Psychology 454: Latent Variable Modeling

The effect of items on latent structures

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Outline

The problem with items

- Maximum Likelihood estimation is based upon continuous normal assumptions
- But items are discrete.
  - Correlations are reduced by forming categories. $\phi < \rho$
  - Correlations will differ as a function of item difficulty.
- Can demonstrate these problems with simulated items.
- Demonstration with dichotomous (e.g., IQ) or polytomous (e.g., mood) items

Simulate items with known structures

- Steps of simulation
  - Create a pure, continuous population model
  - Sample from population model
  - Distort with categorical items
  - Distort with dichotomous items
- Problem of categorical items most pronounced with differences in item difficulty.
  - Functionally, this leads to differences in skew.
  - Skew is a major problem when studying emotion.

Pure congeneric model

- Simulate 9 items with moderate loadings (.5 - .6)
  - Examine the covariances
  - Examine the structure
- Repeat with 4 categories
- Repeat with 2 cateogories

9 congeneric items - pure model

```
set.seed(42)
latent <- sim.congeneric(loads =sample(c(.4,.5,.6),9,replace=TRUE),N=2
latent$model
```

	V1	V2	V3	V4	V5	V6	V7	V8	V9
V1	1.00	0.36	0.24	0.36	0.30	0.30	0.36	0.24	0.30
V2	0.36	1.00	0.24	0.36	0.30	0.30	0.36	0.24	0.30
V3	0.24	0.24	1.00	0.24	0.20	0.20	0.24	0.16	0.20
V4	0.36	0.36	0.24	1.00	0.30	0.30	0.36	0.24	0.30
V5	0.30	0.30	0.20	0.30	1.00	0.25	0.30	0.20	0.25
V6	0.30	0.30	0.20	0.30	0.25	1.00	0.30	0.20	0.25
V7	0.36	0.36	0.24	0.36	0.30	0.30	1.00	0.24	0.30
V8	0.24	0.24	0.16	0.24	0.20	0.20	0.24	1.00	0.20
V9	0.30	0.30	0.20	0.30	0.25	0.25	0.30	0.20	1.00

9 congeneric items – sampled data

```
> round(latent$r,2)

     V1   V2   V3   V4   V5   V6   V7   V8   V9
V1 1.00 0.36 0.34 0.39 0.34 0.37 0.34 0.29 0.41
V2 0.36 1.00 0.35 0.43 0.33 0.22 0.31 0.22 0.33
V3 0.34 0.35 1.00 0.26 0.24 0.29 0.24 0.11 0.28
V4 0.39 0.43 0.26 1.00 0.33 0.30 0.26 0.28 0.35
V5 0.34 0.33 0.24 0.33 1.00 0.26 0.35 0.24 0.22
V6 0.37 0.22 0.29 0.30 0.26 1.00 0.23 0.17 0.23
V7 0.34 0.31 0.24 0.26 0.35 0.23 1.00 0.17 0.29
V8 0.29 0.22 0.11 0.28 0.24 0.17 0.17 1.00 0.32
V9 0.41 0.33 0.28 0.35 0.22 0.23 0.29 0.32 1.00
```

Factor the model

fa(latent$model)

```
Call: fa(r = latent$model)
Standardized loadings based
upon correlation matrix
   MR1   h2   u2
V1 0.6 0.36 0.64
V2 0.6 0.36 0.64
V3 0.4 0.16 0.84
V4 0.6 0.36 0.64
V5 0.5 0.25 0.75
V6 0.5 0.25 0.75
V7 0.6 0.36 0.64
V8 0.4 0.16 0.84
V9 0.5 0.25 0.75

                MR1
SS loadings    2.51
Proportion Var 0.28
```

```
Test of the hypothesis that 1 factor is sufficien

The degrees of freedom for the null model are  36
         the objective function was  1.46
The degrees of freedom for the model are 27  and
              the objective function was  0

The root mean square of the residuals is  0
The df corrected root mean square of the residual

Fit based upon off diagonal values = 1
Measures of factor score adequacy
                                                 M
Correlation of scores with factors               0.
Multiple R square of scores with factors         0.
Minimum correlation of possible factor scores    0.
```

Factor the simulated data

```
> fa(latent$observed)

Factor Analysis using method
             =  minres
Call: fa(r = latent$observed)
Standardized loadings based
      upon correlation matrix
    MR1   h2   u2
V1 0.67 0.45 0.55
V2 0.60 0.36 0.64
V3 0.49 0.24 0.76
V4 0.61 0.38 0.62
V5 0.53 0.28 0.72
V6 0.47 0.23 0.77
V7 0.50 0.25 0.75
V8 0.41 0.17 0.83
V9 0.57 0.32 0.68

                MR1
SS loadings    2.68
Proportion Var 0.30
```

```
Test of the hypothesis that 1 factor is sufficien

The degrees of freedom for the null model are  36
the objective function was  1.75 with Chi Sq
The degrees of freedom for the model are 27  and
 the objective function was  0.12

The root mean square of the residuals is  0.03
The df corrected root mean square of the residual
                  is  0.05
The number of observations was  200
               with Chi Square =  24.02  with pro
Tucker Lewis Index of factoring reliability =  1.
RMSEA index =  0  and the 90 % confidence interva
BIC =  -119.04
Fit based upon off diagonal values = 0.98
Measures of factor score adequacy
                                                 M
Correlation of scores with factors               0.
Multiple R square of scores with factors         0.
Minimum correlation of possible factor scores    0.
```

Create the RAM commands to do this

```
> mod1 <- structure.diagram(fa(latent$observed),errors=TRUE)
> mod1

      Path        Parameter Value
 [1,] "MR1->V1"   "F1V1"    NA
 [2,] "MR1->V2"   "F1V2"    NA
 [3,] "MR1->V3"   "F1V3"    NA
 [4,] "MR1->V4"   "F1V4"    NA
 [5,] "MR1->V5"   "F1V5"    NA
 [6,] "MR1->V6"   "F1V6"    NA
 [7,] "MR1->V7"   "F1V7"    NA
 [8,] "MR1->V8"   "F1V8"    NA
 [9,] "MR1->V9"   "F1V9"    NA
[10,] "V1<->V1"   "x1e"     NA
[11,] "V2<->V2"   "x2e"     NA
[12,] "V3<->V3"   "x3e"     NA
[13,] "V4<->V4"   "x4e"     NA
[14,] "V5<->V5"   "x5e"     NA
[15,] "V6<->V6"   "x6e"     NA
[16,] "V7<->V7"   "x7e"     NA
[17,] "V8<->V8"   "x8e"     NA
[18,] "V9<->V9"   "x9e"     NA
[19,] "MR1<->MR1" NA        "1"
attr(,"class")
[1] "mod"
```

