More on items

Examining the effect of skew

Standard scales and tests

I. SEM/CFA tests are based upon normal theory

II. Scales are thought to

   A. Be normally distributed

   B. Have continuous responses

   C. Joint distributions of scales are multivariate normal distributed

III. In addition, scales are hoped to be reliable measures of one construct

But, we work with items

I. Items are

A. discrete

B. skewed

C. unreliable

D. possibly multi-vocal

Consider emotion words

Consider a simulation

I. Base line case
   A. 24 items with continuous scores
   B. simple structured on two factors
   C. average loadings of .6
   D. Sample size of 500
   E. (Default value of sim.item, except for number of variables)
II. Items with discrete scores
III. Skewed discrete items

Base line simulation

I. Using the sim.item function with default values except for number of items

Simple descriptives

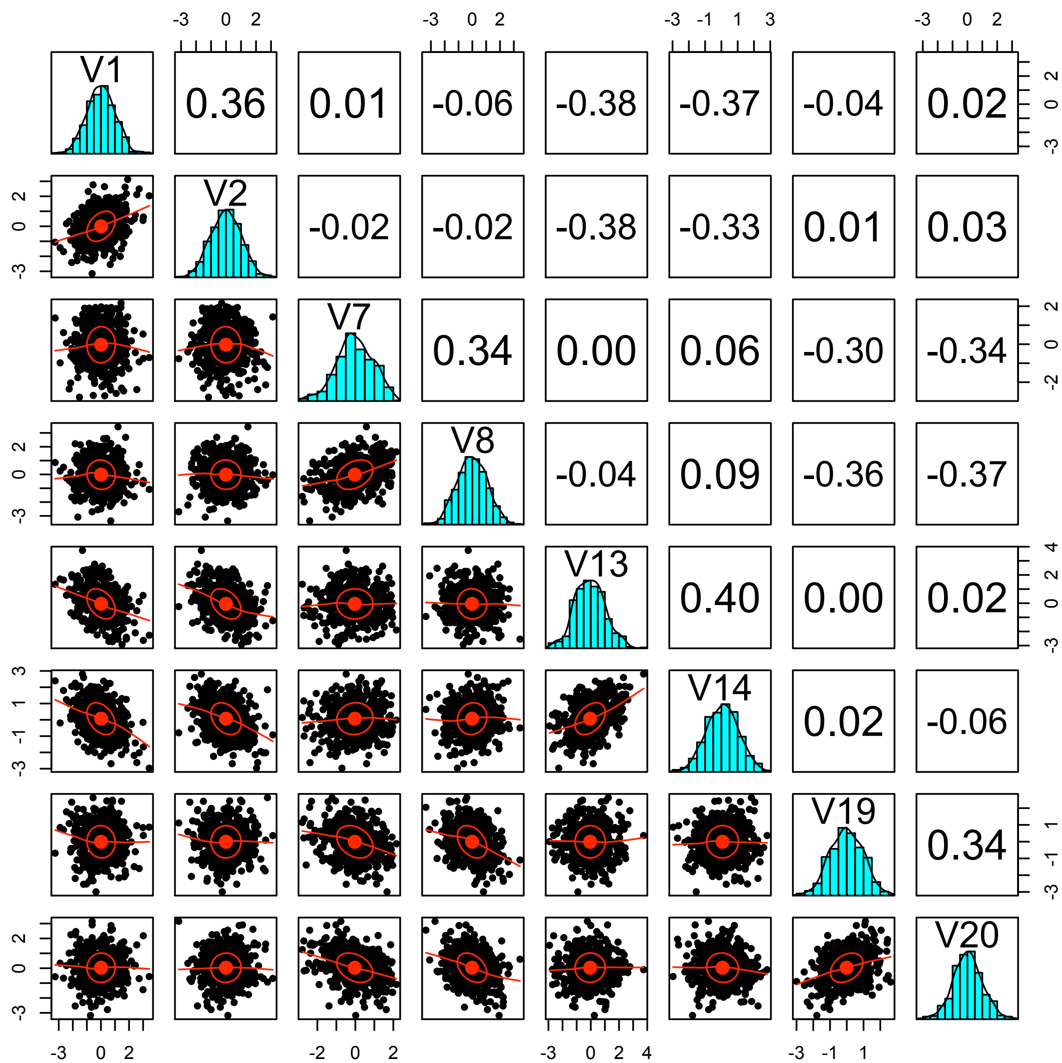
```
> describe(simple)
    var   n  mean   sd median trimmed  mad   min  max range  skew kurtosis   se
V1     1 500  0.01 1.01   0.03    0.01 0.97 -3.26 3.44  6.69  0.05     0.13 0.04
V2     2 500  0.00 1.00   0.00    0.00 1.05 -3.16 3.12  6.28  0.02    -0.14 0.04
V3     3 500 -0.03 1.05  -0.04   -0.04 1.06 -2.95 2.80  5.76  0.10    -0.28 0.05
V4     4 500 -0.04 1.03  -0.05   -0.04 1.07 -3.95 2.90  6.85  0.03     0.08 0.05
V5     5 500 -0.03 0.99  -0.01   -0.02 0.95 -4.04 4.07  8.12 -0.08     0.62 0.04
V6     6 500 -0.04 1.09  -0.07   -0.04 1.06 -3.34 2.96  6.30  0.02    -0.24 0.05
