

Exercises Week 2 Latent Variable Modeling

```
library("lavaan")
```

Exercise 3.1

```
Health.cov <- lav_matrix_lower2full(c(
  0.77,
  0.38, 0.65,
  0.39, 0.39, 0.62,
-0.25,-0.32,-0.27, 6.09,
  0.31, 0.29, 0.26,-0.36, 7.67,
  0.24, 0.25, 0.19,-0.18, 0.51, 1.69,
-3.16,-3.56,-2.63, 6.09,-3.12,-4.58,204.79,
-0.92,-0.88,-0.72, 0.88,-1.49,-1.41, 16.53, 7.24
))
rownames(Health.cov) <- colnames(Health.cov) <-
c("Dep1","Dep2","Dep3", "SocAct", "Falls", "ChronCond",
  "PhysAct", "PersMob")

marker.mod <- '
  F =~ 1*Dep1 + Dep2 + Dep3 + SocAct
'

marker.fit <- cfa(marker.mod, sample.cov = Health.cov, sample.nobs = 6053)
summary(marker.fit, standardized = TRUE)
```

```
## lavaan (0.6-1) converged normally after 27 iterations
##
##   Number of observations              6053
##
##   Estimator                          ML
##   Model Fit Test Statistic            9.620
##   Degrees of freedom                   2
##   P-value (Chi-square)                0.008
##
## Parameter Estimates:
##
##   Information                        Expected
##   Information saturated (h1) model    Structured
##   Standard Errors                    Standard
##
## Latent Variables:
##
##           Estimate  Std.Err  z-value  P(>|z|)  Std.lv  Std.all
##   F =~
##     Dep1           1.000      0.021  47.588   0.000    0.616    0.701
##     Dep2           1.005      0.021  47.588   0.000    0.619    0.768
##     Dep3           1.025      0.022  47.638   0.000    0.631    0.801
##     SocAct        -0.736      0.058 -12.793   0.000   -0.453   -0.184
##
## Variances:
##
##           Estimate  Std.Err  z-value  P(>|z|)  Std.lv  Std.all
##   .Dep1           0.391      0.009  41.276   0.000    0.391    0.508
```

```
##      .Dep2      0.267    0.008   33.581    0.000    0.267    0.411
##      .Dep3      0.222    0.008   28.886    0.000    0.222    0.358
##      .SocAct     5.884    0.108   54.559    0.000    5.884    0.966
##      F           0.379    0.014   27.888    0.000    1.000    1.000
```

```
stdLV.mod <- '
  F =~ NA*Dep1 + Dep2 + Dep3 + SocAct
  F ~~ 1*F
'

stdLV.fit <- cfa(stdLV.mod, sample.cov = Health.cov, sample.nobs = 6053)
summary(stdLV.fit, standardized = TRUE)
```

```
## lavaan (0.6-1) converged normally after 19 iterations
##
##   Number of observations              6053
##
##   Estimator                          ML
##   Model Fit Test Statistic            9.620
##   Degrees of freedom                  2
##   P-value (Chi-square)                0.008
##
## Parameter Estimates:
##
##   Information                        Expected
##   Information saturated (h1) model   Structured
##   Standard Errors                    Standard
##
## Latent Variables:
##           Estimate  Std.Err  z-value  P(>|z|)  Std.lv  Std.all
##   F =~
##     Dep1           0.616    0.011   55.776    0.000    0.616    0.701
##     Dep2           0.619    0.010   61.392    0.000    0.619    0.768
##     Dep3           0.631    0.010   64.285    0.000    0.631    0.801
##     SocAct        -0.453    0.035  -12.967    0.000   -0.453   -0.184
##
## Variances:
##           Estimate  Std.Err  z-value  P(>|z|)  Std.lv  Std.all
##   F             1.000
##   .Dep1          0.391    0.009   41.276    0.000    0.391    0.508
##   .Dep2          0.267    0.008   33.581    0.000    0.267    0.411
##   .Dep3          0.222    0.008   28.886    0.000    0.222    0.358
##   .SocAct        5.884    0.108   54.559    0.000    5.884    0.966
```

```
effects.mod <- '
  F =~ NA*Dep1 + a*Dep1 + b*Dep2 + c*Dep3 + d*SocAct
  a + b + c + d == 4
'

effects.fit <- cfa(effects.mod, sample.cov = Health.cov, sample.nobs = 6053)
summary(effects.fit, standardized = TRUE)
```

```
## lavaan (0.6-1) converged normally after 30 iterations
##
##   Number of observations              6053
##
##   Estimator                          ML
```

```

## Model Fit Test Statistic          9.620
## Degrees of freedom                2
## P-value (Chi-square)              0.008
##
## Parameter Estimates:
##
## Information                        Expected
## Information saturated (h1) model  Structured
## Standard Errors                    Standard
##
## Latent Variables:
##      Estimate Std.Err z-value P(>|z|) Std.lv Std.all
## F =~
## Dep1 (a) 1.744 0.048 36.449 0.000 0.616 0.701
## Dep2 (b) 1.753 0.048 36.367 0.000 0.619 0.768
## Dep3 (c) 1.787 0.049 36.377 0.000 0.631 0.801
## SocAct (d) -1.284 0.131 -9.832 0.000 -0.453 -0.184
##
## Variances:
##      Estimate Std.Err z-value P(>|z|) Std.lv Std.all
## .Dep1 0.391 0.009 41.276 0.000 0.391 0.508
## .Dep2 0.267 0.008 33.581 0.000 0.267 0.411
## .Dep3 0.222 0.008 28.886 0.000 0.222 0.358
## .SocAct 5.884 0.108 54.559 0.000 5.884 0.966
## F 0.125 0.007 17.914 0.000 1.000 1.000
##
## Constraints:
##      |Slack|
## a+b+c+d - (4) 0.000