Run sem

```
library(sem)
sem1 <- sem(mod1,S=cov(latent$observed),N=200)
```

```
 Model Chisquare =  24.571   Df =  27 Pr(>Chisq) = 0.59848
 Chisquare (null model) =  348.95   Df =  36
 Goodness-of-fit index =  0.97387
 Adjusted goodness-of-fit index =  0.95644
 RMSEA index =  0   90% CI: (NA, 0.049115)
 Bentler-Bonnett NFI =  0.92959
 Tucker-Lewis NNFI =  1.0103
 Bentler CFI =  1
 SRMR =  0.03681
 BIC =  -118.48

 Normalized Residuals
    Min.  1st Qu.   Median     Mean  3rd Qu.     Max.
-1.32000 -0.32400  0.00004 -0.00704  0.19300  1.13000
```

Edit the model to fix all loadings to be the same

```
>  mod2 <- edit(mod1)
> mod2
```

```
      Path         Parameter Value
 [1,] "MR1->V1"    "a"       NA
 [2,] "MR1->V2"    "a"       NA
 [3,] "MR1->V3"    "a"       NA
 [4,] "MR1->V4"    "a"       NA
 [5,] "MR1->V5"    "a"       NA
 [6,] "MR1->V6"    "a"       NA
 [7,] "MR1->V7"    "a"       NA
 [8,] "MR1->V8"    "a"       NA
 [9,] "MR1->V9"    "a"       NA
[10,] "V1<->V1"    "x1e"     NA
[11,] "V2<->V2"    "x2e"     NA
[12,] "V3<->V3"    "x3e"     NA
[13,] "V4<->V4"    "x4e"     NA
[14,] "V5<->V5"    "x5e"     NA
[15,] "V6<->V6"    "x6e"     NA
[16,] "V7<->V7"    "x7e"     NA
[17,] "V8<->V8"    "x8e"     NA
[18,] "V9<->V9"    "x9e"     NA
[19,] "MR1<->MR1"  NA        "1"
```

Try the modified SEM model – better BIC, worse RMSEA

```
> sem2 <-sem(mod2,S=cov(latent$observed),N=200)
> summary(sem2)

 Model Chisquare =  36.86   Df =  35 Pr(>Chisq) = 0.38289
 Chisquare (null model) =  348.95   Df =  36
 Goodness-of-fit index =  0.96218
 Adjusted goodness-of-fit index =  0.95138
 RMSEA index =  0.016341   90% CI: (NA, 0.05442)
 Bentler-Bonnett NFI =  0.89437
 Tucker-Lewis NNFI =  0.99389
 Bentler CFI =  0.99406
 SRMR =  0.069728
 BIC =  -148.58

 Normalized Residuals
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
-2.2200 -0.6210 -0.0104 -0.0463  0.6660  2.1800

 Parameter Estimates
    Estimate Std Error z value Pr(>|z|)
a    0.55728  0.035522  15.6880 0        V1 <--- MR1
x1e 0.64944  0.072581   8.9478 0        V1 <--> V1
x2e 0.70441  0.077944   9.0374 0        V2 <--> V2
```

Convert the continuous data to 4 categories

A slightly devious use of the scrub function

```
> cat7 <- round(latent$observed)
> table(cat7)
cat7
 -3  -2  -1   0   1   2   3
 11 119 420 694 421 123  12

  #this does not work
 > cat4 <- scrub(cat7,isvalue=c(-3,-2,-1,0,1,2,3),newvalue=c(1,1,1,2,3
> table(cat4)cat4
   4
1800

#but this does
> cat4 <- scrub(cat7,isvalue=c(-3,-2,-1,0,1,2,3),newvalue=c(4,4,4,5,6,
> table(cat4)
cat4
  1   2   3   4
550 694 421 135
```

Compare the continuous to the categorical correlations

In general, the categorical correlations are smaller.

```
> r4 <- cor(cat4)
> round(r4,2)
     V1   V2   V3   V4   V5   V6   V7   V8   V9
V1 1.00 0.36 0.33 0.33 0.30 0.32 0.25 0.24 0.36
V2 0.36 1.00 0.31 0.39 0.29 0.28 0.25 0.17 0.28
V3 0.33 0.31 1.00 0.20 0.23 0.21 0.20 0.07 0.27
V4 0.33 0.39 0.20 1.00 0.30 0.25 0.25 0.24 0.25
V5 0.30 0.29 0.23 0.30 1.00 0.26 0.28 0.18 0.13
V6 0.32 0.28 0.21 0.25 0.26 1.00 0.18 0.17 0.22
V7 0.25 0.25 0.20 0.25 0.28 0.18 1.00 0.10 0.28
V8 0.24 0.17 0.07 0.24 0.18 0.17 0.10 1.00 0.25
V9 0.36 0.28 0.27 0.25 0.13 0.22 0.28 0.25 1.00
```

```
> round(latent$r - r4,2)
      V1    V2   V3   V4   V5    V6   V7   V8   V9
V1  0.00 -0.01 0.01 0.05 0.04  0.05 0.09 0.05 0.06
V2 -0.01  0.00 0.04 0.04 0.04 -0.06 0.05 0.05 0.06
V3  0.01  0.04 0.00 0.05 0.02  0.08 0.04 0.04 0.02
V4  0.05  0.04 0.05 0.00 0.03  0.05 0.02 0.05 0.10
V5  0.04  0.04 0.02 0.03 0.00  0.01 0.07 0.06 0.10
V6  0.05 -0.06 0.08 0.05 0.01  0.00 0.05 0.00 0.00
V7  0.09  0.05 0.04 0.02 0.07  0.05 0.00 0.07 0.01
V8  0.05  0.05 0.04 0.05 0.06  0.00 0.07 0.00 0.07
V9  0.06  0.06 0.02 0.10 0.10  0.00 0.01 0.07 0.00
```

What about the model fits?

EFA of 4 category data

```
> f4 <- fa(cat4)          Test of the hypothesis that 1 factor is sufficien
> f4                      The degrees of freedom for the null model are  36
Factor Analysis using         and the objective function was  1.39
      method =  minres                                        with Chi Squa
Call: fa(r = cat4)        The degrees of freedom for the model are 27
Standardized loadings based                     and the objective functi
upon correlation matrix
    MR1   h2   u2         The root mean square of the residuals is  0.03
V1 0.64 0.41 0.59         The df corrected root mean square of the residual
V2 0.60 0.36 0.64         The number of observations was  200  with
V3 0.46 0.21 0.79                               Chi Square =  20.99  with p
V4 0.56 0.32 0.68
V5 0.48 0.23 0.77         Tucker Lewis Index of factoring reliability =  1.
V6 0.47 0.22 0.78         RMSEA index =  0  and the 90 % confidence interva
V7 0.44 0.19 0.81         BIC =  -122.06
V8 0.35 0.12 0.88         Fit based upon off diagonal values = 0.98
V9 0.50 0.25 0.75         Measures of factor score adequacy
                                                                          M
                MR1       Correlation of scores with factors             0.
SS loadings    2.31       Multiple R square of scores with factors       0.
Proportion Var 0.26       Minimum correlation of possible factor scores  0.
```

