-0.406	-0.406	-0.406

F10 (Emotional Exhaustion) ON F8 (Self-Esteem) with MI (30.096) and EPC (-1.068) is the most appropriate to include in model 6. High self-esteem acquaint less emotional exhaustion.

Re-specifying model

```
model6 <- '
  F1 =~ ROLEA1 + ROLEA2 + DEC2
  F2 =~ ROLEC1 + ROLEC2
  F3 =~ WORK1 + WORK2
  F4 =~ CCLIM1 + CCLIM2 + CCLIM3 + CCLIM4
  F5 =~ DEC1 + DEC2
  F6 =~ SSUP1 + SSUP2 + DEC2
  F7 =~ PSUP1 + PSUP2
  F8 =~ SELF1 + SELF2 + SELF3
  F9 =~ ELC1 + ELC2 + ELC3 + ELC4 + ELC5
  F10 =~ EE1 + EE2 + EE3
  F11 =~ DP1 + DP2
  F12 =~ PA1 + PA2 + PA3

  F8 ~ F5 + F6 + F7
  F9 ~ F2 + F5 + F8
  F10 ~ F2 + F3 + F4 + F8
  F11 ~ F2 + F4 + F10
  F12 ~ F1 + F5 + F8 + F9 + F10 + F11
'
```

Fitting the model

```
fit6 <- sem(model6, data=alsec, estimator = "MLM")
```

Display summary output

```
fitMeasures(fit6, c("chisq.scaled", "df.scaled", "pvalue.scaled", "cfi.robust", "tli.robust", "rmsea.robust", "srmr"))
```

```
##  chisq.scaled    df.scaled pvalue.scaled    cfi.robust    tli.robust
##      1288.246      422.000         0.000         0.958         0.950
##  rmsea.robust      srmr
##      0.040         0.040
```

The χ^2 is 1288.246, with 422 degrees of freedom. The p-value is 0.000. The CFI and TLI values are 0.958 and 0.950 respectively. The value of RMSEA and SRMR indices are 0.040 and 0.040 respectively.

Comparison of model 1, 2, 3, 4, 5 and 6

```
options(scipen=999)
```

```
compareFit(fit1, fit2, fit3, fit4, fit5, fit6, nested = FALSE)
```

```
## ##### Model Fit Indices #####
##      chisq.scaled df.scaled pvalue.scaled cfi.robust tli.robust      aic
## fit6    1288.246†      422          .000      .958†      .950† 94402.803†
## fit5    1323.061      423          .000      .956      .948 94440.776
## fit4    1356.810      424          .000      .954      .946 94477.933
## fit3    1396.527      425          .000      .952      .944 94520.133
## fit2    1440.864      426          .000      .950      .942 94567.591
## fit1    1541.844      427          .000      .945      .936 94682.256
##      bic rmsea.robust  srmr
## fit6 94960.938†      .040† .040
## fit5 94993.646      .041 .040†
## fit4 95025.537      .042 .042
## fit3 95062.473      .042 .045
## fit2 95104.665      .043 .048
## fit1 95214.064      .045 .053
```

```
anova(fit5, fit6)
```

```
## Scaled Chi Square Difference Test (method = "satorra.bentler.2001")
##
##      Df   AIC   BIC  Chisq Chisq diff Df diff    Pr(>Chisq)
## fit6 422 94403 94961 1447.6
## fit5 423 94441 94994 1487.6      28.646      1 0.00000008691 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

The difference in fit between Model 6 and Model 5 is found to be statistically significant.

Model 7

Model Modification indices for model 7

```
mi5 <- modindices(fit6, minimum.value = 20, sort. = TRUE)
mi5[mi5$op == "~",]
```

```
##      lhs op rhs      mi      epc sepc.lv sepc.all sepc.nox
## 1012  F8  ~ F11 31.478 -0.076  -0.216  -0.216  -0.216
## 1043 F12  ~ F2  22.794  0.339   0.345   0.345   0.345
## 1033 F11  ~ F8  22.713 -0.409  -0.144  -0.144  -0.144
```



```
## 1044 F12 ~ F3 21.857 0.259 0.325 0.325 0.325
## 1039 F11 ~ F3 21.417 -0.937 -0.911 -0.911 -0.911
## 1093 F3 ~ F11 21.099 -0.190 -0.196 -0.196 -0.196
```

F12 (Personal Accomplishment) ON F2 (Role conflict) is the most appropriate to include in model 7.

Specifying model 7

```
model7 <- '
  F1 =~ ROLEA1 + ROLEA2 + DEC2
  F2 =~ ROLEC1 + ROLEC2
  F3 =~ WORK1 + WORK2
  F4 =~ CCLIM1 + CCLIM2 + CCLIM3 + CCLIM4
  F5 =~ DEC1 + DEC2
  F6 =~ SSUP1 + SSUP2 + DEC2
  F7 =~ PSUP1 + PSUP2
  F8 =~ SELF1 + SELF2 + SELF3
  F9 =~ ELC1 + ELC2 + ELC3 + ELC4 + ELC5
  F10 =~ EE1 + EE2 + EE3
  F11 =~ DP1 + DP2
  F12 =~ PA1 + PA2 + PA3

  F8 ~ F5 + F6 + F7
  F9 ~ F2 + F5 + F8
  F10 ~ F2 + F3 + F4 + F8
  F11 ~ F2 + F4 + F10
  F12 ~ F1 + F2 + F5 + F8 + F9 + F10 + F11
'
```

Fitting the model

```
fit7 <- sem(model7, data=alsec, estimator = "MLM")
```

Display summary output

```
fitMeasures(fit7, c("chisq.scaled", "df.scaled", "pvalue.scaled", "cfi.robust", "tli.robust", "rmsea.robust", "srmr"))
```

```
##  chisq.scaled    df.scaled pvalue.scaled    cfi.robust    tli.robust
##      1267.581         421.000          0.000          0.958          0.951
##  rmsea.robust      srmr
##      0.040          0.039
```

The χ^2 is 1267.581, with 421 degrees of freedom. The p-value is 0.000. The CFI and TLI values are 0.958 and 0.951 respectively. The value of RMSEA and SRMR indices are 0.040 and 0.039 respectively.

Comparison of model 1, 2, 3, 4, 5, 6 and 7

```
options(scipen=999)
compareFit(fit1, fit2, fit3, fit4, fit5, fit6, fit7, nested = FALSE)
```

```
## ##### Model Fit Indices #####
##      chisq.scaled df.scaled pvalue.scaled cfi.robust tli.robust      aic
## fit7    1267.581†    421          .000      .958†    .951†  94381.519†
## fit6    1288.246      422          .000      .958      .950  94402.803
## fit5    1323.061      423          .000      .956      .948  94440.776
## fit4    1356.810      424          .000      .954      .946  94477.933
## fit3    1396.527      425          .000      .952      .944  94520.133
## fit2    1440.864      426          .000      .950      .942  94567.591
## fit1    1541.844      427          .000      .945      .936  94682.256
```

```
##          bic rmsea.robust  srmr
## fit7 94944.920†          .040† .039†
## fit6 94960.938          .040  .040
## fit5 94993.646          .041  .040
## fit4 95025.537          .042  .042
## fit3 95062.473          .042  .045
## fit2 95104.665          .043  .048
## fit1 95214.064          .045  .053
```

```
anova(fit6, fit7)
```

```
## Scaled Chi Square Difference Test (method = "satorra.bentler.2001")
##
##      Df   AIC   BIC  Chisq Chisq diff Df diff  Pr(>Chisq)
## fit7 421 94382 94945 1424.4
## fit6 422 94403 94961 1447.6      20.346      1 0.000006463 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

The difference in fit between Model 7 and Model 6 is found to be statistically significant.

Final Model

Identification of all paths in the hypothesized model that remain statistically non-significant till the results of model 7 are F8 ON F7 and F12 ON F1 and will be excluded in the final model.

Specifying final model

```
model8 <- '
  F1 =~ ROLEA1 + ROLEA2 + DEC2
  F2 =~ ROLEC1 + ROLEC2
  F3 =~ WORK1 + WORK2
  F4 =~ CCLIM1 + CCLIM2 + CCLIM3 + CCLIM4
  F5 =~ DEC1 + DEC2
  F6 =~ SSUP1 + SSUP2 + DEC2
  F7 =~ PSUP1 + PSUP2
  F8 =~ SELF1 + SELF2 + SELF3
  F9 =~ ELC1 + ELC2 + ELC3 + ELC4 + ELC5
  F10 =~ EE1 + EE2 + EE3
  F11 =~ DP1 + DP2
  F12 =~ PA1 + PA2 + PA3

  F8 ~ F5 + F6
  F9 ~ F2 + F5 + F8
  F10 ~ F2 + F3 + F4 + F8
  F11 ~ F2 + F4 + F10
  F12 ~ F2 + F5 + F8 + F9 + F10 + F11
'
```

Fitting the model

```
fit8 <- sem(model8, data=alsec, estimator = "MLM", std.ov=TRUE)
```

Display summary output

```
summary(fit8, fit.measures=FALSE, standardized = TRUE)
```

```
## lavaan 0.6-3 ended normally after 93 iterations
```

```

##
## Optimization method NLMINB
## Number of free parameters 105
##
## Number of observations 1430
##
## Estimator ML Robust
## Model Fit Test Statistic 1425.779 1268.075
## Degrees of freedom 423 423
## P-value (Chi-square) 0.000 0.000
## Scaling correction factor 1.124
## for the Satorra-Bentler correction
##
## Parameter Estimates:
##
## Information Expected
## Information saturated (h1) model Structured
## Standard Errors Robust.sem
##
## Latent Variables:
## Estimate Std.Err z-value P(>|z|) Std.lv Std.all
## F1 =~
## ROLEA1 1.000 0.704 0.704
## ROLEA2 1.159 0.054 21.545 0.000 0.816 0.816
## DEC2 0.258 0.080 3.210 0.001 0.182 0.182
## F2 =~
## ROLEC1 1.000 0.698 0.698
## ROLEC2 1.130 0.044 25.495 0.000 0.788 0.789
## F3 =~
## WORK1 1.000 0.792 0.792
## WORK2 0.793 0.035 22.587 0.000 0.629 0.629
## F4 =~
## CCLIM1 1.000 0.618 0.618
## CCLIM2 1.274 0.065 19.675 0.000 0.787 0.787
## CCLIM3 1.052 0.061 17.351 0.000 0.650 0.650
## CCLIM4 0.980 0.058 16.796 0.000 0.605 0.605
## F5 =~
## DEC1 1.000 0.726 0.726
## DEC2 0.473 0.115 4.123 0.000 0.343 0.344
## F6 =~
## SSUP1 1.000 0.862 0.863
## SSUP2 1.084 0.026 42.343 0.000 0.935 0.935
## DEC2 0.729 0.057 12.847 0.000 0.629 0.629
## F7 =~
## PSUP1 1.000 0.798 0.799
## PSUP2 1.128 0.048 23.468 0.000 0.900 0.901
## F8 =~
## SELF1 1.000 0.764 0.765
## SELF2 1.127 0.040 28.076 0.000 0.861 0.862
## SELF3 1.110 0.047 23.691 0.000 0.849 0.849
## F9 =~
## ELC1 1.000 0.682 0.683
## ELC2 0.844 0.042 20.287 0.000 0.575 0.576
## ELC3 1.087 0.047 23.216 0.000 0.741 0.742

```

```

##      ELC4          0.947    0.049   19.184    0.000    0.646    0.646
##      ELC5          1.095    0.049   22.485    0.000    0.747    0.748
##      F10 =~
##      EE1           1.000          0.869    0.871
##      EE2           1.063    0.020   53.246    0.000    0.924    0.927
##      EE3           0.981    0.023   42.735    0.000    0.853    0.855
##      F11 =~
##      DP1           1.000          0.884    0.885
##      DP2           0.830    0.039   21.281    0.000    0.733    0.734
##      F12 =~
##      PA1           1.000          0.821    0.825
##      PA2           0.974    0.035   27.677    0.000    0.800    0.804
##      PA3           0.905    0.038   24.110    0.000    0.743    0.746
##
## Regressions:
##      Estimate Std.Err z-value P(>|z|) Std.lv Std.all
##      F8 ~
##      F5          0.787    0.097    8.105    0.000    0.748    0.748
##      F6         -0.329    0.071   -4.664    0.000   -0.371   -0.371
##      F9 ~
##      F2          0.292    0.054    5.436    0.000    0.299    0.299
##      F5         -0.131    0.054   -2.403    0.016   -0.139   -0.139
##      F8         -0.180    0.035   -5.149    0.000   -0.201   -0.201
##      F10 ~
##      F2         -0.723    0.275   -2.632    0.008   -0.581   -0.581
##      F3          1.190    0.254    4.690    0.000    1.085    1.085
##      F4         -0.223    0.051   -4.398    0.000   -0.158   -0.158
##      F8         -0.307    0.037   -8.290    0.000   -0.270   -0.270
##      F11 ~
##      F2          0.177    0.051    3.466    0.001    0.140    0.140
##      F4         -0.465    0.052   -8.916    0.000   -0.325   -0.325
##      F10         0.362    0.041    8.794    0.000    0.356    0.356
##      F12 ~
##      F2          0.449    0.079    5.655    0.000    0.382    0.382
##      F5          0.506    0.068    7.389    0.000    0.448    0.448
##      F8          0.186    0.045    4.184    0.000    0.174    0.174
##      F9         -0.145    0.041   -3.514    0.000   -0.120   -0.120
##      F10         -0.122    0.042   -2.880    0.004   -0.129   -0.129
##      F11        -0.255    0.039   -6.483    0.000   -0.275   -0.275
##
## Covariances:
##      Estimate Std.Err z-value P(>|z|) Std.lv Std.all
##      F1 ~~
##      F2          0.382    0.026   14.780    0.000    0.777    0.777
##      F3          0.366    0.026   14.278    0.000    0.657    0.657
##      F4         -0.131    0.017   -7.745    0.000   -0.302   -0.302
##      F5         -0.419    0.028  -14.789    0.000   -0.819   -0.819
##      F6         -0.337    0.027  -12.641    0.000   -0.555   -0.555
##      F7         -0.274    0.025  -10.947    0.000   -0.488   -0.488
##      F2 ~~
##      F3          0.512    0.026   19.347    0.000    0.926    0.926
##      F4         -0.137    0.018   -7.729    0.000   -0.317   -0.317
##      F5         -0.386    0.026  -14.879    0.000   -0.762   -0.762
##      F6         -0.323    0.024  -13.488    0.000   -0.537   -0.537