```

All identification methods give the exact same chi-square value.

Additional question:

The paper authors have decided to measure poor psychosocial health by means of three depression items and a measure of social activities. However, it seems that social activities is not strongly associated with depressive symptoms, so one may wonder whether this is a valid model for measuring psychosocial health.

```
fitmeasures(marker.fit)
```

```

##      npar      fmin      chisq
##      8.000      0.001      9.620
##      df      pvalue baseline.chisq
##      2.000      0.008      5907.581
## baseline.df baseline.pvalue      cfi
##      6.000      0.000      0.999
##      tli      nnfi      rfi
##      0.996      0.996      0.995
##      nfi      pnfi      ifi
##      0.998      0.333      0.999
##      rni      logl unrestricted.logl
##      0.999 -33330.619 -33325.809
##      aic      bic      ntotal
##      66677.238 66730.905 6053.000
##      bic2      rmsea      rmsea.ci.lower

```

```
##          66705.483          0.025          0.011
##      rmsea.ci.upper      rmsea.pvalue      rmr
##          0.042          0.994          0.016
##      rmr_nomean          srmr      srmr_bentler
##          0.016          0.008          0.008
## srmr_bentler_nomean      srmr_bollen srmr_bollen_nomean
##          0.008          0.008          0.008
##      srmr_mplus      srmr_mplus_nomean      cn_05
##          0.008          0.008          3770.918
##          cn_01          gfi          agfi
##          5796.282          0.999          0.996
##          pgfi          mfi          ecvi
##          0.200          0.999          0.004
```