What about the SEM model - It is actually better!

```
> sem4.1 <- sem(mod1,S=cov(cat4), N=200)
> summary(sem4.1)


 Model Chisquare =  21.476   Df =  27 Pr(>Chisq) = 0.76349
 Chisquare (null model) =  276.19   Df =  36
 Goodness-of-fit index =  0.9777
 Adjusted goodness-of-fit index =  0.96284
 RMSEA index =  0   90% CI: (NA, 0.039538)
 Bentler-Bonnett NFI =  0.92224
 Tucker-Lewis NNFI =  1.0307
 Bentler CFI =  1
 SRMR =  0.036341
 BIC =  -121.58

 Normalized Residuals
    Min.  1st Qu.   Median     Mean  3rd Qu.     Max.
-1.56000 -0.28400  0.00000 -0.00475  0.40000  1.01000
```

Try the SEM model with equal parameters

```
> sem4.2 <- sem(mod2,S=cov(cat4),N= 200)
> summary(sem4.2)

 Model Chisquare =  33.676   Df =  35 Pr(>Chisq) = 0.532
 Chisquare (null model) =  276.19   Df =  36
 Goodness-of-fit index =  0.96547
 Adjusted goodness-of-fit index =  0.9556
 RMSEA index =  0   90% CI: (NA, 0.048351)
 Bentler-Bonnett NFI =  0.87807
 Tucker-Lewis NNFI =  1.0057
 Bentler CFI =  1
 SRMR =  0.067984
 BIC =  -151.77

 Normalized Residuals
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
-2.2200 -0.6170 -0.0172 -0.0485  0.4700  1.8800
```

Polychorics correct for categorical data

Compare polychoric correlations to the Pearson

```
> rpoly <- polychoric(cat4)
Loading required package: mvtnorm
> round(rpoly$rho,2)
```

	V1	V2	V3	V4	V5	V6	V7	V8	V9
V1	1.00	0.42	0.36	0.39	0.36	0.36	0.29	0.28	0.40
V2	0.42	1.00	0.37	0.44	0.31	0.32	0.30	0.21	0.32
V3	0.36	0.37	1.00	0.22	0.28	0.23	0.23	0.07	0.28
V4	0.39	0.44	0.22	1.00	0.35	0.29	0.28	0.28	0.30
V5	0.36	0.31	0.28	0.35	1.00	0.29	0.33	0.21	0.14
V6	0.36	0.32	0.23	0.29	0.29	1.00	0.21	0.19	0.25
V7	0.29	0.30	0.23	0.28	0.33	0.21	1.00	0.12	0.32
V8	0.28	0.21	0.07	0.28	0.21	0.19	0.12	1.00	0.29
V9	0.40	0.32	0.28	0.30	0.14	0.25	0.32	0.29	1.00

```
> round(latent$r - rpoly$rho,2)
```

	V1	V2	V3	V4	V5	V6	V7	V8	
V1	0.00	-0.06	-0.02	0.00	-0.02	0.01	0.06	0.01	0.
V2	-0.06	0.00	-0.02	-0.01	0.02	-0.10	0.01	0.01	0.
V3	-0.02	-0.02	0.00	0.04	-0.03	0.05	0.01	0.04	0.
V4	0.00	-0.01	0.04	0.00	-0.01	0.02	-0.02	0.01	0.
V5	-0.02	0.02	-0.03	-0.01	0.00	-0.03	0.02	0.03	0.
V6	0.01	-0.10	0.05	0.02	-0.03	0.00	0.02	-0.03	-0.
V7	0.06	0.01	0.01	-0.02	0.02	0.02	0.00	0.05	-0.
V8	0.01	0.01	0.04	0.01	0.03	-0.03	0.05	0.00	0.
V9	0.01	0.01	0.00	0.05	0.09	-0.02	-0.03	0.03	0.

The residuals are much smaller, but what about SEM?

SEM model 1 on polychoric correlation matrix

```
> semp.1 <- sem(mod1,rpoly$rho,N=200)
> summary(semp.1)

 Model Chisquare =  33.745   Df =  27 Pr(>Chisq) = 0.17358
 Chisquare (null model) =  354.99   Df =  36
 Goodness-of-fit index =  0.96645
 Adjusted goodness-of-fit index =  0.94408
 RMSEA index =  0.035431   90% CI: (NA, 0.069201)
 Bentler-Bonnett NFI =  0.90494
 Tucker-Lewis NNFI =  0.9718
 Bentler CFI =  0.97886
 SRMR =  0.042953
 BIC =  -109.31

 Normalized Residuals
    Min.  1st Qu.   Median     Mean  3rd Qu.     Max.
-1.90000 -0.27200  0.00000 -0.00667  0.33000  1.18000
```

SEM on reduced model for polychoric correlations

```
> semp.2 <- sem(mod2,rpoly$rho,N=200)
> summary(semp.2)
```

```
Model Chisquare =  49.485   Df =  35 Pr(>Chisq) = 0.053178
Chisquare (null model) =  354.99   Df =  36
Goodness-of-fit index =  0.95117
Adjusted goodness-of-fit index =  0.93722
RMSEA index =  0.045603   90% CI: (NA, 0.073079)
Bentler-Bonnett NFI =  0.8606
Tucker-Lewis NNFI =  0.9533
Bentler CFI =  0.9546
SRMR =  0.080113
BIC =  -135.96

Normalized Residuals
  Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
-2.780  -0.804  -0.119  -0.088   0.509   2.060
```

Create dichotomous items from the original items

A simple recoding

```
> cat2 <- latent$observed
> cat2[cat2 < 0] <- 0
> cat2[cat2 > 0] <- 1
> table(cat2)
```

```
cat2
  0   1
895 905
```

Correlations of dichotomous variables are smaller yet

```
> r2 <- cor(cat2)
> round(r2,2)

     V1   V2   V3   V4   V5   V6   V7   V8   V9
V1 1.00 0.13 0.22 0.24 0.16 0.26 0.19 0.18 0.31
V2 0.13 1.00 0.19 0.13 0.14 0.23 0.14 0.14 0.17
V3 0.22 0.19 1.00 0.04 0.09 0.18 0.11 0.17 0.16
V4 0.24 0.13 0.04 1.00 0.15 0.14 0.19 0.03 0.18
V5 0.16 0.14 0.09 0.15 1.00 0.11 0.24 0.19 0.17
V6 0.26 0.23 0.18 0.14 0.11 1.00 0.15 0.13 0.14
V7 0.19 0.14 0.11 0.19 0.24 0.15 1.00 0.16 0.13
V8 0.18 0.14 0.17 0.03 0.19 0.13 0.16 1.00 0.15
V9 0.31 0.17 0.16 0.18 0.17 0.14 0.13 0.15 1.00
```

```
> round(latent$r - r2,2)

     V1    V2    V3   V4   V5    V6   V7    V8
V1 0.00  0.23  0.12 0.15 0.17  0.11 0.15  0.11 0
V2 0.23  0.00  0.16 0.30 0.19 -0.01 0.17  0.08 0
V3 0.12  0.16  0.00 0.22 0.15  0.11 0.13 -0.07 0
V4 0.15  0.30  0.22 0.00 0.18  0.16 0.07  0.25 0
V5 0.17  0.19  0.15 0.18 0.00  0.15 0.11  0.04 0
V6 0.11 -0.01  0.11 0.16 0.15  0.00 0.08  0.04 0
V7 0.15  0.17  0.13 0.07 0.11  0.08 0.00  0.01 0
V8 0.11  0.08 -0.07 0.25 0.04  0.04 0.01  0.00 0
V9 0.11  0.16  0.12 0.17 0.06  0.09 0.16  0.17 0
```