```

##	F7	-0.232	0.022	-10.599	0.000	-0.417	-0.417
##	F3 ~~						
##	F4	-0.149	0.020	-7.396	0.000	-0.304	-0.304
##	F5	-0.409	0.026	-15.878	0.000	-0.710	-0.710
##	F6	-0.324	0.025	-13.081	0.000	-0.474	-0.474
##	F7	-0.233	0.023	-9.919	0.000	-0.368	-0.368
##	F4 ~~						
##	F5	0.190	0.020	9.378	0.000	0.425	0.425
##	F6	0.179	0.020	8.836	0.000	0.337	0.337
##	F7	0.107	0.018	5.993	0.000	0.216	0.216
##	F5 ~~						
##	F6	0.510	0.031	16.644	0.000	0.814	0.814
##	F7	0.387	0.028	14.060	0.000	0.667	0.667
##	F6 ~~						
##	F7	0.327	0.026	12.370	0.000	0.475	0.475
##							
##	Variances:						
##		Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
##	.ROLEA1	0.504	0.029	17.397	0.000	0.504	0.504
##	.ROLEA2	0.334	0.028	11.794	0.000	0.334	0.334
##	.DEC2	0.331	0.019	17.754	0.000	0.331	0.331
##	.ROLEC1	0.512	0.024	21.777	0.000	0.512	0.512
##	.ROLEC2	0.378	0.024	15.472	0.000	0.378	0.378
##	.WORK1	0.372	0.023	16.238	0.000	0.372	0.372
##	.WORK2	0.604	0.030	19.962	0.000	0.604	0.605
##	.CCLIM1	0.618	0.027	22.703	0.000	0.618	0.618
##	.CCLIM2	0.380	0.025	15.044	0.000	0.380	0.380
##	.CCLIM3	0.577	0.030	19.345	0.000	0.577	0.577
##	.CCLIM4	0.633	0.029	22.093	0.000	0.633	0.634
##	.DEC1	0.472	0.027	17.704	0.000	0.472	0.472
##	.SSUP1	0.256	0.017	15.194	0.000	0.256	0.256
##	.SSUP2	0.125	0.014	8.788	0.000	0.125	0.125
##	.PSUP1	0.362	0.029	12.270	0.000	0.362	0.362
##	.PSUP2	0.189	0.031	6.163	0.000	0.189	0.189
##	.SELF1	0.415	0.025	16.528	0.000	0.415	0.415
##	.SELF2	0.257	0.020	13.060	0.000	0.257	0.257
##	.SELF3	0.279	0.022	12.942	0.000	0.279	0.279
##	.ELC1	0.533	0.025	20.915	0.000	0.533	0.534
##	.ELC2	0.668	0.028	23.511	0.000	0.668	0.669
##	.ELC3	0.449	0.025	18.271	0.000	0.449	0.450
##	.ELC4	0.582	0.027	21.653	0.000	0.582	0.582
##	.ELC5	0.440	0.024	18.582	0.000	0.440	0.441
##	.EE1	0.240	0.014	17.240	0.000	0.240	0.241
##	.EE2	0.141	0.012	11.761	0.000	0.141	0.141
##	.EE3	0.268	0.015	17.784	0.000	0.268	0.270
##	.DP1	0.215	0.036	5.994	0.000	0.215	0.216
##	.DP2	0.460	0.034	13.668	0.000	0.460	0.461
##	.PA1	0.316	0.026	12.391	0.000	0.316	0.319
##	.PA2	0.351	0.027	13.009	0.000	0.351	0.354
##	.PA3	0.440	0.025	17.423	0.000	0.440	0.444
##	F1	0.496	0.040	12.426	0.000	1.000	1.000
##	F2	0.487	0.034	14.183	0.000	1.000	1.000
##	F3	0.628	0.035	17.776	0.000	1.000	1.000
##	F4	0.381	0.035	10.844	0.000	1.000	1.000

```
##      F5                0.527    0.038    13.831    0.000    1.000    1.000
##      F6                0.744    0.039    19.005    0.000    1.000    1.000
##      F7                0.637    0.046    13.855    0.000    1.000    1.000
##      .F8               0.441    0.043    10.325    0.000    0.755    0.755
##      .F9               0.334    0.028    11.987    0.000    0.718    0.718
##      .F10              0.303    0.034     9.002    0.000    0.401    0.401
##      .F11              0.453    0.039    11.645    0.000    0.580    0.580
##      .F12              0.410    0.029    14.004    0.000    0.608    0.608
```

```
fitMeasures(fit8, c("chisq.scaled", "df.scaled", "pvalue.scaled", "cfi.robust", "tli.robust", "rmsea.robust", "srmr"))
```

```
##  chisq.scaled    df.scaled pvalue.scaled    cfi.robust    tli.robust
##    1268.075      423.000         0.000         0.959         0.951
##  rmsea.robust      srmr
##         0.040         0.039
```

The χ^2 is 1268.075, with 423 degrees of freedom. The p-value is 0.000. The CFI and TLI values are 0.959 and 0.951 respectively. The value of RMSEA and SRMR indices are 0.040 and 0.039 respectively.

High correlation of 0.926 between F3 (Work Overload) and F2 (Role Conflict) is found.

Comparison of model 7 and 8

```
options(scipen=999)
compareFit(fit7, fit8, nested = FALSE)
```

```
## ##### Model Fit Indices #####
##      chisq.scaled df.scaled pvalue.scaled cfi.robust tli.robust
## fit7    1267.581†      421         .000         .958         .951
## fit8    1268.075      423         .000         .959†      .951†
##           aic          bic rmsea.robust  srmr
## fit7  94381.519†  94944.920†         .040  .039†
## fit8 107932.398 108485.268         .040† .039
```

```
anova(fit7, fit8)
```

```
## Scaled Chi Square Difference Test (method = "satorra.bentler.2001")
##
##      Df      AIC      BIC  Chisq Chisq diff Df diff Pr(>Chisq)
## fit7 421  94382  94945 1424.4
## fit8 423 107932 108485 1425.8      1.1236      2      0.5702
```

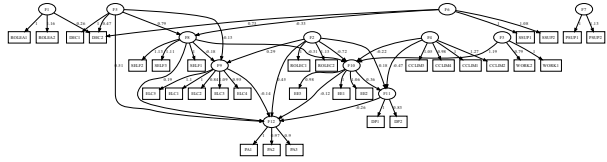
The two structural regression paths has been excluded in the final model which gives 2 degrees of freedom. The CFI value has increased to 0.959 indicating good fit. The difference in fit between final model and Model 7 is not found to be statistically significant.

Creating final graph

```
labels = list(F1 = "Role Ambiguity", F2 = " Role Conflict", F3 = " Work Overload", F4 = " Classroom Climate", F5 = " Teacher Efficacy", F6 = " Teacher Self-efficacy", F7 = " Teacher's Perceived Stress", F8 = " Teacher's Perceived Stress")
semPaths(fit8, "standardized", curvePivot = TRUE, style = "lisrel", edge.label.cex=0.75, edge.color="green")
```



```
# unstandardized path
lavaanPlot(model = fit8, coefs = TRUE, stand = FALSE)
```



The path reflects:

Decision making on external locus of control

Role conflict, emotional exhaustion on depersonalization

Decision making, self-esteem, external locus of control, emotional exhaustion, and depersonalization on personal accomplishment.

Superior support and decision making on self-esteem

Workoverload on emotional exhaustion. The teachers having work overload seems to have increased levels of emotional exhaustion.

Classroom climate on depersonalization. Positive classroom climate associates with low level of depersonalization.

Week 5 SEM Assignment

Shweta Goswami

17-02-2019

TITLE: "CFA invariance & teacher burnout" (ch7)

Exercise 5.1

Reading the data

```
secondary <- read.delim("~/sem2019/mbisec1.DAT", header=FALSE)
elementary <- read.delim("~/sem2019/mbielm1.DAT", header=FALSE)
glimpse(secondary)
```

```
## Observations: 692
## Variables: 22
## $ V1 <dbl> 3, 3, 5, 5, 1, 2, 5, 5, 1, 3, 5, 0, 1, 4, 4, 4, 5, 1, 2, 3...
## $ V2 <dbl> 4, 5, 5, 5, 2, 4, 5, 5, 3, 5, 5, 0, 3, 4, 5, 4, 5, 2, 2, 4...
## $ V3 <dbl> 0, 3, 5, 3, 1, 0, 2, 1, 3, 5, 4, 0, 1, 5, 3, 2, 3, 0, 2, 4...
## $ V4 <dbl> 6, 5, 5, 4, 6, 6, 5, 6, 3, 5, 6, 6, 6, 6, 4, 6, 6, 3, 6, 6...
## $ V5 <dbl> 0, 1, 0, 1, 1, 1, 0, 1, 1, 1, 2, 1, 0, 1, 5, 0, 0, 0, 1, 1...
## $ V6 <dbl> 2, 1, 5, 3, 3, 2, 3, 2, 1, 2, 4, 0, 0, 2, 5, 3, 1, 1, 0, 1...
## $ V7 <dbl> 6, 3, 5, 5, 5, 5, 5, 6, 5, 5, 5, 5, 6, 6, 3, 5, 4, 3, 4, 6...
## $ V8 <dbl> 1, 2, 5, 2, 1, 2, 2, 1, 1, 3, 1, 0, 1, 3, 3, 3, 3, 2, 0, 1...
## $ V9 <dbl> 5, 3, 4, 5, 5, 5, 5, 6, 6, 3, 6, 6, 6, 5, 1, 3, 4, 4, 5, 5...
## $ V10 <dbl> 1, 2, 1, 1, 0, 4, 2, 1, 1, 0, 0, 0, 0, 2, 2, 2, 0, 1, 1, 0...
## $ V11 <dbl> 2, 2, 2, 1, 0, 2, 1, 0, 1, 0, 0, 0, 0, 3, 1, 2, 0, 0, 0, 0...
## $ V12 <dbl> 5, 5, 5, 4, 2, 5, 5, 5, 5, 2, 4, 6, 6, 6, 4, 4, 4, 3, 4, 5...
## $ V13 <dbl> 1, 3, 5, 2, 1, 2, 4, 2, 1, 2, 6, 0, 0, 5, 5, 4, 3, 3, 2, 1...
## $ V14 <dbl> 3, 3, 4, 4, 1, 0, 3, 4, 1, 5, 4, 0, 1, 3, 4, 2, 4, 4, 1, 2...
## $ V15 <dbl> 0, 2, 0, 0, 1, 1, 1, 0, 0, 1, 1, 0, 0, 1, 2, 0, 0, 2, 1, 0...
## $ V16 <dbl> 3, 2, 1, 1, 3, 1, 3, 1, 1, 3, 4, 0, 0, 1, 3, 3, 3, 1, 1, 1...
## $ V17 <dbl> 6, 5, 5, 5, 4, 5, 5, 6, 6, 6, 5, 6, 6, 6, 4, 6, 6, 5, 5, 5...
## $ V18 <dbl> 5, 5, 4, 4, 4, 5, 5, 5, 5, 4, 6, 6, 6, 6, 5, 4, 6, 4, 5, 5...
## $ V19 <dbl> 5, 5, 4, 5, 5, 4, 3, 5, 6, 4, 5, 6, 6, 6, 3, 3, 4, 5, 4, 5...
## $ V20 <dbl> 1, 0, 4, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 1, 2, 0, 2, 0, 1, 1...
## $ V21 <dbl> 5, 5, 4, 3, 4, 3, 5, 6, 3, 3, 5, 3, 6, 6, 4, 6, 0, 1, 5, 6...
## $ V22 <dbl> 1, 1, 0, 1, 5, 2, 1, 1, 2, 2, 2, 1, 2, 1, 4, 0, 0, 0, 1, 0...
```

```
glimpse(elementary)
```

```
## Observations: 580
## Variables: 22
## $ V1 <dbl> 1, 5, 3, 6, 1, 5, 3, 6, 2, 4, 5, 2, 3, 2, 5, 6, 5, 4, 6, 3...
## $ V2 <dbl> 1, 5, 4, 6, 1, 5, 5, 6, 1, 4, 5, 1, 5, 3, 5, 6, 5, 5, 6, 5...
## $ V3 <dbl> 0, 6, 3, 6, 1, 5, 2, 5, 1, 3, 3, 2, 1, 2, 5, 3, 2, 3, 6, 2...
## $ V4 <dbl> 6, 6, 6, 6, 6, 6, 6, 6, 5, 6, 5, 6, 3, 6, 6, 6, 5, 6, 6, 6...
## $ V5 <dbl> 1, 2, 3, 0, 5, 1, 1, 4, 1, 0, 4, 0, 1, 0, 0, 3, 0, 1, 0, 0...
## $ V6 <dbl> 0, 4, 2, 0, 1, 6, 2, 3, 0, 0, 5, 0, 1, 1, 2, 4, 2, 3, 3, 0...
## $ V7 <dbl> 6, 5, 6, 6, 6, 6, 6, 5, 6, 5, 6, 6, 5, 6, 6, 6, 5, 6, 6, 6...
## $ V8 <dbl> 1, 5, 2, 6, 0, 6, 2, 6, 1, 2, 3, 0, 0, 1, 5, 1, 5, 3, 5, 0...
## $ V9 <dbl> 6, 4, 6, 6, 6, 3, 6, 3, 6, 6, 6, 6, 6, 6, 6, 6, 5, 6, 6, 6...
```

```
## $ V10 <dbl> 0, 3, 2, 0, 0, 0, 2, 4, 0, 1, 3, 0, 1, 0, 0, 0, 3, 0, 0, 3...
## $ V11 <dbl> 0, 4, 2, 0, 0, 0, 2, 6, 0, 1, 1, 0, 1, 1, 0, 0, 0, 0, 0, 3...
## $ V12 <dbl> 3, 3, 6, 0, 6, 0, 5, 0, 5, 5, 5, 5, 5, 5, 4, 6, 5, 5, 3, 6...
## $ V13 <dbl> 1, 3, 2, 0, 2, 5, 2, 5, 1, 1, 4, 0, 2, 1, 5, 2, 5, 1, 5, 0...
## $ V14 <dbl> 1, 3, 2, 3, 1, 5, 2, 3, 1, 1, 6, 1, 4, 2, 6, 6, 3, 3, 6, 2...
## $ V15 <dbl> 0, 1, 2, 0, 0, 0, 2, 4, 1, 2, 1, 0, 0, 0, 0, 1, 0, 1, 0, 0...
## $ V16 <dbl> 0, 4, 2, 0, 1, 6, 2, 3, 0, 1, 3, 0, 1, 0, 2, 2, 1, 3, 3, 0...
## $ V17 <dbl> 6, 4, 2, 6, 6, 5, 6, 4, 6, 6, 5, 6, 5, 5, 6, 6, 5, 6, 6, 6...
## $ V18 <dbl> 3, 5, 5, 4, 5, 1, 5, 1, 6, 6, 4, 5, 5, 4, 6, 6, 3, 5, 5, 6...
## $ V19 <dbl> 5, 5, 6, 6, 4, 3, 5, 1, 6, 6, 5, 6, 5, 3, 5, 6, 4, 5, 6, 5...
## $ V20 <dbl> 0, 1, 1, 3, 1, 1, 1, 5, 1, 0, 1, 0, 1, 0, 1, 4, 4, 2, 3, 0...
## $ V21 <dbl> 5, 3, 3, 6, 5, 5, 5, 3, 1, 5, 6, 5, 1, 5, 6, 5, 4, 5, 6, 6...
## $ V22 <dbl> 0, 2, 2, 0, 1, 0, 5, 1, 0, 1, 4, 1, 1, 1, 0, 0, 0, 5, 1, 0...
```

The datasets has sample of elementary (N=580) and secondary (N=692) teachers.

The aim of this analysis is to test the invariance of MBI across the samples. The subject corresponds to the relations among the three dimensions of burnout i.e. Emotional Exhaustion (EE), Depersonalization (DP), Personal Accomplishment (PA) and their invariance across elementary and secondary teachers. This is a multiple-group analyses of SEM.