V7     7 500 -0.03 0.95  -0.04   -0.01 0.93 -2.79 2.16  4.95 -0.19    -0.17 0.04
V8     8 500 -0.02 1.07  -0.02   -0.02 1.12 -3.36 3.45  6.81  0.00    -0.17 0.05
V9     9 500  0.00 1.02  -0.01    0.00 1.05 -3.06 3.37  6.43  0.05    -0.27 0.05
V10   10 500  0.00 0.96   0.00    0.00 0.98 -3.37 2.98  6.35 -0.10     0.09 0.04
V11   11 500 -0.06 0.97  -0.09   -0.07 0.98 -3.16 2.92  6.08  0.12     0.07 0.04
V12   12 500 -0.06 0.97  -0.05   -0.07 0.97 -2.61 2.68  5.29  0.08    -0.19 0.04
V13   13 500 -0.05 1.07  -0.08   -0.07 1.11 -2.93 3.74  6.66  0.13    -0.01 0.05
V14   14 500  0.07 0.98   0.08    0.07 0.97 -2.97 2.81  5.78 -0.04    -0.19 0.04
V15   15 500  0.02 1.03  -0.05    0.01 1.03 -2.89 3.22  6.11  0.08    -0.10 0.05
V16   16 500  0.00 1.05   0.00   -0.01 1.02 -3.43 3.15  6.58  0.06    -0.06 0.05
V17   17 500 -0.03 1.05   0.01   -0.01 1.04 -3.27 3.09  6.36 -0.14     0.05 0.05
V18   18 500  0.03 1.04  -0.01    0.03 1.03 -3.04 3.40  6.44 -0.02     0.02 0.05
V19   19 500 -0.01 0.97  -0.02   -0.01 1.02 -2.99 2.62  5.62 -0.01    -0.23 0.04
V20   20 500  0.03 0.99   0.01    0.03 0.96 -3.17 3.15  6.33  0.04     0.26 0.04
V21   21 500 -0.02 1.05  -0.05   -0.02 1.05 -2.92 3.08  6.00  0.06    -0.08 0.05
V22   22 500  0.05 1.03   0.00    0.04 1.01 -3.15 3.06  6.21  0.04    -0.05 0.05
V23   23 500  0.03 0.98   0.02    0.02 0.95 -2.62 3.03  5.65  0.18     0.15 0.04
V24   24 500  0.02 0.98  -0.03    0.02 0.97 -3.58 3.23  6.81 -0.02     0.28 0.04
```