EFA on dichotomous data

```
> fa(cat2)

Factor Analysis using
 method =  minres
Call: fa(r = cat2)
Standardized loadings
based upon correlation matrix
    MR1   h2   u2
V1 0.55 0.31 0.69
V2 0.37 0.14 0.86
V3 0.36 0.13 0.87
V4 0.35 0.13 0.87
V5 0.37 0.14 0.86
V6 0.42 0.18 0.82
V7 0.39 0.15 0.85
V8 0.35 0.12 0.88
V9 0.45 0.20 0.80

                MR1
SS loadings    1.50
Proportion Var 0.17
```

```
Test of the hypothesis that 1 factor is sufficien
The degrees of freedom for the null model are  36
the objective function was  0.71 with
                   Chi Square of  139.28
The degrees of freedom for the model are 27  and
          the objective function was  0.1

The root mean square of the residuals is  0.03
The df corrected root mean square of the residual
The number of observations was  200  with
            Chi Square =  19.27  with prob <  0.8

Tucker Lewis Index of factoring reliability =  1.
RMSEA index =  0  and the 90 % confidence interva
BIC =  -123.79
Fit based upon off diagonal values = 0.93
Measures of factor score adequacy
                                                M
Correlation of scores with factors              0.
Multiple R square of scores with factors        0.
Minimum correlation of possible factor scores   0.
```

SEM of dichotomous data

```
> semd.1 <- sem(mod1,cov(cat2),N=200)
> summary(semd.1)


 Model Chisquare =  19.714   Df =  27 Pr(>Chisq) = 0.84254
 Chisquare (null model) =  142.01   Df =  36
 Goodness-of-fit index =  0.9783
 Adjusted goodness-of-fit index =  0.96384
 RMSEA index =  0   90% CI: (NA, 0.032607)
 Bentler-Bonnett NFI =  0.86118
 Tucker-Lewis NNFI =  1.0916
 Bentler CFI =  1
 SRMR =  0.039298
 BIC =  -123.34

 Normalized Residuals
    Min.  1st Qu.   Median     Mean  3rd Qu.     Max.
-1.28000 -0.21800  0.00000  0.00376  0.30800  1.30000
```

With parameter estimates of (based upon covariances)

```
 Parameter Estimates
     Estimate Std Error z value Pr(>|z|)
F1V1 0.27652  0.042768  6.4656  1.0090e-10 V1 <--- MR1
F1V2 0.18719  0.043634  4.2899  1.7873e-05 V2 <--- MR1
F1V3 0.18141  0.043373  4.1825  2.8834e-05 V3 <--- MR1
F1V4 0.17737  0.043468  4.0804  4.4950e-05 V4 <--- MR1
F1V5 0.18633  0.043381  4.2951  1.7460e-05 V5 <--- MR1
F1V6 0.21077  0.043083  4.8923  9.9686e-07 V6 <--- MR1
F1V7 0.19647  0.043405  4.5265  5.9956e-06 V7 <--- MR1
F1V8 0.17447  0.043338  4.0258  5.6782e-05 V8 <--- MR1
F1V9 0.22678  0.042843  5.2932  1.2019e-07 V9 <--- MR1
x1e  0.17175  0.023111  7.4316  1.0725e-13 V1 <--> V1
x2e  0.21612  0.023930  9.0310  0.0000e+00 V2 <--> V2
x3e  0.21812  0.023908  9.1234  0.0000e+00 V3 <--> V3
x4e  0.21957  0.023968  9.1610  0.0000e+00 V4 <--> V4
x5e  0.21403  0.023690  9.0346  0.0000e+00 V5 <--> V5
x6e  0.20681  0.023582  8.7697  0.0000e+00 V6 <--> V6
x7e  0.21255  0.023791  8.9342  0.0000e+00 V7 <--> V7
x8e  0.21921  0.023857  9.1886  0.0000e+00 V8 <--> V8
x9e  0.19920  0.023341  8.5342  0.0000e+00 V9 <--> V9
```

These may be converted to standardized coefficients

```
> std.coef(semd.1)

           Std. Estimate
F1V1 F1V1     0.5550216  V1 <--- MR1
F1V2 F1V2     0.3735111  V2 <--- MR1
F1V3 F1V3     0.3620711  V3 <--- MR1
F1V4 F1V4     0.3540061  V4 <--- MR1
F1V5 F1V5     0.3735918  V5 <--- MR1
F1V6 F1V6     0.4205076  V6 <--- MR1
F1V7 F1V7     0.3920419  V7 <--- MR1
F1V8 F1V8     0.3491852  V8 <--- MR1
F1V9 F1V9     0.4529830  V9 <--- MR1
x1e   x1e     0.6919511   V1 <--> V1
x2e   x2e     0.8604895   V2 <--> V2
x3e   x3e     0.8689045   V3 <--> V3
x4e   x4e     0.8746797   V4 <--> V4
x5e   x5e     0.8604292   V5 <--> V5
x6e   x6e     0.8231734   V6 <--> V6
x7e   x7e     0.8463032   V7 <--> V7
x8e   x8e     0.8780697   V8 <--> V8
x9e   x9e     0.7948064   V9 <--> V9
              1.0000000 MR1 <--> MR1
```

Force them to be equal

```
> summary(semd.2)


 Model Chisquare =  24.246   Df =  35 Pr(>Chisq) = 0.9139
 Chisquare (null model) =  142.01   Df =  36
 Goodness-of-fit index =  0.97392
 Adjusted goodness-of-fit index =  0.96646
 RMSEA index =  0   90% CI: (NA, 0.019814)
 Bentler-Bonnett NFI =  0.82927
 Tucker-Lewis NNFI =  1.1043
 Bentler CFI =  1
 SRMR =  0.049417
 BIC =  -161.20

 Normalized Residuals
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
-1.7800 -0.3270 -0.0650 -0.0126  0.3530  2.0700
 Parameter Estimates
    Estimate Std Error z value Pr(>|z|)
a    0.20280  0.016085  12.6077 0        V1 <--- MR1
x1e 0.19161  0.020953   9.1449 0        V1 <--> V1
x2e 0.21167  0.022865   9.2577 0        V2 <--> V2
x3e 0.21559  0.023250   9.2724 0        V3 <--> V3
```