Exercise 3.2

```
Health.mod <- '
  PPsyHealth =~ Dep1 + Dep2 + Dep3 + SocAct
  PPhysHealth =~ ChronCond + PhysAct + Falls
  PersMob ~ PPsyHealth + PPhysHealth
'

Health.fit <- sem(Health.mod, sample.cov = Health.cov, sample.nobs = 6053)
summary(Health.fit, fit.measures = TRUE, standardized = TRUE)
```

```
## lavaan (0.6-1) converged normally after 62 iterations
##
##      Number of observations          6053
##
##      Estimator          ML
##      Model Fit Test Statistic      254.865
##      Degrees of freedom          18
##      P-value (Chi-square)          0.000
##
## Model test baseline model:
##
##      Minimum Function Test Statistic      10290.938
##      Degrees of freedom          28
##      P-value          0.000
##
## User model versus baseline model:
##
##      Comparative Fit Index (CFI)          0.977
##      Tucker-Lewis Index (TLI)          0.964
##
## Loglikelihood and Information Criteria:
##
##      Loglikelihood user model (H0)      -95467.244
##      Loglikelihood unrestricted model (H1) -95339.812
##
##      Number of free parameters          18
##      Akaike (AIC)          190970.488
##      Bayesian (BIC)          191091.238
##      Sample-size adjusted Bayesian (BIC) 191034.038
```

```

##
## Root Mean Square Error of Approximation:
##
##   RMSEA                                0.047
##   90 Percent Confidence Interval      0.042  0.052
##   P-value RMSEA <= 0.05              0.856
##
## Standardized Root Mean Square Residual:
##
##   SRMR                                0.027
##
## Parameter Estimates:
##
##   Information                        Expected
##   Information saturated (h1) model   Structured
##   Standard Errors                   Standard
##
## Latent Variables:
##           Estimate  Std.Err  z-value  P(>|z|)  Std.lv  Std.all
##   PPsyHealth =~
##     Dep1           1.000
##     Dep2           1.015    0.020   49.994    0.000    0.634    0.786
##     Dep3           0.972    0.020   49.608    0.000    0.607    0.771
##     SocAct        -0.771    0.056  -13.683    0.000   -0.481   -0.195
##   PPhysHealth =~
##     ChronCond       1.000
##     PhysAct       -12.005    0.442  -27.173    0.000   -7.319   -0.511
##     Falls          1.073    0.070   15.337    0.000    0.654    0.236
##
## Regressions:
##           Estimate  Std.Err  z-value  P(>|z|)  Std.lv  Std.all
##   PersMob ~
##     PPsyHealth       0.433    0.196    2.215    0.027    0.270    0.101
##     PPhysHealth     -4.034    0.286  -14.107    0.000   -2.459   -0.914
##
## Covariances:
##           Estimate  Std.Err  z-value  P(>|z|)  Std.lv  Std.all
##   PPsyHealth ~~
##     PPhysHealth       0.250    0.011   22.634    0.000    0.656    0.656
##
## Variances:
##           Estimate  Std.Err  z-value  P(>|z|)  Std.lv  Std.all
##   .Dep1           0.380    0.009   41.810    0.000    0.380    0.494
##   .Dep2           0.248    0.007   33.798    0.000    0.248    0.382
##   .Dep3           0.251    0.007   35.721    0.000    0.251    0.405
##   .SocAct         5.858    0.107   54.534    0.000    5.858    0.962
##   .ChronCond       1.318    0.028   46.833    0.000    1.318    0.780
##   .PhysAct       151.194    3.462   43.667    0.000  151.194    0.738
##   .Falls          7.241    0.134   54.019    0.000    7.241    0.944
##   .PersMob        1.990    0.239    8.318    0.000    1.990    0.275
##   PPsyHealth       0.390    0.014   28.811    0.000    1.000    1.000
##   PPhysHealth      0.372    0.024   15.334    0.000    1.000    1.000

```

Poor physical health seems to be a much stronger predictor of personal mobility than poor psychosocial

health.

Additional question:

The χ^2 value is significant, but the sample size is very large. CFI and TLI are both $> .95$, the RMSEA $< .06$ and SRMR is $< .05$, all indicating good model fit. Let's also inspect the residual (co)variances:

```
fitMeasures(Health.fit, c("chisq", "df", "pvalue", "cfi", "rmsea", "srmr"))
```

```
##      chisq      df  pvalue      cfi  rmsea  srmr
## 254.865 18.000   0.000   0.977  0.047  0.027
```

```
modificationIndices(Health.fit, sort = TRUE)[1:10,]
```

```
##           lhs op      rhs      mi      epc sepc.lv sepc.all sepc.nox
## 26 PPhysHealth =~      Dep3 100.581 -0.242  -0.148  -0.188  -0.188
## 28      Dep1 =~      Dep2  90.131 -0.089  -0.089  -0.288  -0.288
## 47      SocAct =~ PhysAct  68.471  3.297   3.297   0.111   0.111
## 29      Dep1 =~      Dep3  37.601  0.054   0.054   0.176   0.176
## 45      Dep3 =~ PersMob  29.876  0.098   0.098   0.139   0.139
## 34      Dep1 =~ PersMob  28.808 -0.108  -0.108  -0.124  -0.124
## 24 PPhysHealth =~      Dep1  25.971  0.135   0.082   0.094   0.094
## 38      Dep2 =~ PhysAct  24.638 -0.503  -0.503  -0.082  -0.082
## 27 PPhysHealth =~ SocAct  22.579 -0.409  -0.249  -0.101  -0.101
## 35      Dep2 =~      Dep3  22.032  0.045   0.045   0.179   0.179
```

```
residuals(Health.fit, type = "cor")
```

```
## $type
## [1] "cor.bollen"
##
## $cor
##           Dep1  Dep2  Dep3  SocAct ChrnCn PhysAc Falls  PersMb
## Dep1           0.000
## Dep2        -0.022  0.000
## Dep3          0.016  0.008  0.000
## SocAct         0.023 -0.008  0.011  0.000
## ChronCond    -0.008 -0.003 -0.051  0.004  0.000
## PhysAct     -0.013 -0.045  0.025  0.107 -0.006  0.000
## Falls         0.017  0.008  0.000 -0.022  0.031  0.042  0.000
## PersMob     -0.035 -0.013  0.045  0.035 -0.005 -0.005  0.000  0.000
##
## $mean
##           Dep1           Dep2           Dep3           SocAct ChronCond           PhysAct           Falls
##           0           0           0           0           0           0           0
## PersMob
##           0
```

If we look at the standardised parameter estimates though, the Falls variable is not well explained by the Physical Health factor. And, as noted earlier, Poor Psychosocial Health is not a strong predictor of Personal Mobility. However, residuals do not suggest this is problematic.