Continuous simple structured

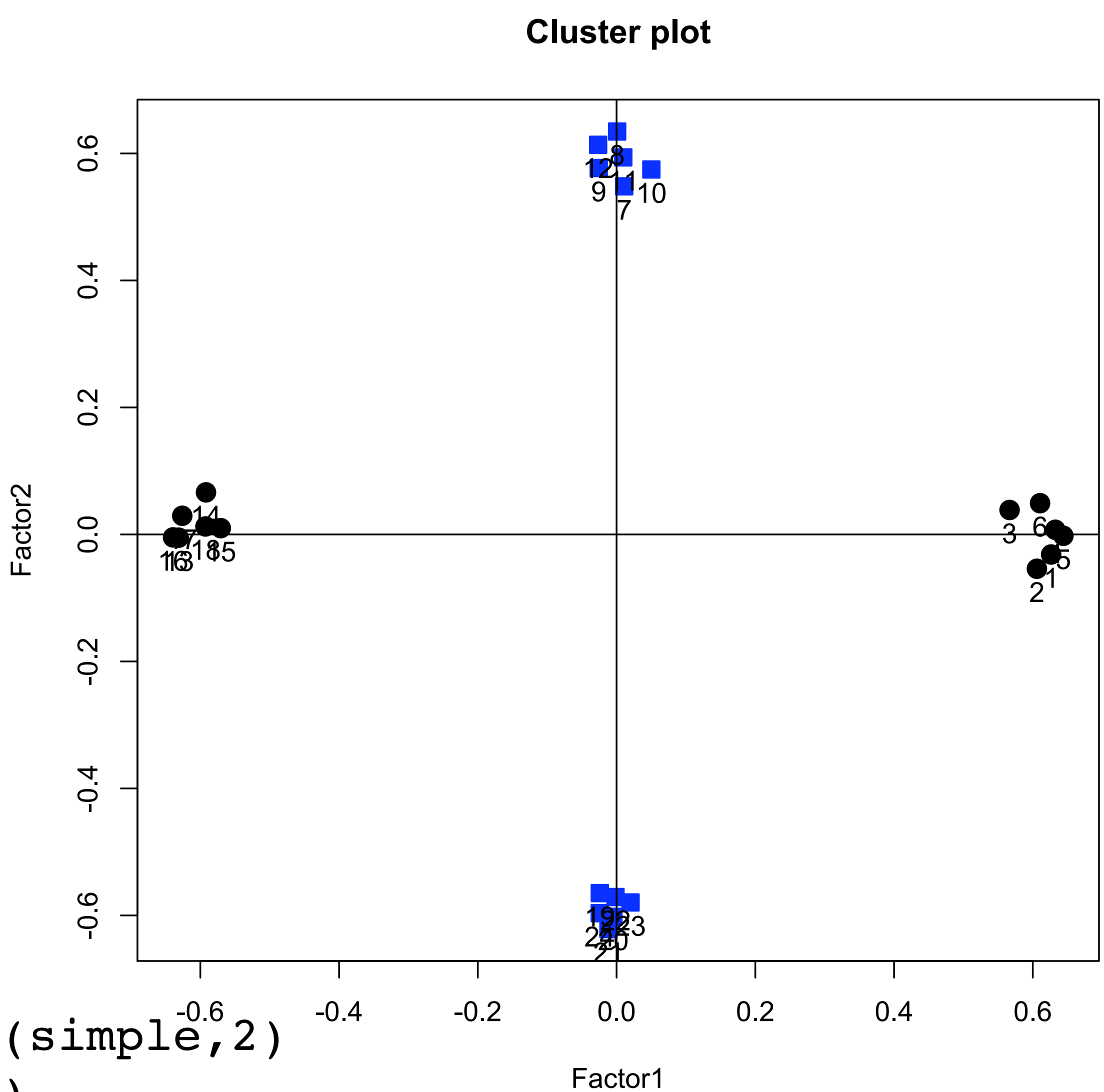
```
> set.seed(42)
> simple <- sim.item(24)
> colnames(simple) <- paste("V",1:24,sep="")
> round(cor(simple)[,1:12],2)
       V1    V2    V3    V4    V5    V6    V7    V8    V9   V10   V11   V12
V1   1.00  0.36  0.38  0.37  0.45  0.39  0.01 -0.06 -0.07  0.02 -0.01 -0.02
V2   0.36  1.00  0.37  0.36  0.40  0.40 -0.02 -0.02 -0.04 -0.01 -0.05 -0.07
V3   0.38  0.37  1.00  0.33  0.35  0.33  0.01 -0.02  0.06  0.05  0.09 -0.07
V4   0.37  0.36  0.33  1.00  0.39  0.43 -0.02 -0.03  0.01  0.05  0.00  0.01
V5   0.45  0.40  0.35  0.39  1.00  0.41  0.02  0.00 -0.01  0.04  0.00  0.00
V6   0.39  0.40  0.33  0.43  0.41  1.00  0.06  0.10  0.02  0.00  0.06  0.01
V7   0.01 -0.02  0.01 -0.02  0.02  0.06  1.00  0.34  0.29  0.29  0.34  0.37
V8  -0.06 -0.02 -0.02 -0.03  0.00  0.10  0.34  1.00  0.39  0.34  0.33  0.39
V9  -0.07 -0.04  0.06  0.01 -0.01  0.02  0.29  0.39  1.00  0.30  0.36  0.32
V10  0.02 -0.01  0.05  0.05  0.04  0.00  0.29  0.34  0.30  1.00  0.39  0.35
V11 -0.01 -0.05  0.09  0.00  0.00  0.06  0.34  0.33  0.36  0.39  1.00  0.38
V12 -0.02 -0.07 -0.07  0.01  0.00  0.01  0.37  0.39  0.32  0.35  0.38  1.00
V13 -0.38 -0.38 -0.39 -0.40 -0.41 -0.36  0.00 -0.04  0.02 -0.05  0.00  0.01
V14 -0.37 -0.33 -0.36 -0.42 -0.39 -0.30  0.06  0.09  0.07  0.01  0.02  0.03
V15 -0.38 -0.35 -0.29 -0.37 -0.32 -0.35  0.00  0.00  0.04 -0.06  0.03  0.00
V16 -0.38 -0.35 -0.36 -0.41 -0.42 -0.37 -0.03 -0.01 -0.01 -0.01 -0.02  0.04
V17 -0.37 -0.40 -0.32 -0.42 -0.39 -0.39  0.01  0.02  0.03 -0.02  0.04  0.06
V18 -0.37 -0.38 -0.37 -0.35 -0.39 -0.38  0.00 -0.03  0.08 -0.02 -0.01 -0.01
V19 -0.04  0.01 -0.01 -0.03 -0.02 -0.03 -0.30 -0.36 -0.29 -0.36 -0.33 -0.36
V20  0.02  0.03 -0.04  0.00  0.00 -0.01 -0.34 -0.37 -0.39 -0.35 -0.35 -0.33
V21  0.00  0.00  0.00 -0.05  0.02 -0.01 -0.34 -0.39 -0.38 -0.37 -0.31 -0.39
V22  0.05  0.03 -0.05 -0.03  0.03 -0.03 -0.35 -0.37 -0.35 -0.31 -0.34 -0.34
V23 -0.02  0.10 -0.04  0.03  0.03  0.01 -0.28 -0.37 -0.31 -0.36 -0.36 -0.37
V24  0.04 -0.01 -0.06  0.00 -0.03 -0.05 -0.33 -0.42 -0.34 -0.33 -0.37 -0.37
```