Standardized coefficients for all equal model

```
> std.coef(semd.2)

        Std. Estimate
1     a     0.4203691  V1 <--- MR1
2     a     0.4033421  V2 <--- MR1
3     a     0.4002575  V3 <--- MR1
4     a     0.3984961  V4 <--- MR1
5     a     0.4048270  V5 <--- MR1
6     a     0.4059531  V6 <--- MR1
7     a     0.4047453  V7 <--- MR1
8     a     0.4008939  V8 <--- MR1
9     a     0.4086144  V9 <--- MR1
10 x1e      0.8232898   V1 <--> V1
11 x2e      0.8373151   V2 <--> V2
12 x3e      0.8397939   V3 <--> V3
13 x4e      0.8412009   V4 <--> V4
14 x5e      0.8361151   V5 <--> V5
15 x6e      0.8352021   V6 <--> V6
16 x7e      0.8361812   V7 <--> V7
17 x8e      0.8392841   V8 <--> V8
18 x9e      0.8330343   V9 <--> V9
19          1.0000000 MR1 <--> MR1
```

Use the tetrachoric correlation to see how well it fits

```
> rtet <- tetrachoric(cat2)
> round(rtet$rho,2)

     V1   V2   V3   V4   V5   V6   V7   V8   V9
V1 1.00 0.20 0.34 0.37 0.26 0.40 0.30 0.28 0.47
V2 0.20 1.00 0.29 0.20 0.22 0.35 0.22 0.22 0.27
V3 0.34 0.29 1.00 0.06 0.15 0.28 0.17 0.27 0.25
V4 0.37 0.20 0.06 1.00 0.24 0.22 0.30 0.05 0.28
V5 0.26 0.22 0.15 0.24 1.00 0.17 0.37 0.30 0.26
V6 0.40 0.35 0.28 0.22 0.17 1.00 0.23 0.21 0.22
V7 0.30 0.22 0.17 0.30 0.37 0.23 1.00 0.25 0.20
V8 0.28 0.22 0.27 0.05 0.30 0.21 0.25 1.00 0.23
V9 0.47 0.27 0.25 0.28 0.26 0.22 0.20 0.23 1.00
```

```
> round(latent$r - rtet$rho,2)

      V1    V2    V3    V4    V5    V6    V7    V8
V1  0.00  0.15  0.00  0.02  0.08 -0.03  0.04  0.01 -0.
V2  0.15  0.00  0.06  0.23  0.11 -0.13  0.09  0.00  0.
V3  0.00  0.06  0.00  0.20  0.10  0.01  0.07 -0.16  0.
V4  0.02  0.23  0.20  0.00  0.09  0.08 -0.03  0.23  0.
V5  0.08  0.11  0.10  0.09  0.00  0.09 -0.02 -0.06 -0.
V6 -0.03 -0.13  0.01  0.08  0.09  0.00  0.00 -0.04  0.
V7  0.04  0.09  0.07 -0.03 -0.02  0.00  0.00 -0.08  0.
V8  0.01  0.00 -0.16  0.23 -0.06 -0.04 -0.08  0.00  0.
V9 -0.05  0.06  0.03  0.07 -0.04  0.01  0.09  0.09  0.
```

SEM of tetrachoric matrix

```
> semdt.1 <- sem(mod1,rtet$rho,N=200)
> summary(semdt.1)

 Model Chisquare =  59.245   Df =  27 Pr(>Chisq) = 0.000331
 Chisquare (null model) =  316.61   Df =  36
 Goodness-of-fit index =  0.93886
 Adjusted goodness-of-fit index =  0.8981
 RMSEA index =  0.077468   90% CI: (0.050605, 0.10431)
 Bentler-Bonnett NFI =  0.81288
 Tucker-Lewis NNFI =  0.84679
 Bentler CFI =  0.88509
 SRMR =  0.06001
 BIC =  -83.81

 Normalized Residuals
    Min.  1st Qu.   Median     Mean  3rd Qu.     Max.
-1.98000 -0.31100  0.00001  0.01280  0.49200  1.99000
```

With standardized coefficients

```
> std.coef(semdt.1)

            Std. Estimate
F1V1 F1V1     0.6913730  V1 <--- MR1
F1V2 F1V2     0.4576086  V2 <--- MR1
F1V3 F1V3     0.4533130  V3 <--- MR1
F1V4 F1V4     0.4467387  V4 <--- MR1
F1V5 F1V5     0.4612190  V5 <--- MR1
F1V6 F1V6     0.5238008  V6 <--- MR1
F1V7 F1V7     0.4838795  V7 <--- MR1
F1V8 F1V8     0.4347005  V8 <--- MR1
F1V9 F1V9     0.5685366  V9 <--- MR1
x1e   x1e     0.5220034   V1 <--> V1
x2e   x2e     0.7905944   V2 <--> V2
x3e   x3e     0.7945073   V3 <--> V3
x4e   x4e     0.8004245   V4 <--> V4
x5e   x5e     0.7872770   V5 <--> V5
x6e   x6e     0.7256328   V6 <--> V6
x7e   x7e     0.7658606   V7 <--> V7
x8e   x8e     0.8110355   V8 <--> V8
x9e   x9e     0.6767661   V9 <--> V9
              1.0000000 MR1 <--> MR1
```

Equal loadings for tetrachoric correlations of dichotomized data

```
> semdt.2 <- sem(mod2,rtet$rho,N=200)
> summary(semdt.2)


 Model Chisquare =  69.536   Df =  35 Pr(>Chisq) = 0.000456
 Chisquare (null model) =  316.61   Df =  36
 Goodness-of-fit index =  0.93068
 Adjusted goodness-of-fit index =  0.91087
 RMSEA index =  0.070416   90% CI: (0.045789, 0.094538)
 Bentler-Bonnett NFI =  0.78038
 Tucker-Lewis NNFI =  0.87341
 Bentler CFI =  0.87693
 SRMR =  0.076466
 BIC =  -115.91

 Normalized Residuals
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
-2.6900 -0.5330 -0.1350 -0.0436  0.4750  3.0900

 Parameter Estimates
    Estimate Std Error z value Pr(>|z|)
a    0.50758  0.033854  14.9932 0        V1 <--- MR1
x1e  0.62738  0.070403   8.9113 0        V1 <--> V1
```

Standardized coefficients for the tetrachoric solution - equal paths

```
> std.coef(semdt.2)

        Std. Estimate
1     a      0.5395490  V1 <--- MR1
2     a      0.5033171  V2 <--- MR1
3     a      0.4968128  V3 <--- MR1
4     a      0.4931004  V4 <--- MR1
5     a      0.5030261  V5 <--- MR1
6     a      0.5101995  V6 <--- MR1
7     a      0.5067306  V7 <--- MR1
8     a      0.4958995  V8 <--- MR1
9     a      0.5157357  V9 <--- MR1
10 x1e      0.7088869   V1 <--> V1
11 x2e      0.7466719   V2 <--> V2
12 x3e      0.7531770   V3 <--> V3
13 x4e      0.7568520   V4 <--> V4
14 x5e      0.7469647   V5 <--> V5
15 x6e      0.7396964   V6 <--> V6
16 x7e      0.7432241   V7 <--> V7
17 x8e      0.7540837   V8 <--> V8
18 x9e      0.7340167   V9 <--> V9
19          1.0000000 MR1 <--> MR1
```