The two questions related to the invariance will be focused as per the lecture materials:

1. Do the **items** operate equivalently across different populations or groups (based on, e.g., gender, age, ability, culture)?
2. Is the **factorial structure** equivalent across populations? (construct validity, measurement and/or structural models)

Creating names for all the variables

```
names(secondary) <- c("ITEM1", "ITEM2", "ITEM3", "ITEM4", "ITEM5", "ITEM6", "ITEM7", "ITEM8", "ITEM9", "ITEM10", "ITEM11", "ITEM12", "ITEM13", "ITEM14", "ITEM15", "ITEM16", "ITEM17", "ITEM18", "ITEM19", "ITEM20")
names(elementary) <- c("ITEM1", "ITEM2", "ITEM3", "ITEM4", "ITEM5", "ITEM6", "ITEM7", "ITEM8", "ITEM9", "ITEM10", "ITEM11", "ITEM12", "ITEM13", "ITEM14", "ITEM15", "ITEM16", "ITEM17", "ITEM18", "ITEM19", "ITEM20")
str(secondary)
```

```
## 'data.frame':    692 obs. of  22 variables:
## $ ITEM1 : num  3 3 5 5 1 2 5 5 1 3 ...
## $ ITEM2 : num  4 5 5 5 2 4 5 5 3 5 ...
## $ ITEM3 : num  0 3 5 3 1 0 2 1 3 5 ...
## $ ITEM4 : num  6 5 5 4 6 6 5 6 3 5 ...
## $ ITEM5 : num  0 1 0 1 1 1 0 1 1 1 ...
## $ ITEM6 : num  2 1 5 3 3 2 3 2 1 2 ...
## $ ITEM7 : num  6 3 5 5 5 5 5 6 5 5 ...
## $ ITEM8 : num  1 2 5 2 1 2 2 1 1 3 ...
## $ ITEM9 : num  5 3 4 5 5 5 5 6 6 3 ...
## $ ITEM10: num  1 2 1 1 0 4 2 1 1 0 ...
## $ ITEM11: num  2 2 2 1 0 2 1 0 1 0 ...
## $ ITEM12: num  5 5 5 4 2 5 5 5 5 2 ...
## $ ITEM13: num  1 3 5 2 1 2 4 2 1 2 ...
## $ ITEM14: num  3 3 4 4 1 0 3 4 1 5 ...
## $ ITEM15: num  0 2 0 0 1 1 1 0 0 1 ...
## $ ITEM16: num  3 2 1 1 3 1 3 1 1 3 ...
## $ ITEM17: num  6 5 5 5 4 5 5 6 6 6 ...
## $ ITEM18: num  5 5 4 4 4 5 5 5 5 4 ...
## $ ITEM19: num  5 5 4 5 5 4 3 5 6 4 ...
## $ ITEM20: num  1 0 4 1 1 1 1 1 1 1 ...
```

```
## $ ITEM21: num 5 5 4 3 4 3 5 6 3 3 ...
## $ ITEM22: num 1 1 0 1 5 2 1 1 2 2 ...
```

```
str(elementary)
```

```
## 'data.frame': 580 obs. of 22 variables:
## $ ITEM1 : num 1 5 3 6 1 5 3 6 2 4 ...
## $ ITEM2 : num 1 5 4 6 1 5 5 6 1 4 ...
## $ ITEM3 : num 0 6 3 6 1 5 2 5 1 3 ...
## $ ITEM4 : num 6 6 6 6 6 6 6 6 5 6 ...
## $ ITEM5 : num 1 2 3 0 5 1 1 4 1 0 ...
## $ ITEM6 : num 0 4 2 0 1 6 2 3 0 0 ...
## $ ITEM7 : num 6 5 6 6 6 6 6 5 6 5 ...
## $ ITEM8 : num 1 5 2 6 0 6 2 6 1 2 ...
## $ ITEM9 : num 6 4 6 6 6 3 6 3 6 6 ...
## $ ITEM10: num 0 3 2 0 0 0 2 4 0 1 ...
## $ ITEM11: num 0 4 2 0 0 0 2 6 0 1 ...
## $ ITEM12: num 3 3 6 0 6 0 5 0 5 5 ...
## $ ITEM13: num 1 3 2 0 2 5 2 5 1 1 ...
## $ ITEM14: num 1 3 2 3 1 5 2 3 1 1 ...
## $ ITEM15: num 0 1 2 0 0 0 2 4 1 2 ...
## $ ITEM16: num 0 4 2 0 1 6 2 3 0 1 ...
## $ ITEM17: num 6 4 2 6 6 5 6 4 6 6 ...
## $ ITEM18: num 3 5 5 4 5 1 5 1 6 6 ...
## $ ITEM19: num 5 5 6 6 4 3 5 1 6 6 ...
## $ ITEM20: num 0 1 1 3 1 1 1 5 1 0 ...
## $ ITEM21: num 5 3 3 6 5 5 5 3 1 5 ...
## $ ITEM22: num 0 2 2 0 1 0 5 1 0 1 ...
```

Specifying baseline model 1 (Secondary)

```
model1 <- '
F1 =~ ITEM1 + ITEM2 + ITEM3 + ITEM6 + ITEM8 + ITEM13 + ITEM14 + ITEM16 + ITEM20
F2 =~ ITEM5 + ITEM10 + ITEM11 + ITEM15 + ITEM22
F3 =~ ITEM4 + ITEM7 + ITEM9 + ITEM12 + ITEM17 + ITEM18 + ITEM19 + ITEM21
'
```

Fitting the model

```
fit1 <- cfa(model1, data=secondary, estimator = "MLM")
```

Display summary output

```
fitMeasures(fit1, c("chisq.scaled", "df.scaled", "pvalue.scaled", "cfi.robust", "tli.robust", "rmsea.robust", "srmr"))
```

	chisq.scaled	df.scaled	pvalue.scaled	cfi.robust	tli.robust	rmsea.robust	srmr
##	971.064	206.000	0.000	0.835	0.815		
##	rmsea.robust						srmr
##	0.084						0.080

Specifying baseline model 1.1 (Elementary)

```
model1.1 <- '
F1 =~ ITEM1 + ITEM2 + ITEM3 + ITEM6 + ITEM8 + ITEM13 + ITEM14 + ITEM16 + ITEM20
F2 =~ ITEM5 + ITEM10 + ITEM11 + ITEM15 + ITEM22
F3 =~ ITEM4 + ITEM7 + ITEM9 + ITEM12 + ITEM17 + ITEM18 + ITEM19 + ITEM21
'
```

Fitting the model

```
fit1.1 <- cfa(model1.1, data=elementary, estimator = "MLM")
```

Display summary output

```
fitMeasures(fit1.1, c("chisq.scaled", "df.scaled", "pvalue.scaled", "cfi.robust", "tli.robust", "rmsea.robust", "srmr"))
```

```
##  chisq.scaled    df.scaled pvalue.scaled    cfi.robust    tli.robust
##      802.743      206.000         0.000         0.858         0.841
##  rmsea.robust      srmr
##      0.079         0.071
```

Comparison of model 1 and 1.1

```
options(scipen=999)
compareFit(fit1, fit1.1, nested = FALSE)
```

```
## ##### Model Fit Indices #####
##      chisq.scaled df.scaled pvalue.scaled cfi.robust tli.robust
## fit1      971.064      206         .000         .835         .815
## fit1.1    802.743†      206         .000         .858†         .841†
##      aic      bic rmsea.robust srmr
## fit1 49296.269 49509.630         .084 .080
## fit1.1 39882.062† 40087.125†         .079† .071†
```

The goodness of fit statistics indicates initial model not a good fit for both secondary and elementary.

For Secondary: (Values less/more than the optimal range) The χ^2 is 802.743, with 206 degrees of freedom. The p-value is 0.000. The CFI and TLI values are 0.858 and 0.841 respectively. The value of RMSEA and SRMR indices are 0.079 and 0.071 respectively.

For Elementary: (Values less/more than the optimal range) The χ^2 is 971.064, with 206 degrees of freedom. The p-value is 0.000. The CFI and TLI values are 0.835 and 0.815 respectively. The value of RMSEA and SRMR indices are 0.084 and 0.080 respectively.

Model Modification indices for model 1 and 1.1

```
modindices(fit1, minimum = 50)
```

```
##      lhs op    rhs      mi    epc sepc.lv sepc.all sepc.nox
## 59      F1 =~ ITEM12 118.156 -0.468 -0.561 -0.419 -0.419
## 95     ITEM1 ~~ ITEM2 171.647 0.627 0.627 0.583 0.583
## 122    ITEM2 ~~ ITEM20 53.024 -0.324 -0.324 -0.316 -0.316
## 158    ITEM6 ~~ ITEM16 127.756 0.686 0.686 0.458 0.458
## 250    ITEM5 ~~ ITEM15 77.216 0.580 0.580 0.355 0.355
## 260   ITEM10 ~~ ITEM11 135.841 1.181 1.181 1.426 1.426
## 271   ITEM11 ~~ ITEM15 60.947 -0.485 -0.485 -0.420 -0.420
```

```
modindices(fit1.1, minimum = 100)
```

```
##      lhs op    rhs      mi    epc sepc.lv sepc.all sepc.nox
## 95     ITEM1 ~~ ITEM2 103.177 0.534 0.534 0.494 0.494
## 158    ITEM6 ~~ ITEM16 180.298 0.893 0.893 0.595 0.595
```

Referring to “CFA of MBI for Male Elementary Teachers (Calibration Group)” and output of both datasets, one cross-loading and three large residual covariances are present. The cross-loading involves loading of Item 12 on Factor 1 (Emotional Exhaustion). The residual covariances involved Items 2 with 1, Items 16 with 6 and Item 11 with 10. Item 16 with 6 is more influential in elementary teachers whereas item 2 with 1 more pronounced in secondary teachers.

Testing for Invariance of MBI across Elementary/Secondary Teachers Common Baseline (Configural) Model (Byrne 2012, p. 209)

Adding all four parameters in a post hoc model

Specifying Model 2 (Secondary)

```
model2 <- '  
  
F1 =~ ITEM1 + ITEM2 + ITEM3 + ITEM6 + ITEM8 + ITEM12 + ITEM13 + ITEM14 + ITEM16 + ITEM20  
F2 =~ ITEM5 + ITEM10 + ITEM11 + ITEM15 + ITEM22  
F3 =~ ITEM4 + ITEM7 + ITEM9 + ITEM12 + ITEM17 + ITEM18 + ITEM19 + ITEM21  
  
#residual covariance  
ITEM6 ~~ ITEM16  
ITEM1  ~~ ITEM2  
ITEM10 ~~ ITEM11  
  
'
```

Fitting the model

```
fit2 <- cfa(model2, data=secondary, estimator = "MLM")
```

Display summary output

```
fitMeasures(fit2, c("chisq.scaled", "df.scaled", "pvalue.scaled", "cfi.robust", "tli.robust", "rmsea.robust"))
```

##	chisq.scaled	df.scaled	pvalue.scaled	cfi.robust	tli.robust
##	572.552	202.000	0.000	0.921	0.909
##	rmsea.robust	srmr			
##	0.059	0.058			

Specifying Model 2.1 (Elementary)

```
model2.1 <- '  
  
F1 =~ ITEM1 + ITEM2 + ITEM3 + ITEM6 + ITEM8 + ITEM12 + ITEM13 + ITEM14 + ITEM16 + ITEM20  
F2 =~ ITEM5 + ITEM10 + ITEM11 + ITEM15 + ITEM22  
F3 =~ ITEM4 + ITEM7 + ITEM9 + ITEM12 + ITEM17 + ITEM18 + ITEM19 + ITEM21  
  
#residual covariance  
ITEM6 ~~ ITEM16  
ITEM1  ~~ ITEM2  
ITEM10 ~~ ITEM11  
  
'
```

Fitting the model

```
fit2.1 <- cfa(model2.1, data=elementary, estimator = "MLM")
```

Display summary output

```
fitMeasures(fit2.1, c("chisq.scaled", "df.scaled", "pvalue.scaled", "cfi.robust", "tli.robust", "rmsea.robust"))
```

##	chisq.scaled	df.scaled	pvalue.scaled	cfi.robust	tli.robust
##	470.377	202.000	0.000	0.937	0.928
##	rmsea.robust	srmr			
##	0.053	0.053			

Comparison of model 2 and 2.1

```
options(scipen=999)
compareFit(fit2, fit2.1, nested = FALSE)
```

```
## ##### Model Fit Indices #####
##      chisq.scaled df.scaled pvalue.scaled cfi.robust tli.robust
## fit2      572.552      202          .000      .921      .909
## fit2.1    470.377†     202          .000      .937†     .928†
##           aic      bic rmsea.robust  srmr
## fit2    48772.074 49003.593      .059  .058
## fit2.1 39462.279† 39684.794†     .053† .053†
```

The goodness of fit statistics has improved from the initial model for both teacher groups:

For Secondary: The χ^2 is 572.552, with 202 degrees of freedom. The p-value is 0.000. The CFI and TLI values are 0.921 and 0.909 respectively. The value of RMSEA and SRMR indices are 0.059 and 0.058 respectively.

For Elementary: The χ^2 is 470.377, with 202 degrees of freedom. The p-value is 0.000. The CFI and TLI values are 0.937 and 0.928 respectively. The value of RMSEA and SRMR indices are 0.053 and 0.053 respectively.

Continuing post hoc modifications

Model Modification indices for model 2 and 2.1

```
modindices(fit2, minimum = 30)
```

```
##      lhs op      rhs      mi      epc sepc.lv sepc.all sepc.nox
## 57      F1 =~ ITEM11 67.177 0.472   0.532   0.339   0.339
## 263 ITEM5 ~~ ITEM15 35.576 0.416   0.416   0.310   0.310
## 318 ITEM9 ~~ ITEM19 43.690 0.355   0.355   0.357   0.357
```

```
modindices(fit2.1, minimum = 30)
```

```
##      lhs op      rhs      mi      epc sepc.lv sepc.all sepc.nox
## 305 ITEM4 ~~ ITEM7 38.931 0.174   0.174   0.284   0.284
## 323 ITEM18 ~~ ITEM19 38.744 0.266   0.266   0.333   0.333
```

For secondary teachers, one misspecified parameter is F1 by ITEM11 and a residual covariance between ITEM 19 and 9 representing large MI. The cross-loading of Item 11 on Factor 1 will be included in the next model.

For Elementary teachers, two MIs that are higher than other MIs are ITEM7 with ITEM4 and ITEM19 with ITEM18. There is an overlap between content ITEM 7 and ITEM 4 and will be included in the next model.

Specifying Model 3 (Secondary)

```
model3 <- '

F1 =~ ITEM1 + ITEM2 + ITEM3 + ITEM6 + ITEM8 + ITEM11 + ITEM12 + ITEM13 + ITEM14 + ITEM16 + ITEM20
F2 =~ ITEM5 + ITEM10 + ITEM11 + ITEM15 + ITEM22
F3 =~ ITEM4 + ITEM7 + ITEM9 + ITEM12 + ITEM17 + ITEM18 + ITEM19 + ITEM21

#residual covariance
ITEM6 ~~ ITEM16
ITEM1 ~~ ITEM2
ITEM10 ~~ ITEM11
'

fit3 <- cfa(model3, data=secondary, estimator = "MLM")
```

Specifying Model 3.1 (Elementary)

```
model3.1 <- '

F1 =~ ITEM1 + ITEM2 + ITEM3 + ITEM6 + ITEM8 + ITEM12 + ITEM13 + ITEM14 + ITEM16 + ITEM20
F2 =~ ITEM5 + ITEM10 + ITEM11 + ITEM15 + ITEM22
F3 =~ ITEM4 + ITEM7 + ITEM9 + ITEM12 + ITEM17 + ITEM18 + ITEM19 + ITEM21

#residual covariance
ITEM6 ~~ ITEM16
ITEM1 ~~ ITEM2
ITEM10 ~~ ITEM11
ITEM4 ~~ ITEM7
'

fit3.1 <- cfa(model3.1, data=elementary, estimator = "MLM")
```

Comparison of model 2 and 2.1

```
options(scipen=999)
compareFit(fit3,fit3.1, nested = FALSE)
```

```
## ##### Model Fit Indices #####
##          chisq.scaled df.scaled pvalue.scaled cfi.robust tli.robust
## fit3      522.982      201          .000          .931          .921
## fit3.1    445.801†      201          .000          .944†          .935†
##          aic          bic rmsea.robust  srmr
## fit3    48706.531  48942.589          .055  .055
## fit3.1  39425.255† 39652.132†          .051† .051†
```

The goodness of fit statistics indicates good fit for both teacher groups:

For Secondary: The χ^2 is 522.982, with 201 degrees of freedom. The p-value is 0.000. The CFI and TLI values are 0.931 and 0.921 respectively. The value of RMSEA and SRMR indices are 0.055 and 0.055 respectively.