We could consider adding a correlated error between Physical Activities and Social Activities. These show the largest residual error ($> .10$) and it makes sense from a substantial point of view: Both measure activity levels. In addition, if both were assessed with the same method (self-report? interview?), measurement errors are likely correlated.

Additional exercise 1

```
data(HolzingerSwineford1939)
summary(HolzingerSwineford1939)
```

```
##          id          sex          ageyr          agemo
## Min.      : 1.0    Min.    :1.000    Min.    :11    Min.    : 0.000
## 1st Qu.: 82.0    1st Qu.:1.000    1st Qu.:12    1st Qu.: 2.000
## Median :163.0    Median :2.000    Median :13    Median : 5.000
## Mean     :176.6    Mean     :1.515    Mean     :13    Mean     : 5.375
## 3rd Qu.:272.0    3rd Qu.:2.000    3rd Qu.:14    3rd Qu.: 8.000
## Max.     :351.0    Max.     :2.000    Max.     :16    Max.     :11.000
##
##          school      grade          x1          x2
## Grant-White:145    Min.    :7.000    Min.    :0.6667    Min.    :2.250
## Pasteur      :156    1st Qu.:7.000    1st Qu.:4.1667    1st Qu.:5.250
##              Median :7.000    Median :5.0000    Median :6.000
##              Mean     :7.477    Mean     :4.9358    Mean     :6.088
##              3rd Qu.:8.000    3rd Qu.:5.6667    3rd Qu.:6.750
##              Max.     :8.000    Max.     :8.5000    Max.     :9.250
##              NA's      :1
##          x3          x4          x5          x6
## Min.      :0.250    Min.    :0.000    Min.    :1.000    Min.    :0.1429
## 1st Qu.:1.375    1st Qu.:2.333    1st Qu.:3.500    1st Qu.:1.4286
## Median :2.125    Median :3.000    Median :4.500    Median :2.0000
## Mean     :2.250    Mean     :3.061    Mean     :4.341    Mean     :2.1856
## 3rd Qu.:3.125    3rd Qu.:3.667    3rd Qu.:5.250    3rd Qu.:2.7143
## Max.     :4.500    Max.     :6.333    Max.     :7.000    Max.     :6.1429
##
##          x7          x8          x9
## Min.      :1.304    Min.    : 3.050    Min.    :2.778
## 1st Qu.:3.478    1st Qu.: 4.850    1st Qu.:4.750
## Median :4.087    Median : 5.500    Median :5.417
## Mean     :4.186    Mean     : 5.527    Mean     :5.374
## 3rd Qu.:4.913    3rd Qu.: 6.100    3rd Qu.:6.083
## Max.     :7.435    Max.     :10.000    Max.     :9.250
##
```

```
HS.mod.1 <- '
  IQ =~ x1 + x2 + x3 + x4 + x5 + x6
'
HS.fit.1 <- cfa(HS.mod.1, data = HolzingerSwineford1939, estimator = "MLR")
summary(HS.fit.1, standardized = TRUE, fit.measures = TRUE)
```

```
## lavaan (0.6-1) converged normally after 34 iterations
##
##      Number of observations                    301
##
##      Estimator                                ML      Robust
##      Model Fit Test Statistic                103.230  100.487
##      Degrees of freedom                       9        9
##      P-value (Chi-square)                    0.000     0.000
##      Scaling correction factor                1.027
##      for the Yuan-Bentler correction (Mplus variant)
```

```

##
## Model test baseline model:
##
##   Minimum Function Test Statistic           668.643      605.920
##   Degrees of freedom                        15           15
##   P-value                                   0.000         0.000
##
## User model versus baseline model:
##
##   Comparative Fit Index (CFI)                0.856       0.845
##   Tucker-Lewis Index (TLI)                  0.760       0.742
##
##   Robust Comparative Fit Index (CFI)                NA
##   Robust Tucker-Lewis Index (TLI)                NA
##
## Loglikelihood and Information Criteria:
##
##   Loglikelihood user model (H0)          -2559.686    -2559.686
##   Loglikelihood unrestricted model (H1)    -2508.071    -2508.071
##
##   Number of free parameters                12           12
##   Akaike (AIC)                            5143.372    5143.372
##   Bayesian (BIC)                          5187.857    5187.857
##   Sample-size adjusted Bayesian (BIC)      5149.800    5149.800
##
## Root Mean Square Error of Approximation:
##
##   RMSEA                                    0.187       0.184
##   90 Percent Confidence Interval          0.155  0.220    0.153  0.217
##   P-value RMSEA <= 0.05                  0.000       0.000
##
##   Robust RMSEA                                NA
##   90 Percent Confidence Interval          NA      NA
##
## Standardized Root Mean Square Residual:
##
##   SRMR                                    0.114       0.114
##
## Parameter Estimates:
##
##   Information                                Observed
##   Observed information based on              Hessian
##   Standard Errors                          Robust.huber.white
##
## Latent Variables:
##
##           Estimate  Std.Err  z-value  P(>|z|)  Std.lv  Std.all
##   IQ =~
##   x1           1.000
##   x2           0.511    0.152    3.354    0.001    0.250    0.212
##   x3           0.468    0.128    3.657    0.000    0.229    0.203
##   x4           2.028    0.322    6.303    0.000    0.990    0.852
##   x5           2.234    0.374    5.974    0.000    1.091    0.847
##   x6           1.882    0.295    6.375    0.000    0.919    0.840
##