Comparing solutions

Table: Comparison of various models

Data	Method	χ^2 Null	χ^2 (model)	RMSEA	df	BIC
Continuous	EFA	342.23	24.02	0	27	-119.04
	CFA	348.95	24.57	0	27	-118.48
	CFA equal	348.95	36.86	0.016	35	-148.58
Categorical (4)	EFA	270.87	20.99	0	27	-122.06
	CFA	276.19	21.476	0	27	-121.58
	CFA equal	276.19	33.676	0	35	-151.77
Polychoric	EFA					
	CFA	354.99	33.745	0.035	27	-109.31
	CFA equal	354.99	49.485	0.045	35	-135.96
Dichotomous	EFA	139.28	19.27	0	27	-123.79
	CFA	142.01	19.714	0	27	-123.34
	CFA equal	142.01	24.246	0	35	-161.20
Tetrachoric	EFA					
	CFA	316.61	59.245	0.077	27	-83.81
	CFA equal	316.61	69.536	0.070	35	-115.91

Real data sets with item level data

- Several examples in *psych* have item level data
  - `iqitems` has 16 iq items collected on the web (need to score multiple choice to convert to true/false)
  - `ability` is the same 16 items already converted to True/False
  - `bfi` has 25 personality items supposedly representing 5 factors of personality (5 items per scale) with 6 alternatives.
  - `msq` has 72 emotion words (0-3 scale) aggregated from multiple studies. Structure can be found for 2-6 dimensions.
- Each data set may be analyzed for single factor data (one bfi scale, just arousal items from msq, g level of iq)

iq items

- Items collected as part of 'SAPA' project.
  - 16 items selected from 80 items.
  - Items were "home brewed" to reflect aspects of iq
  - Items are collected from the web with volunteer participants taking as long as they wanted (power condition) for each item
  - Raw responses in `iq.items`
  - Converted to True False (1/0) in `ability`
- Items can also be analyzed using Item Response Techniques (see `irt.fa`)

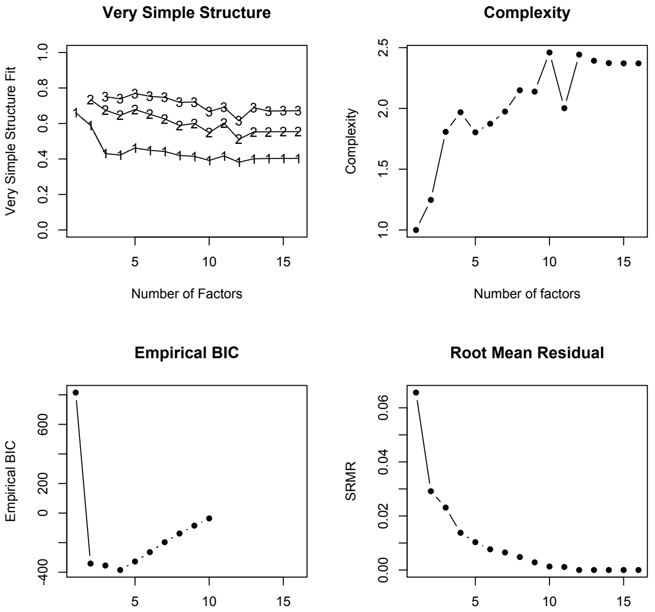
Find factor structure of ability items

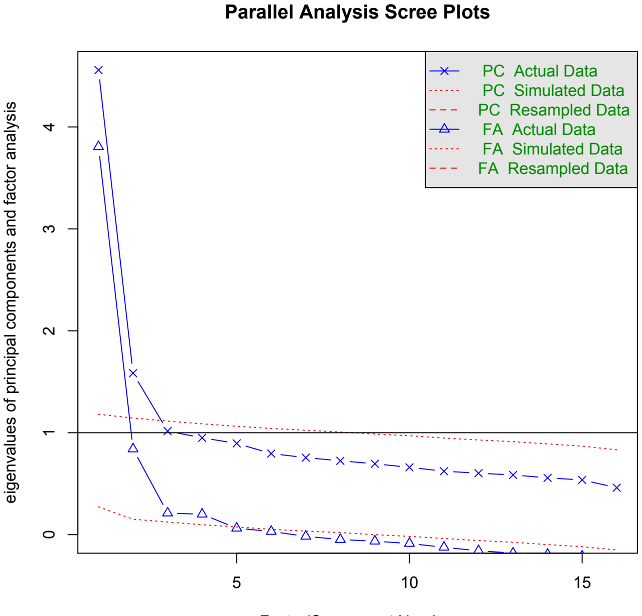
R code

```
nfactors(abilty)
fa.parallel(ability)
```

```
Number of factors
Call: vss(x = x, n = n, rotate = rotate, diagonal = diagonal, fm = fm,
    n.obs = n.obs, plot = FALSE, title = title, use = use, cor = cor)
VSS complexity 1 achieves a maximimum of 0.66  with  1  factors
VSS complexity 2 achieves a maximimum of 0.73  with  2  factors
The Velicer MAP achieves a minimum of 0.01  with  2  factors
Empirical BIC achieves a minimum of  -385.08  with  4  factors
Sample Size adjusted BIC achieves a minimum of  -187.29  with  4  factors

Statistics by number of factors
   vss1 vss2   map dof   chisq     prob sqresid  fit  RMSEA  BIC SABIC complex  eChisq
1  0.66 0.00 0.013 104 1.1e+03 9.9e-159    10.4 0.66 0.0780  301   631     1.0 1.6e+03 6.
2  0.59 0.73 0.012  89 2.8e+02  3.6e-21     8.1 0.73 0.0374 -375   -93     1.2 3.1e+02 2.
3  0.43 0.68 0.018  75 1.7e+02  5.3e-09     7.6 0.75 0.0286 -382  -144     1.8 2.0e+02 2.
4  0.42 0.65 0.024  62 7.0e+01  2.2e-01     6.8 0.78 0.0095 -384  -187     2.0 6.9e+01 1.
5  0.46 0.68 0.035  50 4.4e+01  7.1e-01     6.0 0.80 0.0000 -322  -164     1.8 3.9e+01 1.
6  0.45 0.65 0.046  39 2.4e+01  9.7e-01     5.9 0.81 0.0000 -262  -138     1.9 2.2e+01 7.
7  0.44 0.63 0.063  29 1.6e+01  9.8e-01     5.4 0.82 0.0000 -197  -104     2.0 1.5e+01 6.
8  0.42 0.59 0.084  20 9.7e+00  9.7e-01     5.6 0.82 0.0000 -137   -73     2.1 8.4e+00 4.
9  0.41 0.60 0.113  12 3.8e+00  9.9e-01     5.1 0.83 0.0000  -84   -46     2.1 2.9e+00 2.
10 0.39 0.55 0.164   5 7.9e-01  9.8e-01     5.4 0.82 0.0000  -36   -20     2.5 6.1e-01 1.
11 0.42 0.60 0.214  -1 5.4e-01       NA     4.8 0.84     NA   NA    NA     2.0 4.6e-01 1.
12 0.38 0.51 0.307  -6 8.9e-06       NA     4.8 0.84     NA   NA    NA     2.4 7.0e-06 4.
13 0.40 0.55 0.421 -10 6.7e-07       NA     5.3 0.83     NA   NA    NA     2.4 4.9e-07 1.
```