SPLOM

```
pairs.panels(simple[,c(1,2,7,8,13,14,19,20)])
```



Clear two factor structure




```
> f2 <- factanal(simple,2)
> factor.plot(f2)
```

Clear 2 factor solution

```
Call:
factanal(x = simple, factors = 2)
Uniquenesses:
   V1    V2    V3    V4    V5    V6    V7    V8    V9   V10   V11   V12   V13   V14
V15   V16   V17   V18   V19   V20   V21   V22 V23   V24
0.607 0.630 0.678 0.600 0.585 0.625 0.699 0.597 0.666 0.667 0.647 0.623 0.602 0.645
0.674 0.591 0.607 0.649 0.680 0.637 0.614 0.674 0.664 0.644
Loadings:
    Factor1 Factor2
V1   0.626
V2   0.606
V3   0.567
V4   0.632
V5   0.644
V6   0.610
V7           0.548
V8           0.635
V9           0.577
V10          0.575
V11          0.594
V12          0.614
V13 -0.631
V14 -0.592
V15 -0.571
V16 -0.639
V17 -0.626
V18 -0.593
V19         -0.565
V20         -0.602
V21         -0.622
V22         -0.571
V23         -0.580
V24         -0.597
```

```
Test of the hypothesis that 2 factors
are sufficient.
The chi square statistic is 217.99 on
229 degrees of freedom.
The p-value is 0.689
```

```
                 Factor1 Factor2
SS loadings        4.500   4.195
Proportion Var     0.188   0.175
Cumulative Var     0.188   0.362
```