For Elementary: The χ^2 is 445.801, with 201 degrees of freedom. The p-value is 0.000. The CFI and TLI values are 0.944 and 0.935 respectively. The value of RMSEA and SRMR indices are 0.051 and 0.051 respectively.

Comparison of model 1.1, 2.1 and 3.1 for elementary teachers

```
options(scipen=999)
compareFit(fit1.1, fit2.1, fit3.1, nested = FALSE)
```

```
## ##### Model Fit Indices #####
##          chisq.scaled df.scaled pvalue.scaled cfi.robust tli.robust
## fit3.1    445.801†      201          .000          .944†          .935†
## fit2.1    470.377      202          .000          .937          .928
## fit1.1    802.743      206          .000          .858          .841
##          aic          bic rmsea.robust  srmr
## fit3.1  39425.255† 39652.132†          .051† .051†
## fit2.1  39462.279 39684.794          .053  .053
## fit1.1  39882.062 40087.125          .079  .071
```

Model 3.1 will be the baseline for the elementary teachers taking into account the model parsimony.

Continuing post hoc modifications for secondary teachers

Model Modification indices for model 3

```
modindices(fit3, minimum = 30)
```

```
##      lhs op      rhs      mi      epc sepc.lv sepc.all sepc.nox
## 318 ITEM9 ~~ ITEM19 42.687 0.351 0.351 0.355 0.355
```

The residual covariance between Items 19 and 9 is the misspecified parameter in secondary teacher model and will be included in the next model.

Specifying Model 4 (Secondary)

```
model4 <- '

F1 =~ ITEM1 + ITEM2 + ITEM3 + ITEM6 + ITEM8 + ITEM11 + ITEM12 + ITEM13 + ITEM14 + ITEM16 + ITEM20
F2 =~ ITEM5 + ITEM10 + ITEM11 + ITEM15 + ITEM22
F3 =~ ITEM4 + ITEM7 + ITEM9 + ITEM12 + ITEM17 + ITEM18 + ITEM19 + ITEM21

#residual covariance
ITEM6 ~~ ITEM16
ITEM1 ~~ ITEM2
ITEM10 ~~ ITEM11
ITEM9 ~~ ITEM19
'

fit4 <- cfa(model4, data=secondary, estimator = "MLM")
```

Display summary output

```
fitMeasures(fit4, c("chisq.scaled", "df.scaled", "pvalue.scaled", "cfi.robust", "tli.robust", "rmsea.robust", "srmr"))

##  chisq.scaled    df.scaled pvalue.scaled    cfi.robust    tli.robust
##      492.282      200.000         0.000         0.938         0.928
##  rmsea.robust      srmr
##      0.053         0.054
```

The goodness of fit statistics indicates satisfactory fit for secondary teachers.

For Secondary: The χ^2 is 492.282, with 200 degrees of freedom. The p-value is 0.000. The CFI and TLI values are 0.938 and 0.928 respectively. The value of RMSEA and SRMR indices are 0.053 and 0.054 respectively.

Comparison of model 1, 2,3 and 4 for secondary teachers

```
options(scipen=999)
compareFit(fit1, fit2, fit3, fit4, nested = FALSE)

## ##### Model Fit Indices #####
##      chisq.scaled df.scaled pvalue.scaled cfi.robust tli.robust      aic
## fit4    492.282†      200         .000         .938†      .928† 48669.181†
## fit3    522.982      201         .000         .931         .921 48706.531
## fit2    572.552      202         .000         .921         .909 48772.074
## fit1    971.064      206         .000         .835         .815 49296.269
##      bic rmsea.robust srmr
## fit4 48909.779†      .053† .054†
## fit3 48942.589      .055 .055
## fit2 49003.593      .059 .058
## fit1 49509.630      .084 .080
```

Taking into consideration the model parsimony, Model 4 will be the final model for secondary teachers.

Exercise 5.2

TITLE: Testing for Invariance of MBI across Elementary/Secondary Teachers Common Baseline (Configural) Model (Byrne 2012, p. 209)

```
# Combine data
```

```
secel <- merge(data.frame(elementary, group = "elementary"), data.frame(secondary, group = "secondary"))
```

```
# Configural model
```

```
modelv1 <- '
```

```
F1 =~ ITEM1 + ITEM2 + ITEM3 + ITEM6 + ITEM8 + ITEM13 + ITEM14 + ITEM16 + ITEM20 + ITEM12
```

```
F2 =~ ITEM5 + ITEM10 + ITEM11 + ITEM15 + ITEM22
```

```
F3 =~ ITEM4 + ITEM7 + ITEM9 + ITEM12 + ITEM17 + ITEM18 + ITEM19 + ITEM21
```

```
# Residual Covariances
```

```
ITEM1 ~~ ITEM2
```

```
ITEM6 ~~ ITEM16
```

```
ITEM10 ~~ ITEM11
```

```
# Group specific parameters
```

```
ITEM4 ~~ c(NA,0)*ITEM7
```

```
F1 =~ c(0,NA)*ITEM11
```

```
ITEM9 ~~ c(0,NA)*ITEM19
```

```
'
```

```
# Displaying summary output
```

```
fit_modelv1 <- cfa(modelv1, data = secel, estimator = "MLM", group = "group")
```

```
Configural_model <- fitMeasures(fit_modelv1, c("chisq.scaled","df.scaled", "pvalue.scaled", "cfi.robust", "tli.robust", "rmsea.robust", "srmr"))
```

```
##  chisq.scaled    df.scaled pvalue.scaled    cfi.robust    tli.robust
##      939.696      401.000         0.000         0.940         0.931
##  rmsea.robust      srmr
##      0.052         0.051
```

It incorporates baseline models for elementary and secondary teachers as one and known as the configural model.

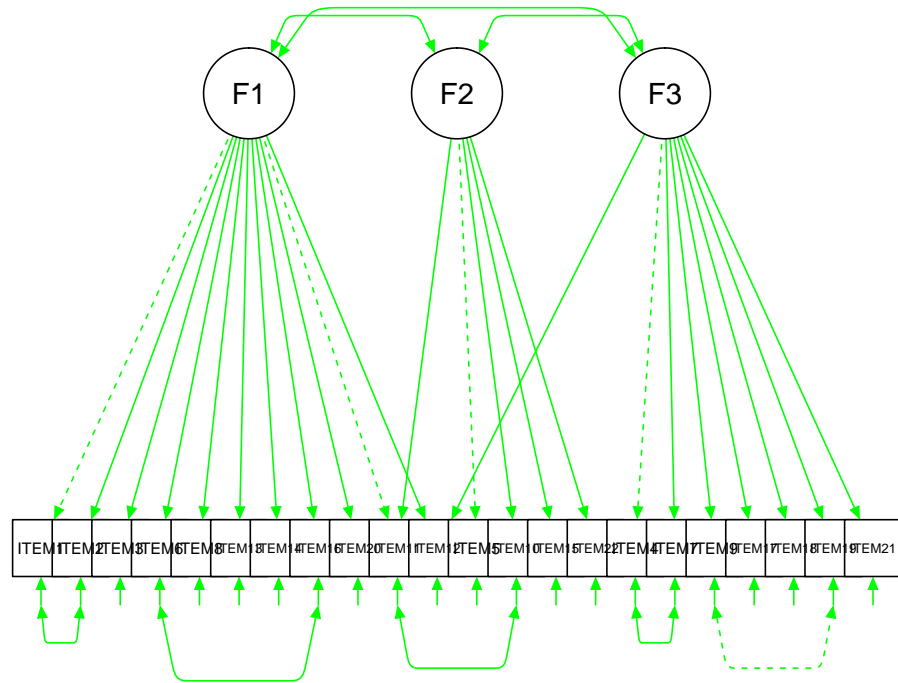
The χ^2 is 939.696, with 401 degrees of freedom. The p-value is 0.000. The CFI and TLI values are 0.940 and 0.931 respectively. The value of RMSEA and SRMR indices are 0.052 and 0.051 respectively.

Creating graph

Graph 1 represents elementary school teachers.

Graph 2 represents secondary school teachers.

```
semPaths(fit_modelv1, curvePivot = TRUE, style = "lisrel", intercepts = FALSE, edge.label.cex=0.75, edge
```



Factor Loadings : testing for the equivalence of factor loadings across groups

```

modelv2 <- '
F1 =~ ITEM1 + ITEM2 + ITEM3 + ITEM6 + ITEM8 + ITEM13 + ITEM14 + ITEM16 + ITEM20 + ITEM12
F2 =~ ITEM5 + ITEM10 + ITEM11 + ITEM15 + ITEM22
F3 =~ ITEM4 + ITEM7 + ITEM9 + ITEM12 + ITEM17 + ITEM18 + ITEM19 + ITEM21

# Residual Covariances
ITEM1 ~~ ITEM2
ITEM6 ~~ ITEM16
ITEM10 ~~ ITEM11

# Froup specific parameters
ITEM4 ~~ c(NA,0)*ITEM7
F1 =~ c(0,NA)*ITEM11
ITEM9 ~~ c(0,NA)*ITEM19
'

fit_modelv2 <- cfa(modelv2, group.equal=c("loadings"), group.partial=c("F1 =~ ITEM11"), data = secel,
  estimator = "MLM", group = "group")

Measurement_Parameter_allfactors <- fitMeasures(fit_modelv2, c("chisq.scaled","df.scaled", "pvalue.scaled"))
Measurement_Parameter_allfactors

##  chisq.scaled    df.scaled pvalue.scaled    cfi.robust    tli.robust

```

```
##          995.433      421.000      0.000      0.937      0.930
## rmsea.robust      srmr
##          0.052      0.057
```

Comparing modelv1 and modelv2

```
options(scipen=999)
compareFit(fit_modelv1, fit_modelv2, nested = FALSE)

## ##### Model Fit Indices #####
##          chisq.scaled df.scaled pvalue.scaled cfi.robust tli.robust
## fit_modelv1      939.696†      401          .000      .940†      .931†
## fit_modelv2      995.433      421          .000      .937      .930
##          aic      bic rmsea.robust srmr
## fit_modelv1 88182.435† 88949.539      .052† .051†
## fit_modelv2 88210.287 88874.424†      .052 .057

anova(fit_modelv1, fit_modelv2)

## Scaled Chi Square Difference Test (method = "satorra.bentler.2001")
##
##          Df   AIC   BIC  Chisq Chisq diff Df diff Pr(>Chisq)
## fit_modelv1 401 88182 88950 1189.8
## fit_modelv2 421 88210 88874 1257.7      56.14      20 0.0000277 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

The difference in degrees of freedom from the configural model is 20. The model statistics suggest not quite a good fit as compared to the configural model.

Partial Invariance model

```
lavTestScore(fit_modelv2)

## Warning in lavTestScore(fit_modelv2): lavaan WARNING: se is not `standard';
## not implemented yet; falling back to ordinary score test

## $test
##
## total score test:
##
##      test      X2 df p.value
## 1 score 68.047 20      0
##
## $uni
##
## univariate score tests:
##
##      lhs op      rhs      X2 df p.value
## 1 .p2. == .p84. 0.001 1 0.973
## 2 .p3. == .p85. 0.075 1 0.784
## 3 .p4. == .p86. 1.184 1 0.276
## 4 .p5. == .p87. 0.393 1 0.531
## 5 .p6. == .p88. 0.715 1 0.398
## 6 .p7. == .p89. 0.037 1 0.848
## 7 .p8. == .p90. 1.560 1 0.212
## 8 .p9. == .p91. 0.024 1 0.876
## 9 .p10. == .p92. 1.512 1 0.219
```

```
## 10 .p12. == .p94. 4.667 1 0.031
## 11 .p13. == .p95. 31.564 1 0.000
## 12 .p14. == .p96. 11.596 1 0.001
## 13 .p15. == .p97. 6.198 1 0.013
## 14 .p17. == .p99. 8.970 1 0.003
## 15 .p18. == .p100. 0.474 1 0.491
## 16 .p19. == .p101. 0.011 1 0.917
## 17 .p20. == .p102. 5.006 1 0.025
## 18 .p21. == .p103. 0.167 1 0.682
## 19 .p22. == .p104. 0.063 1 0.801
## 20 .p23. == .p105. 0.119 1 0.730
```

partable(fit_modelv2) according to the output .p13 is F2 =~ ITEM11

The factor loading of Item 11 on Factor 2 (.p13) possess highest chi-square difference and will be included in the next model.

```
modelv3 <- '
F1 =~ ITEM1 + ITEM2 + ITEM3 + ITEM6 + ITEM8 + ITEM13 + ITEM14 + ITEM16 + ITEM20 + ITEM12
F2 =~ ITEM5 + ITEM10 + ITEM11 + ITEM15 + ITEM22
F3 =~ ITEM4 + ITEM7 + ITEM9 + ITEM12 + ITEM17 + ITEM18 + ITEM19 + ITEM21
```

Residual Covariances

```
ITEM1 ~~ ITEM2
ITEM6 ~~ ITEM16
ITEM10 ~~ ITEM11
```

Froup specific parameters

```
ITEM4 ~~ c(NA,0)*ITEM7
F1 =~ c(0,NA)*ITEM11
ITEM9 ~~ c(0,NA)*ITEM19
'
```

```
fit_modelv3 <- cfa(modelv3, group.equal=c("loadings"), group.partial=c("F1 =~ ITEM11", "F2 =~ ITEM11"),
```

```
Measurement_Parameter_item11 <-fitMeasures(fit_modelv3, c("chisq.scaled","df.scaled", "pvalue.scaled",
Measurement_Parameter_item11
```

```
## chisq.scaled df.scaled pvalue.scaled cfi.robust tli.robust
## 969.990 420.000 0.000 0.939 0.933
## rmsea.robust srmr
## 0.051 0.054
```

Comparing modelv2 and modelv3

```
options(scipen=999)
compareFit(fit_modelv2, fit_modelv3, nested = FALSE)
```

```
## ##### Model Fit Indices #####
## chisq.scaled df.scaled pvalue.scaled cfi.robust tli.robust
## fit_modelv3 969.990† 420 .000 .939† .933†
## fit_modelv2 995.433 421 .000 .937 .930
## aic bic rmsea.robust srmr
## fit_modelv3 88180.031† 88849.316† .051† .054†
## fit_modelv2 88210.287 88874.424 .052 .057
```

```
anova(fit_modelv2, fit_modelv3)
```

```
## Scaled Chi Square Difference Test (method = "satorra.bentler.2001")
##
##           Df    AIC    BIC  Chisq Chisq diff Df diff   Pr(>Chisq)
## fit_modelv3 420 88180 88849 1225.4
## fit_modelv2 421 88210 88874 1257.7      24.604      1 0.0000007041 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

There is loss of 1df. The χ^2 is 969.990, with 420 degrees of freedom. The p-value is 0.000. The CFI and TLI values are 0.939 and 0.933 respectively. The value of RMSEA and SRMR indices are 0.051 and 0.054 respectively.