Very Simple Structure
Very Simple Structure Fit
Number of Factors
Complexity
Complexity
Number of factors
Empirical BIC
Empirical BIC
Root Mean Residual
SRMR


Parallel Analysis Scree Plots
eigenvalues of principal components and factor analysis
PC Actual Data
PC Simulated Data
PC Resampled Data
FA Actual Data
FA Simulated Data
FA Resampled Data
0
1
2
3
4
5
10
15

Factor the raw items

R code

```
ab.fa <- fa(ability,4)
ab.fa
```

```
Factor Analysis using method =  minres
Call: fa(r = ability, nfactors = 4)
Standardized loadings (pattern matrix) based upon correlation matrix
            MR2   MR1   MR4   MR3   h2   u2 com
reason.4   0.09  0.09  0.42  0.11 0.34 0.66 1.3
reason.16  0.05  0.15  0.32  0.03 0.23 0.77 1.5
reason.17 -0.02  0.00  0.73 -0.01 0.52 0.48 1.0
reason.19  0.04  0.17  0.32  0.07 0.25 0.75 1.7
letter.7   0.00  0.61  0.03 -0.01 0.39 0.61 1.0
letter.33  0.03  0.53  0.00  0.03 0.31 0.69 1.0
letter.34 -0.02  0.66  0.00  0.00 0.43 0.57 1.0
letter.58  0.16  0.35  0.12  0.02 0.28 0.72 1.7
matrix.45 -0.01 -0.01 -0.01  0.78 0.59 0.41 1.0
matrix.46  0.02  0.20  0.07  0.31 0.24 0.76 1.9
matrix.47  0.07  0.26  0.13  0.14 0.23 0.77 2.3
matrix.55  0.16  0.08  0.06  0.17 0.12 0.88 2.6
rotate.3   0.72  0.02 -0.06  0.01 0.50 0.50 1.0
rotate.4   0.72  0.08 -0.05 -0.01 0.54 0.46 1.0
rotate.6   0.58 -0.02  0.15 -0.03 0.41 0.59 1.1
rotate.8   0.63 -0.10  0.06  0.04 0.40 0.60 1.1

                       MR2  MR1  MR4  MR3
SS loadings           1.98 1.66 1.25 0.90
Proportion Var        0.12 0.10 0.08 0.06
```

Raw vs. Tetrachoric

R code

```
R <- lowerCor(ability)
RTet <- tetrachoric(ability)
Rcomp <- lowerUpper(lower=R,upper=RTet$rho)
 round(Rcomp,2)
```

	reason.4	reason.16	reason.17	reason.19	letter.7	letter.33	letter.34	letter.58	ma
reason.4	NA	0.45	0.61	0.46	0.45	0.37	0.46	0.47	
reason.16	0.28	NA	0.51	0.40	0.43	0.32	0.41	0.35	
reason.17	0.40	0.32	NA	0.53	0.47	0.42	0.47	0.48	
reason.19	0.30	0.25	0.34	NA	0.40	0.39	0.43	0.40	
letter.7	0.28	0.27	0.29	0.25	NA	0.52	0.60	0.51	
letter.33	0.23	0.20	0.26	0.25	0.34	NA	0.56	0.43	
letter.34	0.29	0.26	0.29	0.27	0.40	0.37	NA	0.50	
letter.58	0.29	0.21	0.29	0.25	0.33	0.28	0.32	NA	
matrix.45	0.25	0.18	0.20	0.22	0.20	0.20	0.21	0.19	
matrix.46	0.25	0.18	0.24	0.18	0.24	0.23	0.27	0.21	
matrix.47	0.24	0.24	0.27	0.23	0.27	0.23	0.30	0.23	
matrix.55	0.16	0.15	0.16	0.15	0.14	0.17	0.14	0.23	
rotate.3	0.23	0.16	0.17	0.18	0.18	0.17	0.19	0.24	
rotate.4	0.25	0.20	0.20	0.21	0.23	0.21	0.21	0.27	
rotate.6	0.25	0.20	0.27	0.19	0.20	0.21	0.19	0.26	
rotate.8	0.21	0.16	0.18	0.16	0.13	0.14	0.15	0.22	

Raw vs. Tetrachoric

R code

```
R <- lowerCor(ability)
RTet <- tetrachoric(ability)
Rcomp <- lowerUpper(lower=R,upper=RTet$rho)
 round(Rcomp,2)
```

```
Rcomp <- lowerUpper(lower=R,upper=RTet$rho,diff=TRUE)
> round(Rcomp,2)
            reason.4 reason.16 reason.17 reason.19 letter.7 letter.33 letter.34 letter.58
reason.4          NA     -0.17     -0.21     -0.17    -0.16     -0.14     -0.17     -0.18
reason.16       0.28        NA     -0.19     -0.15    -0.16     -0.13     -0.16     -0.14
reason.17       0.40      0.32        NA     -0.19    -0.18     -0.16     -0.18     -0.19
reason.19       0.30      0.25      0.34        NA    -0.14     -0.14     -0.15     -0.15
letter.7        0.28      0.27      0.29      0.25       NA     -0.18     -0.20     -0.18
letter.33       0.23      0.20      0.26      0.25     0.34        NA     -0.19     -0.15
letter.34       0.29      0.26      0.29      0.27     0.40      0.37        NA     -0.18
letter.58       0.29      0.21      0.29      0.25     0.33      0.28      0.32        NA
matrix.45       0.25      0.18      0.20      0.22     0.20      0.20      0.21      0.19
matrix.46       0.25      0.18      0.24      0.18     0.24      0.23      0.27      0.21
matrix.47       0.24      0.24      0.27      0.23     0.27      0.23      0.30      0.23
matrix.55       0.16      0.15      0.16      0.15     0.14      0.17      0.14      0.23
rotate.3        0.23      0.16      0.17      0.18     0.18      0.17      0.19      0.24
rotate.4        0.25      0.20      0.20      0.21     0.23      0.21      0.21      0.27
rotate.6        0.25      0.20      0.27      0.19     0.20      0.21      0.19      0.26
rotate.8        0.21      0.16      0.18      0.16     0.13      0.14      0.15      0.22
```