Categorical items

I. using the sim.item function with categorical=TRUE

   A. This just rounds items to integer values

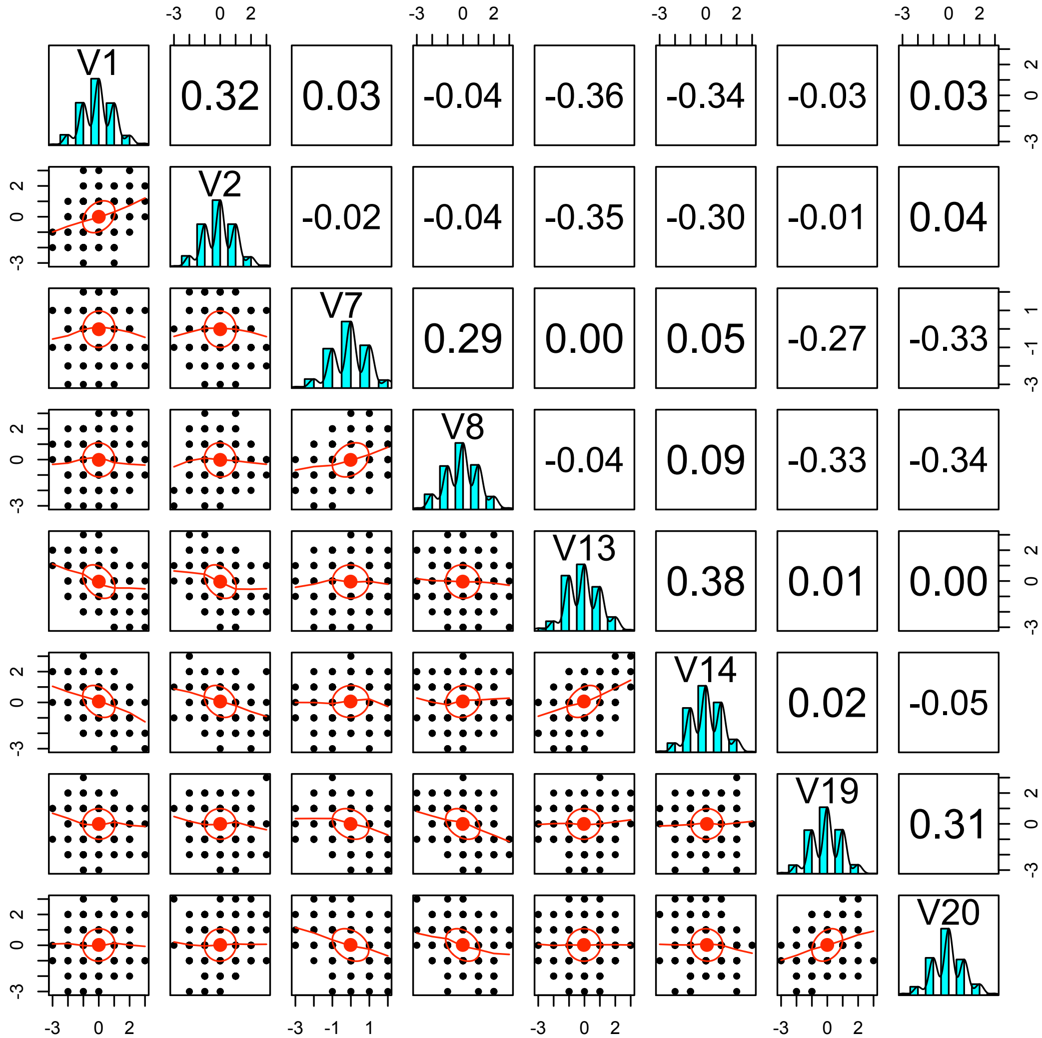
   B. Setting other parameters to default values