```



```
## Variances:
##           Estimate Std.Err z-value P(>|z|) Std.lv Std.all
##    .x1           1.120   0.109  10.321   0.000   1.120   0.824
##    .x2           1.319   0.128  10.272   0.000   1.319   0.955
##    .x3           1.223   0.078  15.715   0.000   1.223   0.959
##    .x4           0.370   0.050   7.341   0.000   0.370   0.274
##    .x5           0.470   0.058   8.132   0.000   0.470   0.283
##    .x6           0.351   0.046   7.635   0.000   0.351   0.294
##    IQ            0.238   0.077   3.113   0.002   1.000   1.000
```

a) The model does not fit very well. Also, the standardized loadings of X1, X2 and X3 are much smaller than those of X4, X5 and X6, so do not seem well explained by the model.

b) The robust ML χ^2 value is lower than the ML, but the difference is small (103.230 vs. 100.487).

c) Let's see whether and how we can improve model fit:

```
residuals(HS.fit.1, type = "cor")
```

```
## $type
## [1] "cor.bollen"
##
## $cor
##      x1      x2      x3      x4      x5      x6
## x1  0.000
## x2  0.208  0.000
## x3  0.356  0.297  0.000
## x4  0.016 -0.028 -0.014  0.000
## x5 -0.061 -0.040 -0.094  0.012  0.000
## x6  0.005  0.014  0.027 -0.012  0.008  0.000
##
## $mean
## x1 x2 x3 x4 x5 x6
##  0  0  0  0  0  0
```

```
modificationIndices(HS.fit.1, sort. = TRUE)
```

```
##      lhs op rhs      mi      epc sepc.lv sepc.all sepc.nox
## 15  x1  ~~  x3 49.835  0.484   0.484   0.414   0.414
## 19  x2  ~~  x3 29.298  0.399   0.399   0.314   0.314
## 14  x1  ~~  x2 17.170  0.295   0.295   0.243   0.243
## 24  x3  ~~  x5 14.774 -0.206  -0.206  -0.271  -0.271
## 17  x1  ~~  x5  7.829 -0.149  -0.149  -0.205  -0.205
## 26  x4  ~~  x5  7.807  0.260   0.260   0.623   0.623
## 27  x4  ~~  x6  7.107 -0.207  -0.207  -0.573  -0.573
## 28  x5  ~~  x6  3.327  0.154   0.154   0.380   0.380
## 21  x2  ~~  x5  2.742 -0.092  -0.092  -0.117  -0.117
## 20  x2  ~~  x4  1.399 -0.059  -0.059  -0.085  -0.085
## 25  x3  ~~  x6  1.179  0.050   0.050   0.076   0.076
## 16  x1  ~~  x4  0.540  0.035   0.035   0.055   0.055
## 23  x3  ~~  x4  0.342 -0.028  -0.028  -0.042  -0.042
## 22  x2  ~~  x6  0.308  0.026   0.026   0.039   0.039
## 18  x1  ~~  x6  0.042  0.009   0.009   0.015   0.015
```