Additional invariant factor loadings

```
lavTestScore(fit_modelv3)
```

```
## Warning in lavTestScore(fit_modelv3): lavaan WARNING: se is not `standard`;
## not implemented yet; falling back to ordinary score test

## $test
##
## total score test:
##
##      test      X2 df p.value
## 1 score 35.979 19  0.011
##
## $uni
##
## univariate score tests:
##
##      lhs op   rhs      X2 df p.value
## 1  .p2. == .p84.  0.003  1  0.958
## 2  .p3. == .p85.  0.071  1  0.789
## 3  .p4. == .p86.  1.195  1  0.274
## 4  .p5. == .p87.  0.386  1  0.534
## 5  .p6. == .p88.  0.732  1  0.392
## 6  .p7. == .p89.  0.048  1  0.827
## 7  .p8. == .p90.  1.500  1  0.221
## 8  .p9. == .p91.  0.034  1  0.853
## 9  .p10. == .p92.  1.479  1  0.224
## 10 .p12. == .p94.  3.577  1  0.059
## 11 .p14. == .p96. 10.395  1  0.001
## 12 .p15. == .p97.  3.305  1  0.069
## 13 .p17. == .p99.  8.897  1  0.003
## 14 .p18. == .p100. 0.480  1  0.488
## 15 .p19. == .p101. 0.003  1  0.960
## 16 .p20. == .p102. 4.945  1  0.026
## 17 .p21. == .p103. 0.156  1  0.693
## 18 .p22. == .p104. 0.048  1  0.827
## 19 .p23. == .p105. 0.106  1  0.745
```

The univariate score test i.e. the chi-square difference test is used to see which equality constraint should be relaxed. Here, .p14 ($F_2 \approx \text{ITEM15}$) has the largest chi-square difference.

```

modelv4 <- '
F1 =~ ITEM1 + ITEM2 + ITEM3 + ITEM6 + ITEM8 + ITEM13 + ITEM14 + ITEM16 + ITEM20 + ITEM12
F2 =~ ITEM5 + ITEM10 + ITEM11 + ITEM15 + ITEM22
F3 =~ ITEM4 + ITEM7 + ITEM9 + ITEM12 + ITEM17 + ITEM18 + ITEM19 + ITEM21

# Residual Covariances
ITEM1 ~~ ITEM2
ITEM6 ~~ ITEM16
ITEM10 ~~ ITEM11

# Froup specific parameters
ITEM4 ~~ c(NA,0)*ITEM7
F1 =~ c(0,NA)*ITEM11
ITEM9 ~~ c(0,NA)*ITEM19
'

fit_modelv4 <- cfa(modelv4, group.equal=c("loadings"), group.partial=c("F1 =~ ITEM11", "F2 =~ ITEM11",
                                "F2 =~ ITEM15"), data = secel, estimator = "MLM", group = "group")

Measurement_Parameter_item11and15 <- fitMeasures(fit_modelv4, c("chisq.scaled", "df.scaled", "pvalue.scaled",
Measurement_Parameter_item11and15

```

```

##  chisq.scaled    df.scaled pvalue.scaled    cfi.robust    tli.robust
##      961.653      419.000         0.000         0.940         0.934
##  rmsea.robust      srmr
##      0.051         0.054

```

The model has slightly improved as compared to the previous model. The χ^2 is 961.653, with 419 degrees of freedom. The p-value is 0.000. The CFI and TLI values are 0.940 and 0.934 respectively. The value of RMSEA and SRMR indices are 0.051 and 0.054 respectively.

Comparing modelv3 and modelv4

```

options(scipen=999)
compareFit(fit_modelv3, fit_modelv4, nested = FALSE)

## ##### Model Fit Indices #####
##           chisq.scaled df.scaled pvalue.scaled cfi.robust tli.robust
## fit_modelv4    961.653†    419          .000      .940†    .934†
## fit_modelv3    969.990      420          .000      .939     .933
##           aic          bic rmsea.robust srmr
## fit_modelv4 88171.685† 88846.119†    .051† .054†
## fit_modelv3 88180.031 88849.316    .051 .054

anova(fit_modelv3, fit_modelv4)

```

```

## Scaled Chi Square Difference Test (method = "satorra.bentler.2001")
##
##           Df    AIC    BIC  Chisq Chisq diff Df diff Pr(>Chisq)
## fit_modelv4 419 88172 88846 1215.1
## fit_modelv3 420 88180 88849 1225.4      8.7529      1  0.003091 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

```

Comparison of modelV4 with the con???gural model

```
anova(fit_modelv1, fit_modelv4)
```

```
## Scaled Chi Square Difference Test (method = "satorra.bentler.2001")
##
##           Df    AIC    BIC  Chisq Chisq diff Df diff Pr(>Chisq)
## fit_modelv1 401 88182 88950 1189.8
## fit_modelv4 419 88172 88846 1215.1      20.964      18      0.2812
```

The chi-square difference between the final and the configural model is 20.964 and is not statistically significant(0.28). And all the items in MBI operate equivalently in both teacher groups except (for items 11 and 15, both of which load on Factor2).

Residual Covariances (constrained equal)

```
modelv5 <- '
F1 =~ ITEM1 + ITEM2 + ITEM3 + ITEM6 + ITEM8 + ITEM13 + ITEM14 + ITEM16 + ITEM20 + ITEM12
F2 =~ ITEM5 + ITEM10 + ITEM11 + ITEM15 + ITEM22
F3 =~ ITEM4 + ITEM7 + ITEM9 + ITEM12 + ITEM17 + ITEM18 + ITEM19 + ITEM21

# Residual Covariances
ITEM1 ~~ c(v1,v1)*ITEM2
ITEM6 ~~ c(v2,v2)*ITEM16
ITEM10 ~~ c(v3,v3)*ITEM11

# Group specific parameters
ITEM4 ~~ c(NA,0)*ITEM7
F1 =~ c(0,NA)*ITEM11
ITEM9 ~~ c(0,NA)*ITEM19
'

fit_modelv5 <- cfa(modelv5, group.equal=c("loadings"), group.partial=c("F1 =~ ITEM11", "F2 =~ ITEM11",
                                "F2 =~ ITEM15"), data = secel, estimator = "MLM", group = "group")

Measurement_Parameter_item11and15_3rescor <- fitMeasures(fit_modelv5, c("chisq.scaled", "df.scaled", "pva
Measurement_Parameter_item11and15_3rescor
```

```
##   chisq.scaled    df.scaled pvalue.scaled    cfi.robust    tli.robust
##     973.378        422.000         0.000         0.939         0.933
##  rmsea.robust      srmr
##      0.051         0.054
```

Comparing modelv4 and modelv5

```
options(scipen=999)
compareFit(fit_modelv4, fit_modelv5, nested = FALSE)

## ##### Model Fit Indices #####
##           chisq.scaled df.scaled pvalue.scaled cfi.robust tli.robust
## fit_modelv4     961.653†      419           .000      .940†      .934†
## fit_modelv5     973.378      422           .000      .939      .933
##           aic      bic rmsea.robust  srmr
## fit_modelv4 88171.685† 88846.119      .051† .054†
## fit_modelv5 88181.753 88840.742†      .051 .054
```

```
anova(fit_modelv4, fit_modelv5)
```

```
## Scaled Chi Square Difference Test (method = "satorra.bentler.2001")
##
```



```
##           Df    AIC    BIC  Chisq Chisq diff Df diff Pr(>Chisq)
## fit_modelv4 419 88172 88846 1215.1
## fit_modelv5 422 88182 88841 1231.1      11.123      3    0.01108 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

The statistics changed a bit as compared to the previous model. The χ^2 is 973.378, with 422 degrees of freedom. The p-value is 0.000. The CFI and TLI values are 0.939 and 0.933 respectively. The value of RMSEA and SRMR indices are 0.051 and 0.054 respectively and similar to the previous model.

Contrary to Byrne output, the chi-square difference between the current and the previous model is 11.12 and is statistically significant(0.01). However, modelv5 will be considered as the final model with all the three residual covariances operating equivalently across the groups (according to the lecture material)

Testing the invariance of the structural parameters

```
modelv6 <- '
F1 =~ ITEM1 + ITEM2 + ITEM3 + ITEM6 + ITEM8 + ITEM13 + ITEM14 + ITEM16 + ITEM20 + ITEM12
F2 =~ ITEM5 + ITEM10 + ITEM11 + ITEM15 + ITEM22
F3 =~ ITEM4 + ITEM7 + ITEM9 + ITEM12 + ITEM17 + ITEM18 + ITEM19 + ITEM21

# Residual Covariances
ITEM1 ~~ c(v1,v1)*ITEM2
ITEM6 ~~ c(v2,v2)*ITEM16
ITEM10 ~~ c(v3,v3)*ITEM11

# Group specific parameters
ITEM4 ~~ c(NA,0)*ITEM7
F1 =~ c(0,NA)*ITEM11
ITEM9 ~~ c(0,NA)*ITEM19
'

fit_modelv6 <- cfa(modelv6, group.equal=c("loadings", "lv.variances", "lv.covariances"), group.partial=
  "F2 =~ ITEM15"), data = secel, estimator = "MLM", group = "group")

Structural_parameter_facvar_covar <- fitMeasures(fit_modelv6, c("chisq.scaled","df.scaled", "pvalue.scaled",
  "rmsea.robust", "srmr"), group = "group")
Structural_parameter_facvar_covar
```

```
##  chisq.scaled    df.scaled pvalue.scaled    cfi.robust    tli.robust
##      986.389      428.000      0.000      0.938      0.933
##  rmsea.robust      srmr
##      0.051      0.059
```

Comparing modelv5 and modelv6

```
options(scipen=999)
compareFit(fit_modelv5, fit_modelv6, nested = FALSE)

## ##### Model Fit Indices #####
##           chisq.scaled df.scaled pvalue.scaled cfi.robust tli.robust
## fit_modelv5    973.378†      422      .000      .939†      .933
## fit_modelv6    986.389      428      .000      .938      .933†
##           aic          bic rmsea.robust srmr
## fit_modelv5 88181.753† 88840.742      .051      .054†
## fit_modelv6 88184.837 88812.935†      .051†      .059

anova(fit_modelv6, fit_modelv5)
```

```
## Scaled Chi Square Difference Test (method = "satorra.bentler.2001")
##
##           Df    AIC    BIC   Chisq Chisq diff Df diff Pr(>Chisq)
## fit_modelv5 422 88182 88841 1231.1
## fit_modelv6 428 88185 88813 1246.2      12.941      6    0.04398 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Contrary to the lecture materials, the x2 difference is 12.94 and is statistically significant (0.04). The factor variances and covariances are not operating equivalent across the groups.

Exercise 5.3

Summarize the whole invariance

```
options(scipen=999)

compareFit(fit_modelv1, fit_modelv2, fit_modelv3, fit_modelv4, fit_modelv5, fit_modelv6, nested = FALSE)

## ##### Model Fit Indices #####
##           chisq.scaled df.scaled pvalue.scaled cfi.robust tli.robust
## fit_modelv1    939.696†      401          .000      .940†      .931
## fit_modelv4    961.653      419          .000      .940      .934†
## fit_modelv3    969.990      420          .000      .939      .933
## fit_modelv2    995.433      421          .000      .937      .930
## fit_modelv5    973.378      422          .000      .939      .933
## fit_modelv6    986.389      428          .000      .938      .933
##           aic          bic rmsea.robust srmr
## fit_modelv1 88182.435 88949.539      .052  .051†
## fit_modelv4 88171.685† 88846.119      .051†  .054
## fit_modelv3 88180.031 88849.316      .051  .054
## fit_modelv2 88210.287 88874.424      .052  .057
## fit_modelv5 88181.753 88840.742      .051  .054
## fit_modelv6 88184.837 88812.935†      .051  .059

final <- rbind(Configural_model, Measurement_Parameter_allfactors, Measurement_Parameter_item11, Measurement_Parameter_item15, Measurement_Parameter_item11and15, Measurement_Parameter_item11and15_3rescor, Structural_parameter_facvar_covar)

kable(final, "latex", caption = "Summarizing model fit", booktabs = T) %>%
kable_styling(latex_options = c("striped", "hold_position", "scale_down"))
```

Table 1: Summarizing model fit

	chisq.scaled	df.scaled	pvalue.scaled	cfi.robust	tli.robust	rmsea.robust	srmr
Configural_model	939.6961	401	0	0.9403789	0.9313093	0.0517150	0.0507315
Measurement_Parameter_allfactors	995.4334	421	0	0.9365608	0.9303827	0.0520626	0.0566389
Measurement_Parameter_item11	969.9898	420	0	0.9392658	0.9331924	0.0510012	0.0543186
Measurement_Parameter_item11and15	961.6527	419	0	0.9400668	0.9339161	0.0507242	0.0538569
Measurement_Parameter_item11and15_3rescor	973.3782	422	0	0.9390411	0.9332630	0.0509743	0.0543318
Structural_parameter_facvar_covar	986.3891	428	0	0.9383339	0.9334352	0.0509085	0.0590753

As per my results, all the items in MBI operate equivalently in both teacher groups except (for items 11 and 15, both of which load on Factor2). All the three residual covariances does not operate equivalently across

the groups. The factor variances and covariances does not remain equivalent across elementary and secondary teachers.

Week 6 SEM Assignment

Shweta Goswami

24-02-2019

TITLE: Validating Hypothesized Causal Structure for Calibration Group Initial Baseline model (Byrne 2012, p. 264)

Exercise 6.1

Specify and establish – step by step – a well fitting and parsimonious baseline model for the calibration group.

```
data1 <- read.table("~/sem2019/ELEMIND1.txt", quote="\"", comment.char="")
data2 <- read.table("~/sem2019/ELEMIND2.txt", quote="\"", comment.char="")
```

Creating names for all the variables

```
var <-c("ROLEA1","ROLEA2","ROLEC1","ROLEC2", "WORK1","WORK2","CCLIM1","CCLIM2", "CCLIM3","CCLIM4","DEC1","DEC2")

colnames(data1) <- var

var1 <- c("ROLEA1","ROLEA2","ROLEC1","ROLEC2", "WORK1","WORK2","CCLIM1","CCLIM2", "CCLIM3","CCLIM4","DEC1","DEC2")

colnames(data2) <- var1
```

This is an example of the multiple-group analyses of SEM: testing the invariance (equivalence) of a causal structure using the approach of cross-validation.

The dataset has sample of Elementary School Teachers (N=1203), randomly split into the calibration group (N=602) and validation group (N=601).

The first sample serves as the calibration sample on which the initially hypothesized model is tested along with any post hoc analyses necessary for attaining a well fitting model.

The second sample is then used as the validation sample for testing the structure of the final model that was created with the calibration sample.

The aim is to to test the replicability of a full SEM across groups.

Establishing a baseline model for the calibration group

```
model1<- '
F1 =~ ROLEA1 + ROLEA2
F2 =~ ROLEC1 + ROLEC2
F3 =~ WORK1 + WORK2
F4 =~ CCLIM1 + CCLIM2 + CCLIM3 + CCLIM4
F5 =~ DEC1 + DEC2
F6 =~ SSUP1 + SSUP2
F7 =~ PSUP1 + PSUP2
F8 =~ SELF1 + SELF2 + SELF3
F9 =~ ELC1 + ELC2 + ELC3 + ELC4 + ELC5
F10 =~ EE1 + EE2 + EE3
F11 =~ DP1 + DP2
```

```
F12 =~ PA1 + PA2 + PA3
```

```
#Regressions
```

```
F8 ~ F5 + F6 + F7
```

```
F9 ~ F5
```

```
F10 ~ F2 + F3 + F4
```

```
F11 ~ F2 + F10
```

```
F12 ~ F1 + F8 + F9 + F10 + F11
```

```
,
```

```
fit1<-cfa(model1, data=data1, estimator="MLM")
```

```
## Warning in lav_object_post_check(object): lavaan WARNING: covariance matrix of latent variables
##           is not positive definite;
##           use lavInspect(fit, "cov.lv") to investigate.
```

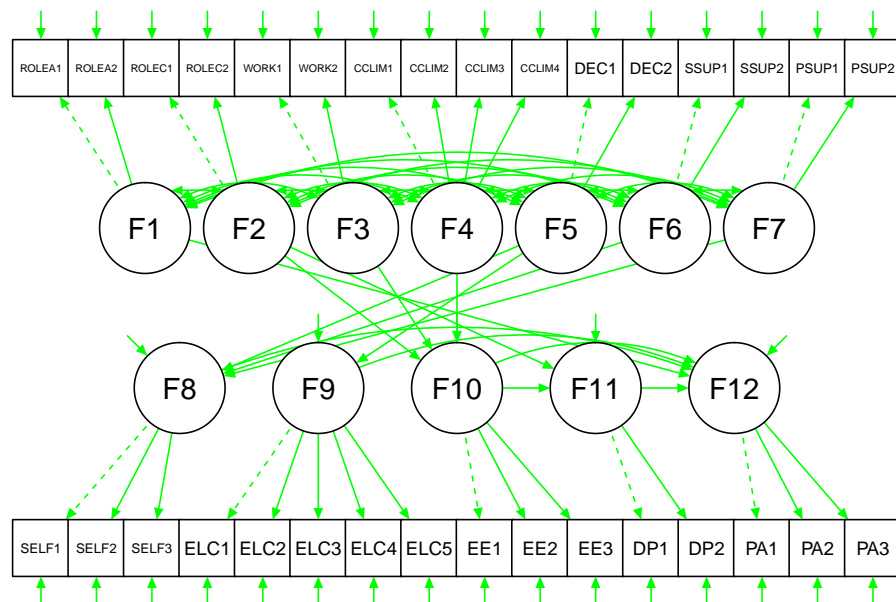
```
Model1 <- fitMeasures(fit1, c("chisq.scaled", "df.scaled", "pvalue.scaled", "cfi.robust", "tli.robust",
```

Testing the hypothesized model and then modify it step by step to fit the sample data considering both parsimony and goodness-of-fit.