R code

```
ab.fa.tet <- fa(RTet$rho,4)
 ab.fa.tet
```

```
Factor Analysis using method =  minres
Call: fa(r = RTet$rho, nfactors = 4)
Standardized loadings (pattern matrix) based upon correlation matrix
            MR2   MR4   MR1   MR3   h2    u2 com
reason.4    0.22  0.18  0.34  0.16 0.51 0.489 2.9
reason.16   0.15  0.27  0.27  0.06 0.36 0.641 2.6
reason.17   0.00  0.03  0.97  0.00 0.98 0.024 1.0
reason.19   0.09  0.27  0.29  0.12 0.38 0.620 2.5
letter.7    0.00  0.76  0.03 -0.01 0.60 0.404 1.0
letter.33   0.03  0.62  0.03  0.04 0.46 0.542 1.0
letter.34  -0.02  0.79  0.01  0.02 0.63 0.366 1.0
letter.58   0.19  0.45  0.12  0.03 0.44 0.557 1.5
matrix.45  -0.01 -0.02 -0.01  0.90 0.79 0.212 1.0
matrix.46   0.01  0.23  0.09  0.41 0.38 0.615 1.7
matrix.47   0.13  0.33  0.11  0.19 0.36 0.635 2.3
matrix.55   0.22  0.08  0.02  0.24 0.21 0.793 2.2
rotate.3    0.88  0.05 -0.09  0.01 0.76 0.243 1.0
rotate.4    0.84  0.14 -0.06 -0.02 0.78 0.217 1.1
rotate.6    0.73 -0.05  0.21 -0.04 0.65 0.347 1.2
rotate.8    0.81 -0.14  0.07  0.07 0.65 0.347 1.1

                       MR2  MR4  MR1  MR3
SS loadings           3.18 2.66 1.71 1.40
Proportion Var        0.20 0.17 0.11 0.09
Cumulative Var        0.20 0.37 0.47 0.56
Proportion Explained  0.36 0.30 0.19 0.16
Cumulative Proportion 0.36 0.65 0.84 1.00
```

Factor the raw items

R code

```
ab.fa <- fa(ability,4)
ab.fa
```

```
Factor Analysis using method =  minres
Call: fa(r = ability, nfactors = 4)
Standardized loadings (pattern matrix) based upon correlation matrix
             MR2   MR1   MR4   MR3   h2   u2 com
reason.4    0.09  0.09  0.42  0.11 0.34 0.66 1.3
reason.16   0.05  0.15  0.32  0.03 0.23 0.77 1.5
reason.17  -0.02  0.00  0.73 -0.01 0.52 0.48 1.0
reason.19   0.04  0.17  0.32  0.07 0.25 0.75 1.7
letter.7    0.00  0.61  0.03 -0.01 0.39 0.61 1.0
letter.33   0.03  0.53  0.00  0.03 0.31 0.69 1.0
letter.34  -0.02  0.66  0.00  0.00 0.43 0.57 1.0
letter.58   0.16  0.35  0.12  0.02 0.28 0.72 1.7
matrix.45  -0.01 -0.01 -0.01  0.78 0.59 0.41 1.0
matrix.46   0.02  0.20  0.07  0.31 0.24 0.76 1.9
matrix.47   0.07  0.26  0.13  0.14 0.23 0.77 2.3
matrix.55   0.16  0.08  0.06  0.17 0.12 0.88 2.6
rotate.3    0.72  0.02 -0.06  0.01 0.50 0.50 1.0
rotate.4    0.72  0.08 -0.05 -0.01 0.54 0.46 1.0
rotate.6    0.58 -0.02  0.15 -0.03 0.41 0.59 1.1
rotate.8    0.63 -0.10  0.06  0.04 0.40 0.60 1.1

                       MR2  MR1  MR4  MR3
SS loadings           1.98 1.66 1.25 0.90
Proportion Var        0.12 0.10 0.08 0.06
```

Compare Omega estimates from Raw versus Tetrachoric

R code

```
om.ab <- omega(ability,4)
summary(om.ab)
```

```
Omega
Alpha:                 0.83
G.6:                   0.84
Omega Hierarchical:    0.65
Omega H asymptotic:    0.76
Omega Total            0.86

With eigenvalues of:
   g  F1*  F2*  F3*  F4*
3.04 1.32 0.46 0.42 0.55
The degrees of freedom for the model is 62  and the fit was  0.05
The number of observations was  1525  with Chi Square =  70.19  with prob <  0.22

The root mean square of the residuals is  0.01
The df corrected root mean square of the residuals is  0.02

RMSEA and the  0.1 confidence intervals are  0.01 NA 0.019
BIC =  -384.25Explained Common Variance of the general factor =  0.53

 Total, General and Subset omega for each subset
                                                 g  F1*  F2*  F3*  F4*
Omega total for total scores and subscales    0.86 0.77 0.69 0.64 0.53
Omega general for total scores and subscales  0.65 0.23 0.52 0.47 0.27
```

Compare Omega estimates from Raw versus Tetrachoric

R code

```
om.ab.tet <- omega(RTet$rho,4)
summary(om.ab.tet)
```

```
Omega
Alpha:                 0.91
G.6:                   0.92
Omega Hierarchical:    0.73
Omega H asymptotic:    0.78
Omega Total            0.94

With eigenvalues of:
   g  F1*  F2*  F3*  F4*
5.12 1.65 0.77 0.75 0.66
The degrees of freedom for the model is 62  and the fit was  0.23

The root mean square of the residuals is  0.02
The df corrected root mean square of the residuals is  0.04
Explained Common Variance of the general factor =  0.57

 Total, General and Subset omega for each subset
                                                 g  F1*  F2*  F3*  F4*
Omega total for total scores and subscales    0.94 0.90 0.82 0.68 0.76
Omega general for total scores and subscales  0.73 0.41 0.61 0.37 0.59
Omega group for total scores and subscales    0.11 0.50 0.21 0.32 0.18

 ob.ab <-omega(ability,4)
```

Compare Omega estimates from Raw versus Tetrachoric

R code

```
om.ab.tet <- omega(RTet$rho,4)
summary(om.ab.tet)
```

```
Omega
Alpha:                 0.91
G.6:                   0.92
Omega Hierarchical:    0.73
Omega H asymptotic:    0.78
Omega Total            0.94

With eigenvalues of:
   g  F1*  F2*  F3*  F4*
5.12 1.65 0.77 0.75 0.66

 ob.ab <-omega(ability,4)
> summary(om.ab)
Omega
Alpha:                 0.83
G.6:                   0.84
Omega Hierarchical:    0.65
Omega H asymptotic:    0.76
Omega Total            0.86

With eigenvalues of:
   g  F1*  F2*  F3*  F4*
3.04 1.32 0.46 0.42 0.55
```

Motivational State Questionnaire (MSQ)

- Items taken from several popular measures of mood.
  - Positive Affect - Negative Affect Scales (PANAS) (Watson, Clark & Tellegen, 1988)
  - Activation-Deactivation Adjective Check List (ADACL) (Thayer, 1970)
  - Circumplex measures of affect (Larsen & Diener, 1992)
- Given as part of all studies conducted in the Personality-Motivation-Cognition lab over 10 years.
- Total $N = 3896$

Larsen, R. J. & Diener, E. (1992). Promises and problems with the circumplex model of emotion. In M. S. Clark (Ed.), *Emotion* (pp. 25–59). Thousand Oaks, CA: Sage Publications, Inc.

Thayer, R. E. (1970). Activation states as assessed by verbal report and four psychophysiological variables. *Psychophysiology*, *7*(1), 86–94.

Watson, D., Clark, L. A., & Tellegen, A. (1988). Development and validation of brief measures of positive and negative affect: The PANAS scales. *Journal of Personality and Social Psychology*, *54*(6), 1063–1070.