Residuals among X1, X2 and X3 are largest. Highest modification indices are for correlations between X1, X2 and X3. This matches what we already expected based on the standardized loadings, that the model can maybe be improved by adding a separate factor for X1, X2 and X3:

```

HS.mod.2 <- '
  IQ1 =~ x1 + x2 + x3
  IQ2 =~ x4 + x5 + x6
'

HS.fit.2 <- cfa(HS.mod.2, data = HolzingerSwineford1939, estimator = "MLR")
summary(HS.fit.2, standardized = TRUE, fit.measures = TRUE)

## lavaan (0.6-1) converged normally after 28 iterations
##
##   Number of observations              301
##
##   Estimator                        ML      Robust
##   Model Fit Test Statistic          24.361    24.373
##   Degrees of freedom                  8        8
##   P-value (Chi-square)              0.002    0.002
##   Scaling correction factor          1.000
##   for the Yuan-Bentler correction (Mplus variant)
##
## Model test baseline model:
##
##   Minimum Function Test Statistic      668.643    605.920
##   Degrees of freedom                    15        15
##   P-value                              0.000    0.000
##
## User model versus baseline model:
##
##   Comparative Fit Index (CFI)          0.975    0.972
##   Tucker-Lewis Index (TLI)            0.953    0.948
##
##   Robust Comparative Fit Index (CFI)          NA
##   Robust Tucker-Lewis Index (TLI)            NA
##
## Loglikelihood and Information Criteria:
##
##   Loglikelihood user model (H0)          -2520.252    -2520.252
##   Loglikelihood unrestricted model (H1)    -2508.071    -2508.071
##
##   Number of free parameters              13        13
##   Akaike (AIC)                          5066.503    5066.503
##   Bayesian (BIC)                         5114.696    5114.696
##   Sample-size adjusted Bayesian (BIC)      5073.467    5073.467
##
## Root Mean Square Error of Approximation:
##
##   RMSEA                                0.082    0.082
##   90 Percent Confidence Interval          0.046    0.121    0.046    0.121
##   P-value RMSEA <= 0.05                  0.067    0.067
##
##   Robust RMSEA                          NA
##   90 Percent Confidence Interval          NA      NA
##
## Standardized Root Mean Square Residual:
##
##   SRMR                                0.047    0.047

```

```
##
## Parameter Estimates:
##
##      Information                      Observed
##      Observed information based on      Hessian
##      Standard Errors                    Robust.huber.white
##
## Latent Variables:
##      Estimate  Std.Err  z-value  P(>|z|)  Std.lv  Std.all
##      IQ1 =~
##      x1          1.000
##      x2          0.559    0.163    3.436    0.001    0.507    0.431
##      x3          0.708    0.162    4.369    0.000    0.642    0.568
##      IQ2 =~
##      x4          1.000
##      x5          1.111    0.066   16.910    0.000    1.101    0.854
##      x6          0.925    0.062   14.966    0.000    0.917    0.838
##
## Covariances:
##      Estimate  Std.Err  z-value  P(>|z|)  Std.lv  Std.all
##      IQ1 ~~
##      IQ2          0.414    0.106    3.889    0.000    0.461    0.461
##
## Variances:
##      Estimate  Std.Err  z-value  P(>|z|)  Std.lv  Std.all
##      .x1          0.536    0.194    2.766    0.006    0.536    0.395
##      .x2          1.125    0.120    9.401    0.000    1.125    0.814
##      .x3          0.863    0.110    7.832    0.000    0.863    0.677
##      .x4          0.369    0.051    7.311    0.000    0.369    0.274
##      .x5          0.449    0.057    7.830    0.000    0.449    0.270
##      .x6          0.356    0.047    7.639    0.000    0.356    0.298
##      IQ1          0.822    0.215    3.831    0.000    1.000    1.000
##      IQ2          0.981    0.122    8.053    0.000    1.000    1.000
```

d) Looking at the estimated parameters, the standardized factor loadings of X1, X2 and X3 have substantially increased. Looking at model fit, that definitely improved. Chi-square value is much smaller (although still significant, but that is to be expected with $N = 300$). RMSEA is nearly adequate. CFI and SRMR indicate good model fit. AIC for the 2D model is lower than that for the 1D model. Furthermore, robust CFI and TLI are now $> .95$. Although the value of RMSEA $> .08$, the p-value for the test of the RMSEA being $< .05$ is $> .05$, and the confidence interval for the RMSEA includes .05, which seems acceptable. Finally, looking at the residuals:

```
residuals(HS.fit.2, type="cor")
```

```
## $type
## [1] "cor.bollen"
##
## $cor
##      x1      x2      x3      x4      x5      x6
## x1  0.000
## x2 -0.038  0.000
## x3 -0.002  0.095  0.000
## x4  0.067 -0.016 -0.065  0.000
## x5 -0.013 -0.030 -0.146  0.005  0.000
## x6  0.056  0.026 -0.022 -0.010  0.004  0.000
```

```
##
## $mean
## x1 x2 x3 x4 x5 x6
## 0 0 0 0 0 0
```

We do see that there is one residual correlation $> .1$ (between X3 and X5). All other correlations seem well explained by the model.