So, the output includes a warning that “the latent variable covariance matrix is not positive definite.”

Creating the graph

```
semPaths(fit1, style = "lisrel", intercepts = FALSE, edge.label.cex=0.75, edge.color="green")
```



Model Modification indices for model 1

```
modindices(fit1, minimum = 20, sort. = TRUE)
```

```
## Warning in lav_start_check_cov(lavpartable = lavpartable, start = START): lavaan WARNING: starting v
## variables involved are: F2 F3
```

##	lhs	op	rhs	mi	epc	sepc.lv	sepc.all	sepc.nox
## 1019	F9	~	F2	50.706	0.264	0.491	0.491	0.491
## 151	F2	=~	DEC2	47.464	0.771	0.605	0.487	0.487
## 170	F2	=~	PA2	47.097	0.773	0.606	0.696	0.696
## 1020	F9	~	F3	47.056	0.234	0.475	0.475	0.475
## 181	F3	=~	DEC2	44.391	0.647	0.553	0.446	0.446
## 939	EE2	~~	EE3	43.458	-0.716	-0.716	-1.911	-1.911
## 271	F6	=~	DEC2	35.370	0.979	1.068	0.860	0.860
## 1017	F9	~	F6	34.747	0.362	0.938	0.938	0.938
## 1038	F11	~	F4	34.215	-0.797	-0.292	-0.292	-0.292
## 1022	F9	~	F1	32.749	0.306	0.497	0.497	0.497
## 1058	F6	~	F9	30.179	0.395	0.153	0.153	0.153
## 986	F6	~~	F9	30.141	0.056	0.136	0.136	0.136
## 225	F4	=~	DP1	30.030	-0.674	-0.231	-0.206	-0.206
## 196	F3	=~	EE3	29.805	0.351	0.300	0.221	0.221
## 1013	F9	~	F8	28.735	-0.311	-0.268	-0.268	-0.268
## 751	DEC2	~~	SSUP2	26.439	0.132	0.132	0.446	0.446
## 136	F1	=~	EE3	21.603	0.302	0.207	0.152	0.152
## 341	F8	=~	EE1	20.933	0.462	0.168	0.124	0.124
## 933	EE1	~~	EE3	20.810	-0.336	-0.336	-0.807	-0.807
## 731	DEC1	~~	SSUP2	20.793	-0.101	-0.101	-0.342	-0.342
## 882	ELC1	~~	ELC2	20.631	0.048	0.048	0.225	0.225

The output says starting values imply a correlation larger than 1; variables involved are: F2 and F3 suggest overlapping between the factors of Role Conflict and Work Overload. So, combination these two factors into one will be involved in the next model.

Validating Causal Structure for Calibration Group Combined F2 (Role Conflict) and F3 (Work Overload)

```
model2<-
'

F1 =~ ROLEA1 + ROLEA2
F2 =~ ROLEC1 + ROLEC2
F3 =~ WORK1 + WORK2
F4 =~ CCLIM1 + CCLIM2 + CCLIM3 + CCLIM4
F5 =~ DEC1 + DEC2
F6 =~ SSUP1 + SSUP2
F7 =~ PSUP1 + PSUP2
F8 =~ SELF1 + SELF2 + SELF3
F9 =~ ELC1 + ELC2 + ELC3 + ELC4 + ELC5
F10 =~ EE1 + EE2 + EE3
F11 =~ DP1 + DP2
F12 =~ PA1 + PA2 + PA3

# Regressions
'

fit2 <-cfa(model2, data=data1, estimator="MLM")
```

```
## Warning in lav_object_post_check(object): lavaan WARNING: covariance matrix of latent variables
##           is not positive definite;
##           use lavInspect(fit, "cov.lv") to investigate.
```

```
Model2 <- fitMeasures(fit2, c("chisq.scaled", "df.scaled", "pvalue.scaled", "cfi.robust", "tli.robust",
```

Comparison of model 1 and 2

```
options(scipen=999)
compareFit(fit1, fit2, nested = FALSE)
```

```
## ##### Model Fit Indices #####
##      chisq.scaled df.scaled pvalue.scaled cfi.robust tli.robust      aic
## fit2      717.033†      398          .000      .965†      .956† 39658.557†
## fit1      885.812      429          .000      .950      .942 39784.710
##      bic rmsea.robust  srmr
## fit2 40230.590      .038† .038†
## fit1 40220.336†      .044 .057
```

```
anova(fit1, fit2)
```

```
## Scaled Chi Square Difference Test (method = "satorra.bentler.2001")
##
##      Df   AIC   BIC  Chisq Chisq diff Df diff      Pr(>Chisq)
## fit2 398 39659 40231 792.31
## fit1 429 39785 40220 980.46      166.38      31 < 0.00000000000000022 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

For Model 1: The χ^2 is 885.812, with 429 degrees of freedom. The p-value is 0.000. The CFI and TLI values are 0.950 and 0.942 respectively. The value of RMSEA and SRMR indices are 0.044 and 0.057 respectively.

For Model 2: The χ^2 is 942.192, with 436 degrees of freedom. The p-value is 0.000. The CFI and TLI values are 0.944 and 0.936 respectively. The value of RMSEA and SRMR indices are 0.046 and 0.062 respectively.

The chi-square difference is significant.

The model has improved with the calibration data.

Model Modification indices for model 2

```
modindices(fit2, minimum = 20, sort. = TRUE)
```

```
## Warning in lav_start_check_cov(lavpartable = lavpartable, start = START): lavaan WARNING: starting v
##           variables involved are: F2 F3
##
##      lhs op   rhs      mi      epc sepc.lv sepc.all sepc.nox
## 492 F12 =~   EE3 38.090 -0.356 -0.252 -0.186 -0.186
## 963 EE1 ~~   EE2 36.067  0.246  0.246  0.725  0.725
## 782 DEC2 ~~  SSUP2 31.564  0.149  0.149  0.560  0.560
## 490 F12 =~   EE1 27.455  0.289  0.205  0.151  0.151
## 167 F1 =~    EE3 21.861  0.298  0.204  0.150  0.150
## 913 ELC1 ~~   ELC2 21.329  0.048  0.048  0.225  0.225
## 762 DEC1 ~~  SSUP2 20.464 -0.103 -0.103 -0.368 -0.368
```

Based on the modification indices mentioned above, F8 ON F2 (External Locus of Control on Role Conflict/Work Overload) and EE1 WITH EE2 (covariance between residuals) will be taken into consideration in the next models one by one.

Validating Hypothesized Causal Structure for Calibration Group Modified Baseline model (Byrne 2012, p. 268) Combined F2 and F3, re-numbered the factors Added F8 ON F2 (External

Locus of Control on Role Conflict/Work Overload)

```
model3 <-  
  
'  
F1 =~ ROLEA1 + ROLEA2  
F2 =~ ROLEC1 + ROLEC2 + WORK1 + WORK2  
F3 =~ CCLIM1 + CCLIM2 + CCLIM3 + CCLIM4  
F4 =~ DEC1 + DEC2  
F5 =~ SSUP1 + SSUP2  
F6 =~ PSUP1 + PSUP2  
F7 =~ SELF1 + SELF2 + SELF3  
F8 =~ ELC1 + ELC2 + ELC3 + ELC4 + ELC5  
F9 =~ EE1 + EE2 + EE3  
F10 =~ DP1 + DP2  
F11 =~ PA1 + PA2 + PA3  
  
# Regressions  
F7 ~ F4 + F5 + F6  
F8 ~ F2 + F4  
F9 ~ F2 + F3  
F10 ~ F2 + F9  
F11 ~ F1 + F7 + F8 + F9 + F10  
'  
  
fit3 <-cfa(model3, data=data1, estimator="MLM")  
  
Model3 <- fitMeasures(fit3, c("chisq.scaled", "df.scaled", "pvalue.scaled", "cfi.robust", "tli.robust",
```

Validating Hypothesized Causal Structure for Calibration Group Modified Baseline model (Byrne 2012, p. 268-) Combined F2 and F3, re-numbered the factors Added F8 ON F2 Added EE1 WITH EE2(covariance between residuals)

```
model4 <-  
  
'  
F1 =~ ROLEA1 + ROLEA2  
F2 =~ ROLEC1 + ROLEC2 + WORK1 + WORK2  
F3 =~ CCLIM1 + CCLIM2 + CCLIM3 + CCLIM4  
F4 =~ DEC1 + DEC2  
F5 =~ SSUP1 + SSUP2  
F6 =~ PSUP1 + PSUP2  
F7 =~ SELF1 + SELF2 + SELF3  
F8 =~ ELC1 + ELC2 + ELC3 + ELC4 + ELC5  
F9 =~ EE1 + EE2 + EE3  
F10 =~ DP1 + DP2  
F11 =~ PA1 + PA2 + PA3  
  
# Regressions  
F7 ~ F4 + F5 + F6  
F8 ~ F2 + F4  
F9 ~ F2 + F3  
F10 ~ F2 + F9  
F11 ~ F1 + F7 + F8 + F9 + F10
```



```
# Covariances
```

```
EE1 ~~ EE2
```

```
'
```

```
fit4 <-cfa(model4, data=data1, estimator="MLM")
```

```
summary(fit4)
```

```
## lavaan 0.6-3 ended normally after 102 iterations
```

```
##
```

```
## Optimization method NLMINB
```

```
## Number of free parameters 94
```

```
##
```

```
## Number of observations 602
```

```
##
```

```
## Estimator ML Robust
```

```
## Model Fit Test Statistic 943.702 856.472
```

```
## Degrees of freedom 434 434
```

```
## P-value (Chi-square) 0.000 0.000
```

```
## Scaling correction factor 1.102
```

```
## for the Satorra-Bentler correction
```

```
##
```

```
## Parameter Estimates:
```

```
##
```

```
## Information Expected
```

```
## Information saturated (h1) model Structured
```

```
## Standard Errors Robust.sem
```

```
##
```

```
## Latent Variables:
```

```
## Estimate Std.Err z-value P(>|z|)
```

```
## F1 =~
```

```
## ROLEA1 1.000
```

```
## ROLEA2 1.184 0.077 15.307 0.000
```

```
## F2 =~
```

```
## ROLEC1 1.000
```

```
## ROLEC2 1.334 0.080 16.638 0.000
```

```
## WORK1 1.119 0.064 17.373 0.000
```

```
## WORK2 1.014 0.085 11.930 0.000
```

```
## F3 =~
```

```
## CCLIM1 1.000
```

```
## CCLIM2 1.342 0.105 12.794 0.000
```

```
## CCLIM3 1.002 0.091 10.982 0.000
```

```
## CCLIM4 1.424 0.109 13.086 0.000
```

```
## F4 =~
```

```
## DEC1 1.000
```

```
## DEC2 1.300 0.069 18.767 0.000
```

```
## F5 =~
```

```
## SSUP1 1.000
```

```
## SSUP2 1.064 0.029 36.593 0.000
```

```
## F6 =~
```

```
## PSUP1 1.000
```

```
## PSUP2 1.039 0.061 17.026 0.000
```

```
## F7 =~
```

```
## SELF1 1.000
```

```
## SELF2 1.223 0.075 16.239 0.000
```

```

##      SELF3          1.371    0.078   17.611    0.000
##      F8 =~
##      ELC1          1.000
##      ELC2          0.845    0.061   13.760    0.000
##      ELC3          1.029    0.068   15.104    0.000
##      ELC4          1.039    0.068   15.306    0.000
##      ELC5          1.288    0.080   16.054    0.000
##      F9 =~
##      EE1           1.000
##      EE2           1.033    0.028   37.081    0.000
##      EE3           1.142    0.048   23.595    0.000
##      F10 =~
##      DP1           1.000
##      DP2           0.898    0.067   13.329    0.000
##      F11 =~
##      PA1           1.000
##      PA2           0.879    0.062   14.181    0.000
##      PA3           0.848    0.074   11.434    0.000
##
## Regressions:
##      Estimate Std.Err z-value P(>|z|)
##      F7 ~
##      F4          1.072    0.361    2.974    0.003
##      F5         -0.588    0.219   -2.684    0.007
##      F6         -0.104    0.088   -1.179    0.239
##      F8 ~
##      F2           0.276    0.039    6.997    0.000
##      F4          -0.047    0.034   -1.382    0.167
##      F9 ~
##      F2           0.838    0.078   10.787    0.000
##      F3          -0.685    0.147   -4.648    0.000
##      F10 ~
##      F2           0.081    0.085    0.944    0.345
##      F9           0.525    0.060    8.692    0.000
##      F11 ~
##      F1          -0.107    0.077   -1.386    0.166
##      F7           0.299    0.109    2.754    0.006
##      F8          -0.058    0.093   -0.620    0.535
##      F9          -0.115    0.048   -2.400    0.016
##      F10         -0.221    0.065   -3.384    0.001
##
## Covariances:
##      Estimate Std.Err z-value P(>|z|)
##      .EE1 ~~
##      .EE2          0.268    0.050    5.344    0.000
##      F1 ~~
##      F2           0.420    0.042    9.939    0.000
##      F3          -0.088    0.015   -5.726    0.000
##      F4          -0.401    0.040   -9.970    0.000
##      F5          -0.503    0.053   -9.533    0.000
##      F6          -0.280    0.032   -8.744    0.000
##      F2 ~~
##      F3          -0.107    0.017   -6.339    0.000
##      F4          -0.398    0.043   -9.360    0.000

```

##	F5	-0.474	0.052	-9.092	0.000
##	F6	-0.262	0.034	-7.672	0.000
##	F3 ~~				
##	F4	0.097	0.017	5.539	0.000
##	F5	0.108	0.023	4.702	0.000
##	F6	0.068	0.017	4.108	0.000
##	F4 ~~				
##	F5	0.806	0.063	12.864	0.000
##	F6	0.398	0.041	9.647	0.000
##	F5 ~~				
##	F6	0.433	0.049	8.760	0.000
##					
##	Variances:				
##		Estimate	Std.Err	z-value	P(> z)
##	.ROLEA1	0.440	0.040	11.078	0.000
##	.ROLEA2	0.318	0.045	7.082	0.000
##	.ROLEC1	0.669	0.044	15.285	0.000
##	.ROLEC2	0.651	0.055	11.801	0.000
##	.WORK1	0.589	0.046	12.848	0.000
##	.WORK2	0.873	0.076	11.526	0.000
##	.CCLIM1	0.189	0.012	15.681	0.000
##	.CCLIM2	0.147	0.013	11.026	0.000
##	.CCLIM3	0.158	0.012	13.415	0.000
##	.CCLIM4	0.253	0.021	11.916	0.000
##	.DEC1	0.577	0.038	15.277	0.000
##	.DEC2	0.559	0.047	11.811	0.000
##	.SSUP1	0.316	0.037	8.574	0.000
##	.SSUP2	0.161	0.030	5.346	0.000
##	.PSUP1	0.322	0.045	7.201	0.000
##	.PSUP2	0.168	0.038	4.436	0.000
##	.SELF1	0.088	0.009	9.523	0.000
##	.SELF2	0.095	0.013	7.477	0.000
##	.SELF3	0.067	0.008	8.265	0.000
##	.ELC1	0.185	0.013	14.069	0.000
##	.ELC2	0.245	0.017	14.599	0.000
##	.ELC3	0.159	0.012	13.707	0.000
##	.ELC4	0.237	0.017	13.902	0.000
##	.ELC5	0.174	0.017	10.479	0.000
##	.EE1	0.621	0.055	11.237	0.000
##	.EE2	0.538	0.059	9.120	0.000
##	.EE3	0.253	0.045	5.594	0.000
##	.DP1	0.385	0.060	6.390	0.000
##	.DP2	0.489	0.068	7.192	0.000
##	.PA1	0.166	0.026	6.398	0.000
##	.PA2	0.374	0.041	9.204	0.000
##	.PA3	0.385	0.043	8.931	0.000
##	F1	0.469	0.054	8.709	0.000
##	F2	0.577	0.063	9.200	0.000
##	F3	0.118	0.018	6.684	0.000
##	F4	0.582	0.060	9.780	0.000
##	F5	1.194	0.096	12.385	0.000
##	F6	0.619	0.056	10.990	0.000
##	.F7	0.095	0.015	6.500	0.000
##	.F8	0.121	0.014	8.412	0.000