Categorical items

```
> set.seed(42)
> cate <- sim.item(24,categorical=TRUE)
> colnames(cate) <- paste("V",1:24,sep="")
> describe(cate)
    var   n  mean   sd median trimmed  mad min max range  skew kurtosis   se
V1    1 500  0.00 1.05      0    0.00 1.48  -3   3     6  0.06     0.03 0.05
V2    2 500  0.00 1.03      0    0.00 1.48  -3   3     6  0.05    -0.08 0.05
V3    3 500 -0.04 1.07      0   -0.06 1.48  -3   3     6  0.15    -0.23 0.05
V4    4 500 -0.04 1.07      0   -0.04 1.48  -3   3     6  0.11    -0.05 0.05
V5    5 500 -0.01 1.00      0   -0.01 1.48  -3   3     6 -0.03     0.04 0.04
V6    6 500 -0.04 1.13      0   -0.06 1.48  -3   3     6  0.02    -0.34 0.05
V7    7 500 -0.02 0.99      0    0.01 1.48  -3   2     5 -0.21    -0.09 0.04
V8    8 500 -0.02 1.11      0   -0.01 1.48  -3   3     6 -0.02    -0.22 0.05
V9    9 500  0.01 1.06      0    0.00 1.48  -3   3     6  0.04    -0.37 0.05
V10  10 500  0.00 1.01      0    0.02 1.48  -3   3     6 -0.14    -0.10 0.05
V11  11 500 -0.04 1.00      0   -0.06 1.48  -3   3     6  0.10    -0.01 0.04
V12  12 500 -0.08 1.02      0   -0.08 1.48  -3   3     6  0.08    -0.22 0.05
V13  13 500 -0.04 1.09      0   -0.06 1.48  -3   3     6  0.03    -0.08 0.05
V14  14 500  0.06 1.04      0    0.06 1.48  -3   3     6 -0.06    -0.22 0.05
V15  15 500  0.02 1.05      0    0.01 1.48  -3   3     6  0.05    -0.30 0.05
V16  16 500  0.00 1.08      0   -0.02 1.48  -3   3     6  0.15    -0.05 0.05
V17  17 500 -0.03 1.08      0   -0.03 1.48  -3   3     6 -0.08    -0.01 0.05
V18  18 500  0.04 1.08      0    0.05 1.48  -3   3     6 -0.14    -0.11 0.05
V19  19 500 -0.01 0.99      0    0.00 1.48  -3   3     6 -0.07    -0.15 0.04
V20  20 500  0.02 1.05      0    0.01 1.48  -3   3     6  0.04     0.22 0.05
V21  21 500 -0.02 1.11      0   -0.03 1.48  -3   3     6  0.09    -0.20 0.05
V22  22 500  0.04 1.05      0    0.02 1.48  -3   3     6  0.00    -0.13 0.05
V23  23 500  0.02 1.02      0   -0.01 1.48  -3   3     6  0.17     0.03 0.05
V24  24 500  0.05 1.02      0    0.04 1.48  -3   3     6 -0.01    -0.10 0.05
```