Additional question 2

a) Fit the depicted model to the data:

```
## Input covariances:
cormat <- lav_matrix_lower2full(c(
  1.000,
  0.700, 1.000,
  0.713, 0.636, 1.000,
  0.079, 0.066, 0.076, 1.000,
  0.088, 0.058, 0.070, 0.681, 1.000,
  0.084, 0.056, 0.074, 0.712, 0.633, 1.000,
  0.279, 0.248, 0.240, 0.177, 0.155, 0.170, 1.000,
  0.250, 0.214, 0.222, 0.157, 0.143, 0.152, 0.373, 1.000,
  0.280, 0.236, 0.251, 0.173, 0.178, 0.171, 0.448, 0.344, 1.000
))

## Input standard deviations:
sds = c(2.5, 2.1, 3.0, 4.1, 3.9, 4.4, 1.2, 1.0, 1.2)

## Reconstruct covariance matrix from correlations and sds:
covmat <- diag(sds) %*% cormat %*% diag(sds)

## Assign row and column names:
rownames(covmat) <- colnames(covmat) <- c("Y1", "Y2", "Y3", "Y4", "Y5", "Y6",
                                           "X1", "X2", "X3")

## Define formative model:
form.mod <- '
  SATISFACTION =~ Y1 + Y2 + Y3
  OPTIMISM =~ Y4 + Y5 + Y6
  STRESS <~ 1*X1 + X2 +X3
  SATISFACTION ~ STRESS
  OPTIMISM ~ STRESS
'

## Fit model:
form.fit <- cfa(form.mod, sample.cov=covmat, sample.nobs = 500)
summary(form.fit, standardized = TRUE, fit.measures = TRUE)

## lavaan (0.6-1) converged normally after 67 iterations
##
##   Number of observations              500
##
##   Estimator                          ML
##   Model Fit Test Statistic           2.166
##   Degrees of freedom                 22
```

```

## P-value (Chi-square) 1.000
##
## Model test baseline model:
##
## Minimum Function Test Statistic 1542.629
## Degrees of freedom 33
## P-value 0.000
##
## User model versus baseline model:
##
## Comparative Fit Index (CFI) 1.000
## Tucker-Lewis Index (TLI) 1.020
##
## Loglikelihood and Information Criteria:
##
## Loglikelihood user model (H0) -9192.919
## Loglikelihood unrestricted model (H1) -9191.836
##
## Number of free parameters 17
## Akaike (AIC) 18419.837
## Bayesian (BIC) 18491.486
## Sample-size adjusted Bayesian (BIC) 18437.526
##
## Root Mean Square Error of Approximation:
##
## RMSEA 0.000
## 90 Percent Confidence Interval 0.000 0.000
## P-value RMSEA <= 0.05 1.000
##
## Standardized Root Mean Square Residual:
##
## SRMR 0.005
##
## Parameter Estimates:
##
## Information Expected
## Information saturated (h1) model Structured
## Standard Errors Standard
##
## Latent Variables:
## Estimate Std.Err z-value P(>|z|) Std.lv Std.all
## SATISFACTION =~
## Y1 1.000 2.217 0.888
## Y2 0.746 0.038 19.570 0.000 1.655 0.789
## Y3 1.086 0.055 19.930 0.000 2.409 0.804
## OPTIMISM =~
## Y4 1.000 3.579 0.874
## Y5 0.848 0.045 18.733 0.000 3.035 0.779
## Y6 1.000 0.051 19.441 0.000 3.579 0.814
##
## Composites:
## Estimate Std.Err z-value P(>|z|) Std.lv Std.all
## STRESS <~
## X1 1.000 0.366 0.439

```

```
##      X2                1.053    0.445    2.369    0.018    0.386    0.385
##      X3                1.073    0.434    2.469    0.014    0.393    0.471
##
## Regressions:
##              Estimate Std.Err z-value P(>|z|) Std.lv Std.all
## SATISFACTION ~
##   STRESS          0.317    0.083    3.806    0.000    0.390    0.390
## OPTIMISM ~
##   STRESS          0.338    0.101    3.358    0.001    0.258    0.258
##
## Covariances:
##              Estimate Std.Err z-value P(>|z|) Std.lv Std.all
## .SATISFACTION ~~
##   .OPTIMISM        0.052    0.367    0.142    0.887    0.007    0.007
##
## Variances:
##              Estimate Std.Err z-value P(>|z|) Std.lv Std.all
## .Y1              1.321    0.186    7.083    0.000    1.321    0.212
## .Y2              1.662    0.142   11.735    0.000    1.662    0.378
## .Y3              3.181    0.284   11.213    0.000    3.181    0.354
## .Y4              3.964    0.528    7.509    0.000    3.964    0.236
## .Y5              5.971    0.506   11.795    0.000    5.971    0.393
## .Y6              6.510    0.622   10.459    0.000    6.510    0.337
## .SATISFACTION    4.169    0.364   11.458    0.000    0.848    0.848
## .OPTIMISM       11.960    1.064   11.238    0.000    0.933    0.933
##   STRESS          0.000                0.000    0.000
```