```
##      .F9                0.633    0.061    10.350    0.000
##      .F10               0.485    0.066     7.340    0.000
##      .F11               0.331    0.040     8.279    0.000
```

```
Model4 <- fitMeasures(fit4, c("chisq.scaled","df.scaled", "pvalue.scaled", "cfi.robust", "tli.robust",
```

Comparison of model 3 and 4

```
options(scipen=999)
compareFit(fit3,fit4, nested = FALSE)
```

```
## ##### Model Fit Indices #####
##      chisq.scaled df.scaled pvalue.scaled cfi.robust tli.robust      aic
## fit4      856.472†      434          .000      .954†      .947† 39737.952†
## fit3      894.660      435          .000      .949      .942 39781.271
##      bic rmsea.robust  srmr
## fit4 40151.576†      .042† .049†
## fit3 40190.495      .044 .052
```

```
anova(fit3, fit4)
```

```
## Scaled Chi Square Difference Test (method = "satorra.bentler.2001")
##
##      Df    AIC    BIC  Chisq Chisq diff Df diff Pr(>Chisq)
## fit4 434 39738 40152 943.70
## fit3 435 39781 40190 989.02      16.922      1 0.00003896 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

For Model 3: The χ^2 is 894.660, with 435 degrees of freedom. The p-value is 0.000. The CFI and TLI values are 0.949 and 0.942 respectively. The value of RMSEA and SRMR indices are 0.044 and 0.052 respectively.

For Model 4: The χ^2 is 856.472, with 434 degrees of freedom. The p-value is 0.000. The CFI and TLI values are 0.954 and 0.947 respectively. The value of RMSEA and SRMR indices are 0.042 and 0.049 respectively.

The chi-square difference is again significant.

Model Modification indices for model 4

```
modindices(fit4, minimum = 20, sort. = TRUE)
```

```
##      lhs op    rhs    mi    epc sepc.lv sepc.all sepc.nox
## 976    F9 ~    F7 28.572 -0.687 -0.226 -0.226 -0.226
## 187    F3 =~   DP1 27.526 -0.658 -0.226 -0.202 -0.202
## 990   F10 ~    F3 27.471 -0.718 -0.264 -0.264 -0.264
## 978    F9 ~    F10 27.471 -1.367 -1.157 -1.157 -1.157
## 958    F9 ~~   F10 27.470 -0.664 -1.197 -1.197 -1.197
## 933    F3 ~~   F9 27.302  0.485  1.772  1.772  1.772
## 1039   F3 ~    F9 27.301  0.765  2.457  2.457  2.457
## 938    F4 ~~   F9 26.924 -0.055 -0.090 -0.090 -0.090
## 999    F4 ~    F9 26.924 -0.086 -0.125 -0.125 -0.125
## 340    F9 =~   ROLEC1 26.176 -0.264 -0.291 -0.261 -0.261
## 143    F2 =~   DEC2 24.923  0.501  0.381  0.307  0.307
## 563  WORK1 ~~   EE1 24.824  0.122  0.122  0.202  0.202
## 934    F3 ~~   F10 24.325 -0.066 -0.274 -0.274 -0.274
## 962    F7 ~    F9 23.982 -0.101 -0.306 -0.306 -0.306
## 693   DEC1 ~~  SSUP2 23.926 -0.111 -0.111 -0.363 -0.363
## 342    F9 =~   WORK1 23.703  0.248  0.274  0.239  0.239
## 952    F7 ~~   F9 23.129 -0.063 -0.257 -0.257 -0.257
```

## 963	F7 ~	F10	22.273	-0.097	-0.249	-0.249	-0.249
## 1009	F5 ~	F9	21.455	0.125	0.126	0.126	0.126
## 943	F5 ~~	F9	21.455	0.079	0.091	0.091	0.091
## 844	ELC1 ~~	ELC2	20.528	0.047	0.047	0.222	0.222
## 233	F5 =~	DEC2	20.101	0.944	1.031	0.830	0.830

As seen from the summary of model 4, there are five parameter estimates statistically non-significant. These non-significant paths will be deleted to establish baseline model for the calibration group.

Validating Hypothesized Causal Structure for Calibration Group Modified Baseline model (Byrne 2012, p. 268-) Combined F2 and F3, re-numbered the factors Added F8 ON F2 Added EE1 WITH EE2 Deleted n.s. params: F7 ON F6, F8 ON F4, F10 ON F2, F11 ON F1, F11 ON F8

```
model5 <-
'
F1 =~ ROLEA1 + ROLEA2
F2 =~ ROLEC1 + ROLEC2 + WORK1 + WORK2
F3 =~ CCLIM1 + CCLIM2 + CCLIM3 + CCLIM4
F4 =~ DEC1 + DEC2
F5 =~ SSUP1 + SSUP2
F6 =~ PSUP1 + PSUP2
F7 =~ SELF1 + SELF2 + SELF3
F8 =~ ELC1 + ELC2 + ELC3 + ELC4 + ELC5
F9 =~ EE1 + EE2 + EE3
F10 =~ DP1 + DP2
F11 =~ PA1 + PA2 + PA3

# Regressions
F7 ~ F4 + F5
F8 ~ F2
F9 ~ F2 + F3
F10 ~ F9
F11 ~ F1 + F7 + F10

# Covariances
EE1 ~~ EE2
'
```

```
fit5 <-cfa(model5, data=data1, estimator="MLM")
summary(fit5)
```

```
## lavaan 0.6-3 ended normally after 91 iterations
##
## Optimization method          NLMINB
## Number of free parameters    90
##
## Number of observations       602
##
## Estimator                    ML      Robust
## Model Fit Test Statistic     954.105 865.112
## Degrees of freedom           438      438
## P-value (Chi-square)         0.000    0.000
## Scaling correction factor    1.103
## for the Satorra-Bentler correction
```

```

##
## Parameter Estimates:
##
## Information Expected
## Information saturated (h1) model Structured
## Standard Errors Robust.sem
##
## Latent Variables:
## Estimate Std.Err z-value P(>|z|)
## F1 =~
## ROLEA1 1.000
## ROLEA2 1.183 0.077 15.310 0.000
## F2 =~
## ROLEC1 1.000
## ROLEC2 1.330 0.080 16.633 0.000
## WORK1 1.118 0.064 17.398 0.000
## WORK2 1.011 0.085 11.895 0.000
## F3 =~
## CCLIM1 1.000
## CCLIM2 1.341 0.105 12.808 0.000
## CCLIM3 1.001 0.091 10.996 0.000
## CCLIM4 1.422 0.109 13.098 0.000
## F4 =~
## DEC1 1.000
## DEC2 1.298 0.069 18.803 0.000
## F5 =~
## SSUP1 1.000
## SSUP2 1.067 0.030 36.109 0.000
## F6 =~
## PSUP1 1.000
## PSUP2 1.030 0.060 17.115 0.000
## F7 =~
## SELF1 1.000
## SELF2 1.221 0.075 16.241 0.000
## SELF3 1.369 0.078 17.641 0.000
## F8 =~
## ELC1 1.000
## ELC2 0.846 0.061 13.767 0.000
## ELC3 1.028 0.068 15.094 0.000
## ELC4 1.036 0.068 15.294 0.000
## ELC5 1.289 0.080 16.077 0.000
## F9 =~
## EE1 1.000
## EE2 1.032 0.028 36.979 0.000
## EE3 1.128 0.047 23.855 0.000
## F10 =~
## DP1 1.000
## DP2 0.918 0.068 13.560 0.000
## F11 =~
## PA1 1.000
## PA2 0.892 0.064 14.014 0.000
## PA3 0.857 0.077 11.158 0.000
##
## Regressions:

```

```

##               Estimate Std.Err z-value P(>|z|)
## F7 ~
## F4             0.765   0.176   4.336   0.000
## F5            -0.419   0.122  -3.424   0.001
## F8 ~
## F2             0.312   0.030  10.299   0.000
## F9 ~
## F2             0.848   0.077  11.016   0.000
## F3            -0.694   0.147  -4.724   0.000
## F10 ~
## F9             0.564   0.043  13.032   0.000
## F11 ~
## F1            -0.184   0.063  -2.929   0.003
## F7             0.317   0.109   2.905   0.004
## F10            -0.313   0.051  -6.111   0.000
##
## Covariances:
##               Estimate Std.Err z-value P(>|z|)
## .EE1 ~~
## .EE2           0.254   0.050   5.114   0.000
## F1 ~~
## F2            0.422   0.042   9.976   0.000
## F3           -0.089   0.015  -5.767   0.000
## F4           -0.409   0.040 -10.172   0.000
## F5           -0.501   0.053  -9.482   0.000
## F6           -0.283   0.032  -8.822   0.000
## F2 ~~
## F3           -0.107   0.017  -6.317   0.000
## F4           -0.410   0.042  -9.748   0.000
## F5           -0.477   0.052  -9.150   0.000
## F6           -0.267   0.034  -7.795   0.000
## F3 ~~
## F4            0.101   0.018   5.755   0.000
## F5            0.107   0.023   4.644   0.000
## F6            0.068   0.017   4.089   0.000
## F4 ~~
## F5            0.806   0.063  12.838   0.000
## F6            0.389   0.040   9.659   0.000
## F5 ~~
## F6            0.437   0.050   8.828   0.000
## .F8 ~~
## .F11          -0.012   0.012  -1.001   0.317
##
## Variances:
##               Estimate Std.Err z-value P(>|z|)
## .ROLEA1       0.441   0.040  11.111   0.000
## .ROLEA2       0.320   0.045   7.148   0.000
## .ROLEC1       0.667   0.043  15.344   0.000
## .ROLEC2       0.656   0.055  11.857   0.000
## .WORK1        0.588   0.046  12.837   0.000
## .WORK2        0.874   0.076  11.519   0.000
## .CCLIM1       0.189   0.012  15.674   0.000
## .CCLIM2       0.147   0.013  11.054   0.000
## .CCLIM3       0.158   0.012  13.437   0.000

```

```
## .CCLIM4      0.253    0.021   11.923    0.000
## .DEC1        0.574    0.038   15.251    0.000
## .DEC2        0.558    0.047   11.784    0.000
## .SSUP1       0.318    0.037    8.491    0.000
## .SSUP2       0.157    0.030    5.172    0.000
## .PSUP1       0.316    0.044    7.149    0.000
## .PSUP2       0.174    0.038    4.623    0.000
## .SELF1       0.087    0.009    9.519    0.000
## .SELF2       0.095    0.013    7.490    0.000
## .SELF3       0.067    0.008    8.306    0.000
## .ELC1        0.185    0.013   14.082    0.000
## .ELC2        0.245    0.017   14.561    0.000
## .ELC3        0.159    0.012   13.691    0.000
## .ELC4        0.237    0.017   13.941    0.000
## .ELC5        0.173    0.016   10.515    0.000
## .EE1         0.607    0.055   10.998    0.000
## .EE2         0.524    0.059    8.898    0.000
## .EE3         0.275    0.044    6.225    0.000
## .DP1         0.412    0.060    6.848    0.000
## .DP2         0.480    0.067    7.146    0.000
## .PA1         0.173    0.026    6.614    0.000
## .PA2         0.368    0.040    9.107    0.000
## .PA3         0.382    0.044    8.769    0.000
## F1          0.468    0.054    8.702    0.000
## F2          0.579    0.063    9.213    0.000
## F3          0.118    0.018    6.691    0.000
## F4          0.585    0.060    9.801    0.000
## F5          1.193    0.097   12.355    0.000
## F6          0.625    0.057   11.060    0.000
## .F7          0.097    0.013    7.175    0.000
## .F8          0.121    0.014    8.379    0.000
## .F9          0.633    0.061   10.317    0.000
## .F10         0.453    0.063    7.164    0.000
## .F11         0.323    0.040    8.074    0.000
```

```
Model5 <- fitMeasures(fit5, c("chisq.scaled", "df.scaled", "pvalue.scaled", "cfi.robust", "tli.robust",
```

Comparison of model 4 and 5

```
options(scipen=999)
compareFit(fit4, fit5, nested = FALSE)
```

```
## ##### Model Fit Indices #####
##      chisq.scaled df.scaled pvalue.scaled cfi.robust tli.robust      aic
## fit4      856.472†      434          .000      .954†      .947† 39737.952†
## fit5      865.112      438          .000      .953      .947 39740.355
##      bic rmsea.robust srmr
## fit4 40151.576      .042† .049†
## fit5 40136.378†      .042 .051
```

```
anova(fit4, fit5)
```

```
## Scaled Chi Square Difference Test (method = "satorra.bentler.2001")
```

```
##
##      Df    AIC    BIC  Chisq Chisq diff Df diff Pr(>Chisq)
## fit4 434 39738 40152 943.70
```



```
## fit5 438 39740 40136 954.11      8.572      4      0.07273 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

The chi-square difference is not statistically significant here with slight change in model fit as compared to the previous model.

Since there are no specified relations between either F1 or F6 and the rest of the factors, they will be deleted in the next model.

Validating Hypothesized Causal Structure for Calibration Group Modified Baseline model (Byrne 2012, p. 268-) Combined F2 and F3, re-numbered the factors Added F8 ON F2 Added EE1 WITH EE2 Deleted n.s. params: F7 ON F6, F8 ON F4, F10 ON F2, F11 ON F1, F11 ON F8 Removed factors F1 and F6 and their items (no specified relations)! (not yet renamed factors!)

```
model6 <-
'
F2 =~ ROLEC1 + ROLEC2 + WORK1 + WORK2
F3 =~ CCLIM1 + CCLIM2 + CCLIM3 + CCLIM4
F4 =~ DEC1 + DEC2
F5 =~ SSUP1 + SSUP2
F7 =~ SELF1 + SELF2 + SELF3
F8 =~ ELC1 + ELC2 + ELC3 + ELC4 + ELC5
F9 =~ EE1 + EE2 + EE3
F10 =~ DP1 + DP2
F11 =~ PA1 + PA2 + PA3

#Regressions

F7 ~ F4 + F5
F8 ~ F2
F9 ~ F2 + F3
F10 ~ F9
F11 ~ F7 + F9 + F10

#Covariance

EE1 ~~ EE2

'

fit6 <-cfa(model6, data=data1, estimator="MLM")

Model6 <- fitMeasures(fit6, c("chisq.scaled", "df.scaled", "pvalue.scaled", "cfi.robust", "tli.robust",
```

Comparison of model 5 and 6

```
anova(fit5, fit6)
```

```
## Warning in lavTestLRT(object = new("lavaan", version = "0.6.3", call =
## lavaan::lavaan(model = model5, : lavaan WARNING: some models are based on a
## different set of observed variables

## Scaled Chi Square Difference Test (method = "satorra.bentler.2001")
##
```

```
##      Df    AIC    BIC  Chisq Chisq diff Df diff Pr(>Chisq)
## fit6 333 34447 34768 787.96
## fit5 438 39740 40136 954.11      147.05      105    0.004267 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Validating Hypothesized Causal Structure for Calibration Group Modified Baseline model (Byrne 2012, p. 268-) Combined F2 and F3, re-numbered the factors Added F8 ON F2 Added EE1 WITH EE2 Deleted n.s. params: F7 ON F6, F8 ON F4, F10 ON F2, F11 ON F1, F11 ON F8 Removed factors F1 and F6 and their items (no specified relations)! Renamed factors, deleted items from USEVARS, “revised model” (Byrne, p.275)

```
model7 <-
```

```
'
F1 =~ ROLEC1 + ROLEC2 + WORK1 + WORK2
F2 =~ CCLIM1 + CCLIM2 + CCLIM3 + CCLIM4
F3 =~ DEC1 + DEC2
F4 =~ SSUP1 + SSUP2
F5 =~ SELF1 + SELF2 + SELF3
F6 =~ ELC1 + ELC2 + ELC3 + ELC4 + ELC5
F7 =~ EE1 + EE2 + EE3
F8 =~ DP1 + DP2
F9 =~ PA1 + PA2 + PA3
```

```
#Regressions
F5 ~ F3 + F4
F6 ~ F1
F7 ~ F1 + F2
F8 ~ F7
F9 ~ F5 + F7 + F8
```

```
#Res.covariance
EE1 ~~ EE2
'
```

```
fit7 <-cfa(model7, data=data1, estimator="MLM")
```

```
Model7 <- fitMeasures(fit7, c("chisq.scaled","df.scaled", "pvalue.scaled", "cfi.robust", "tli.robust",
```

TITLE: Validating Hypothesized Causal Structure for Calibration Group Modified Baseline model (Byrne 2012, p. 268-) Combined F2 and F3, re-numbered the factors Added F8 ON F2 Added EE1 WITH EE2 Deleted n.s. params: F7 ON F6, F8 ON F4, F10 ON F2, F11 ON F1, F11 ON F8 Removed factors F1 and F6 and their items (no specified relations)! Renamed factors, deleted items from USEVARS, “revised model” (Byrne, p.275) Fine-tuning: remove unwanted parameter F9 WITH F6 (see p.272, 278).

```
model8 <-
```

```
'
F1 =~ ROLEC1 + ROLEC2 + WORK1 + WORK2
F2 =~ CCLIM1 + CCLIM2 + CCLIM3 + CCLIM4
F3 =~ DEC1 + DEC2
F4 =~ SSUP1 + SSUP2
F5 =~ SELF1 + SELF2 + SELF3
```

```

F6 =~ ELC1 + ELC2 + ELC3 + ELC4 + ELC5
F7 =~ EE1 + EE2 + EE3
F8 =~ DP1 + DP2
F9 =~ PA1 + PA2 + PA3

#Regressions
F5 ~ F3 + F4
F6 ~ F1
F7 ~ F1 + F2
F8 ~ F7
F9 ~ F5 + F7 + F8

#Res.covariance
EE1 ~~ EE2
F9 ~~ 0*F6
'

fit8 <- cfa(model8, data=data1, estimator="MLM")

Final_model <- fitMeasures(fit8, c("chisq.scaled", "df.scaled", "pvalue.scaled", "cfi.robust", "tli.robust", "rmsea.robust", "srmsr"))

/

options(scipen=999)
compareFit(fit1, fit2, fit3, fit4, fit5, fit6, fit7, fit8, nested = FALSE)

## ##### Model Fit Indices #####
##      chisq.scaled df.scaled pvalue.scaled cfi.robust tli.robust      aic
## fit6      720.018      333          .000      .951      .944 34446.650
## fit7      720.018      333          .000      .951      .944 34446.650
## fit8      721.523      334          .000      .951      .944 34446.550†
## fit2      717.033†      398          .000      .965†      .956† 39658.557
## fit1      885.812      429          .000      .950      .942 39784.710
## fit4      856.472      434          .000      .954      .947 39737.952
## fit3      894.660      435          .000      .949      .942 39781.271
## fit5      865.112      438          .000      .953      .947 39740.355
##      bic rmsea.robust  srmsr
## fit6 34767.869      .046 .053
## fit7 34767.869      .046 .053
## fit8 34763.368†      .046 .053
## fit2 40230.590      .038† .038†
## fit1 40220.336      .044 .057
## fit4 40151.576      .042 .049
## fit3 40190.495      .044 .052
## fit5 40136.378      .042 .051

final <- rbind(Model1, Model2, Model3, Model4, Model5, Model6, Model7, Final_model)

kable(final, "latex", caption = "Summarizing model fit", booktabs = T) %>%
kable_styling(latex_options = c("striped", "hold_position", "scale_down"))

```

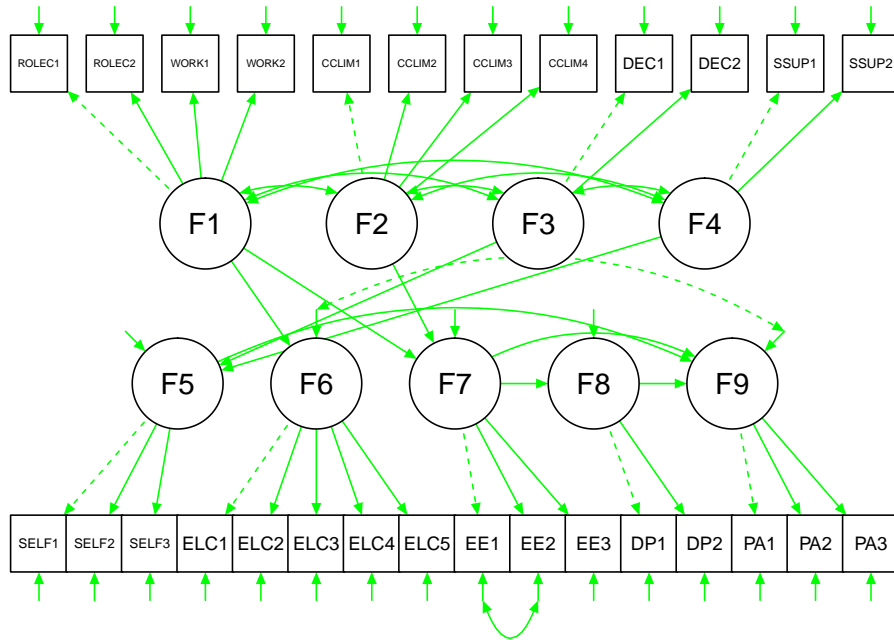
Final model seems to be parsimonious baseline model for the calibration group.

Creating the graph

Table 1: Summarizing model fit

	chisq.scaled	df.scaled	pvalue.scaled	cfi.robust	tli.robust	rmsea.robust	srmr
Model1	885.8116	429	0	0.9495947	0.9417226	0.0442472	0.0569313
Model2	717.0333	398	0	0.9648569	0.9562036	0.0383579	0.0380282
Model3	894.6600	435	0	0.9493436	0.9422401	0.0440504	0.0515388
Model4	856.4721	434	0	0.9535945	0.9469651	0.0422101	0.0492962
Model5	865.1122	438	0	0.9530414	0.9468231	0.0422666	0.0511050
Model6	720.0179	333	0	0.9510270	0.9444091	0.0459648	0.0525617
Model7	720.0179	333	0	0.9510270	0.9444091	0.0459648	0.0525617
Final_model	721.5229	334	0	0.9509475	0.9444855	0.0459332	0.0531382

```
semPaths(fit8, style = "lisrel", intercepts = FALSE, edge.label.cex=0.75, edge.color="green")
```



Exercise 6.2

** Testing for Equivalence of causal Structure Across Calibration and Validation groups Configural Model (no parameter constraints) (Byrne 2012, p. 278).**

The next step is to form and test the multigroup configural model with no parameter constraints.

```
# Combine data
```

```
cacel <- merge(data.frame(data1, group = "data1"), data.frame(data2, group = "data2"), all = TRUE, sort
```

```

dim(cacel)

## [1] 1203 33
fit9 <- cfa(model8, data=cacel, group="group", estimator="MLM")

Multigroup_configural_model <- fitMeasures(fit9, c("chisq.scaled", "df.scaled", "pvalue.scaled", "cfi.robust", "rmsea.robust", "srmr", "tli.robust"))

options(scipen=999)
compareFit(fit8, fit9, nested = FALSE)

## Warning in compareFit(fit8, fit9, nested = FALSE): fitMeasures() returned
## vectors of different lengths for different models, probably because
## certain options are not the same. Check lavInspect(fit, "options")
## [c("estimator", "test", "meanstructure")] for each model, or run
## fitMeasures() on each model to investigate.

## ##### Model Fit Indices #####
##          aic          bic cfi.robust chisq.scaled df.scaled pvalue.scaled
## fit8 34446.550† 34763.368†    .951†    721.523†      334          .000
## fit9 68153.123 69171.638    .949    1484.062      668          .000
##          rmsea.robust srmr tli.robust
## fit8          .046† .053†    .944†
## fit9          .047 .056    .942

final <- rbind(Final_model, Multigroup_configural_model)

kable(final, "latex", caption = "Summarizing final and multigroup configural model fit", booktabs = T)
kable_styling(latex_options = c("striped", "hold_position", "scale_down"))

```

Table 2: Summarizing final and multigroup configural model fit

	chisq.scaled	df.scaled	pvalue.scaled	cfi.robust	tli.robust	rmsea.robust	srmr
Final_model	721.5229	334	0	0.9509475	0.9444855	0.0459332	0.0531382
Multigroup_configural_model	1484.0618	668	0	0.9486303	0.9418630	0.0471248	0.0561398

Exercise 6.3

Testing for Equivalence of causal Structure Across Calibration and Validation groups Constrained Equal: factor loadings, intercepts, structural paths (Byrne 2012, p. 280)

```

model9 <-
'
F1 =~ ROLEC1 + ROLEC2 + WORK1 + WORK2
F2 =~ CCLIM1 + CCLIM2 + CCLIM3 + CCLIM4
F3 =~ DEC1 + DEC2
F4 =~ SSUP1 + SSUP2
F5 =~ SELF1 + SELF2 + SELF3
F6 =~ ELC1 + ELC2 + ELC3 + ELC4 + ELC5
F7 =~ EE1 + EE2 + EE3
F8 =~ DP1 + DP2
F9 =~ PA1 + PA2 + PA3

```

```

#Regressions
F5 ~ F3 + F4
F6 ~ F1
F7 ~ F1 + F2
F8 ~ F7
F9 ~ F5 + F7 + F8

#Res.covariance
EE1 ~~ EE2
F9 ~~ 0*F6
'

fit10 <- cfa(model9, data=cacel, group="group", estimator="MLM", group.equal=c("loadings"))

Model_loadings <- fitMeasures(fit10, c("chisq.scaled", "df.scaled", "pvalue.scaled", "cfi.robust", "tli.

model10 <-

'
F1 =~ ROLEC1 + ROLEC2 + WORK1 + WORK2
F2 =~ CCLIM1 + CCLIM2 + CCLIM3 + CCLIM4
F3 =~ DEC1 + DEC2
F4 =~ SSUP1 + SSUP2
F5 =~ SELF1 + SELF2 + SELF3
F6 =~ ELC1 + ELC2 + ELC3 + ELC4 + ELC5
F7 =~ EE1 + EE2 + EE3
F8 =~ DP1 + DP2
F9 =~ PA1 + PA2 + PA3

#Regressions
F5 ~ F3 + F4
F6 ~ F1
F7 ~ F1 + F2
F8 ~ F7
F9 ~ F5 + F7 + F8

#Res.covariance
EE1 ~~ EE2
F9 ~~ 0*F6
'

fit11 <- cfa(model10, data=cacel, group="group", estimator="MLM", group.equal=c("loadings", "intercepts

Model_loadings_intercepts <- fitMeasures(fit11, c("chisq.scaled", "df.scaled", "pvalue.scaled", "cfi.robust

model11 <-

'
F1 =~ ROLEC1 + ROLEC2 + WORK1 + WORK2
F2 =~ CCLIM1 + CCLIM2 + CCLIM3 + CCLIM4
F3 =~ DEC1 + DEC2
F4 =~ SSUP1 + SSUP2
F5 =~ SELF1 + SELF2 + SELF3
F6 =~ ELC1 + ELC2 + ELC3 + ELC4 + ELC5

```

```

F7 =~ EE1 + EE2 + EE3
F8 =~ DP1 + DP2
F9 =~ PA1 + PA2 + PA3

#Regressions
F5 ~ F3 + F4
F6 ~ F1
F7 ~ F1 + F2
F8 ~ F7
F9 ~ F5 + F7 + F8

#Res.covariance
EE1 ~~ EE2
F9 ~~ 0*F6
'

fit12 <- cfa(model11, data=cacel, group="group", estimator="MLM", group.equal=c("loadings", "intercepts"))
Model_loadings_intercepts_regression <- fitMeasures(fit12, c("chisq.scaled", "df.scaled", "pvalue.scaled"))

```

Comparison of models

```

options(scipen=999)
compareFit(fit9, fit10, fit11, fit12, nested = FALSE)

## ##### Model Fit Indices #####
##          chisq.scaled df.scaled pvalue.scaled cfi.robust tli.robust
## fit9      1484.062†      668          .000      .949      .942
## fit10     1497.677      687          .000      .949†     .944
## fit11     1525.165      706          .000      .949      .945
## fit12     1533.400      715          .000      .949      .946†
##          aic          bic rmsea.robust  srmr
## fit9  68153.123  69171.638      .047  .056†
## fit10  68130.404  69052.160      .046  .057
## fit11  68115.851  68940.848      .046  .057
## fit12  68109.697† 68888.861†      .046† .058

final <- rbind(Final_model, Multigroup_configural_model, Model_loadings, Model_loadings_intercepts, Model_loadings_intercepts_regression)

kable(final, "latex", caption = "Summarizing final, multigroup configural model and testing for equivalence models",
kable_styling(latex_options = c("striped", "hold_position", "scale_down"))

```

Table 3: Summarizing final, multigroup configural model and testing for equivalence models

	chisq.scaled	df.scaled	pvalue.scaled	cfi.robust	tli.robust	rmsea.robust	srmr
Final_model	721.5229	334	0	0.9509475	0.9444855	0.0459332	0.0531382
Multigroup_configural_model	1484.0618	668	0	0.9486303	0.9418630	0.0471248	0.0561398
Model_loadings	1497.6766	687	0	0.9489570	0.9438304	0.0463206	0.0569002
Model_loadings_intercepts	1525.1651	706	0	0.9486271	0.9449888	0.0458404	0.0570396
Model_loadings_intercepts_regression	1533.3998	715	0	0.9485868	0.9456386	0.0455689	0.0580282

```
anova(fit9, fit12)
```

```
## Scaled Chi Square Difference Test (method = "satorra.bentler.2001")
##
```

```
##          Df    AIC    BIC  Chisq Chisq diff Df diff Pr(>Chisq)
## fit9    668 68153 69172 1622.7
## fit12   715 68110 68889 1673.3      47.713      47      0.4436
```

The final output shows good fit of the data. The CFI, RMSEA and SRMR has tiny changes as compared to the configural model. The chi-square difference is not statistically significant.

Creating the graph

```
semPaths(fit12, style = "lisrel", intercepts = FALSE, edge.label.cex=0.75, edge.color="green")
```

1