b) Fit a model with stress as a reflective LV:

```
refl.mod <- '
  SATISFACTION =~ Y1 + Y2 + Y3
  OPTIMISM =~ Y4 + Y5 + Y6
  STRESS =~ 1*X1 + X2 +X3
  SATISFACTION ~ STRESS
  OPTIMISM ~ STRESS
'
refl.fit <- cfa(refl.mod, sample.cov = covmat, sample.nobs = 500)
summary(refl.fit, standardized = TRUE, fit.measures = TRUE)
```

```
## lavaan (0.6-1) converged normally after 65 iterations
##
##   Number of observations                    500
##
##   Estimator                                ML
##   Model Fit Test Statistic                  3.010
##   Degrees of freedom                        24
##   P-value (Chi-square)                      1.000
##
## Model test baseline model:
##
##   Minimum Function Test Statistic          1752.818
##   Degrees of freedom                        36
##   P-value                                  0.000
##
## User model versus baseline model:
```

```

##
## Comparative Fit Index (CFI) 1.000
## Tucker-Lewis Index (TLI) 1.018
##
## Loglikelihood and Information Criteria:
##
## Loglikelihood user model (H0) -9193.341
## Loglikelihood unrestricted model (H1) -9191.836
##
## Number of free parameters 21
## Akaike (AIC) 18428.681
## Bayesian (BIC) 18517.188
## Sample-size adjusted Bayesian (BIC) 18450.533
##
## Root Mean Square Error of Approximation:
##
## RMSEA 0.000
## 90 Percent Confidence Interval 0.000 0.000
## P-value RMSEA <= 0.05 1.000
##
## Standardized Root Mean Square Residual:
##
## SRMR 0.008
##
## Parameter Estimates:
##
## Information Expected
## Information saturated (h1) model Structured
## Standard Errors Standard
##
## Latent Variables:
## Estimate Std.Err z-value P(>|z|) Std.lv Std.all
## SATISFACTION =~
## Y1 1.000 2.217 0.888
## Y2 0.747 0.038 19.570 0.000 1.655 0.789
## Y3 1.086 0.055 19.926 0.000 2.408 0.804
## OPTIMISM =~
## Y4 1.000 3.580 0.874
## Y5 0.848 0.045 18.731 0.000 3.034 0.779
## Y6 1.000 0.051 19.440 0.000 3.579 0.814
## STRESS =~
## X1 1.000 0.812 0.677
## X2 0.675 0.078 8.696 0.000 0.548 0.548
## X3 0.962 0.103 9.314 0.000 0.781 0.652
##
## Regressions:
## Estimate Std.Err z-value P(>|z|) Std.lv Std.all
## SATISFACTION ~
## STRESS 1.299 0.177 7.345 0.000 0.476 0.476
## OPTIMISM ~
## STRESS 1.388 0.272 5.110 0.000 0.315 0.315
##
## Covariances:
## Estimate Std.Err z-value P(>|z|) Std.lv Std.all

```

```

## .SATISFACTION ~~
## .OPTIMISM      -0.337    0.378   -0.892    0.372   -0.051   -0.051
##
## Variances:
##           Estimate Std.Err z-value P(>|z|) Std.lv Std.all
## .Y1           1.321   0.187   7.082   0.000   1.321   0.212
## .Y2           1.661   0.142  11.731   0.000   1.661   0.377
## .Y3           3.182   0.284  11.214   0.000   3.182   0.354
## .Y4           3.963   0.528   7.506   0.000   3.963   0.236
## .Y5           5.972   0.506  11.796   0.000   5.972   0.393
## .Y6           6.510   0.622  10.459   0.000   6.510   0.337
## .X1           0.778   0.080   9.758   0.000   0.778   0.542
## .X2           0.698   0.054  12.810   0.000   0.698   0.700
## .X3           0.827   0.079  10.497   0.000   0.827   0.576
## .SATISFACTION  3.804   0.367  10.353   0.000   0.774   0.774
## .OPTIMISM     11.545   1.065  10.837   0.000   0.901   0.901
## STRESS         0.659   0.099   6.662   0.000   1.000   1.000

```

- c) For both models, fit indices indicate excellent model fit. The formative model fits slightly better than the reflective model according to the SRMR, but the difference is very small.