SPLOM (selected variables)

```
pairs.panels(cate[,c(1,2,7,8,13,14,19,20)])
```

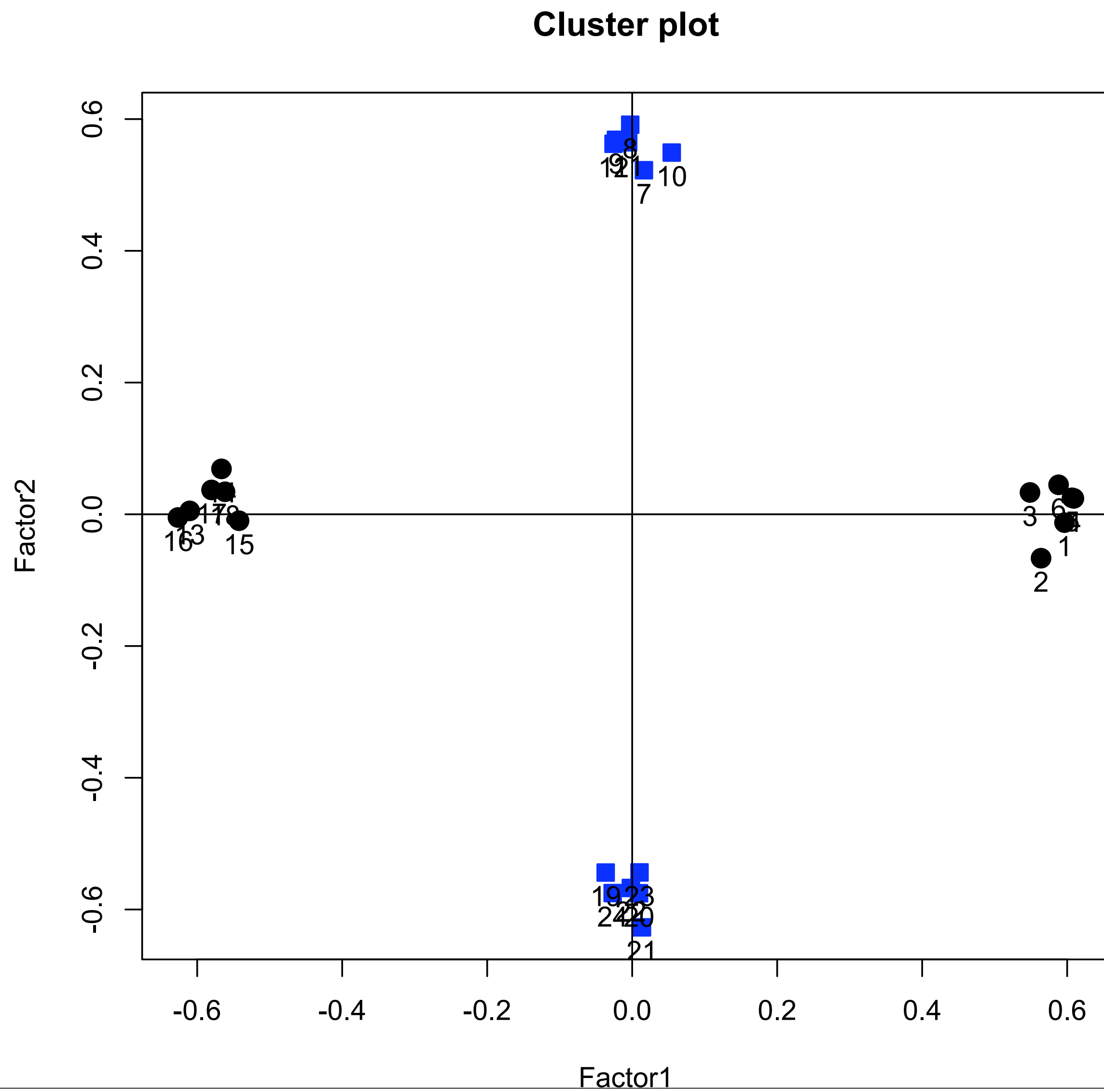


Correlations similar to original

```
> colnames(cate) <- paste("V",1:24,sep="")
> round(cor(cate)[,1:12],2)
       V1    V2    V3    V4    V5    V6    V7    V8    V9   V10   V11   V12
V1   1.00  0.32  0.35  0.33  0.42  0.35  0.03 -0.04 -0.05  0.03  0.01 -0.03
V2   0.32  1.00  0.33  0.33  0.34  0.35 -0.02 -0.04 -0.05  0.00 -0.07 -0.05
V3   0.35  0.33  1.00  0.31  0.32  0.30  0.01 -0.01  0.07  0.06  0.07 -0.10
V4   0.33  0.33  0.31  1.00  0.35  0.40  0.01 -0.02  0.03  0.05  0.01  0.02
V5   0.42  0.34  0.32  0.35  1.00  0.39  0.05  0.01  0.01  0.07  0.00  0.01
V6   0.35  0.35  0.30  0.40  0.39  1.00  0.06  0.09  0.03  0.00  0.04  0.02
V7   0.03 -0.02  0.01  0.01  0.05  0.06  1.00  0.29  0.27  0.25  0.33  0.32
V8  -0.04 -0.04 -0.01 -0.02  0.01  0.09  0.29  1.00  0.37  0.29  0.28  0.33
V9  -0.05 -0.05  0.07  0.03  0.01  0.03  0.27  0.37  1.00  0.32  0.33  0.26
V10  0.03  0.00  0.06  0.05  0.07  0.00  0.25  0.29  0.32  1.00  0.36  0.31
V11  0.01 -0.07  0.07  0.01  0.00  0.04  0.33  0.28  0.33  0.36  1.00  0.34
V12 -0.03 -0.05 -0.10  0.02  0.01  0.02  0.32  0.33  0.26  0.31  0.34  1.00
V13 -0.36 -0.35 -0.37 -0.38 -0.36 -0.31  0.00 -0.04  0.04 -0.06  0.03  0.02
V14 -0.34 -0.30 -0.32 -0.37 -0.36 -0.29  0.05  0.09  0.09  0.02  0.01  0.03
V15 -0.36 -0.34 -0.29 -0.34 -0.26 -0.30 -0.02 -0.02  0.06 -0.07  0.03 -0.02
V16 -0.34 -0.32 -0.34 -0.37 -0.38 -0.36 -0.01  0.00 -0.02 -0.02  0.02  0.03
V17 -0.33 -0.33 -0.28 -0.40 -0.32 -0.34  0.03  0.03  0.03  0.01  0.04  0.05
V18 -0.33 -0.34 -0.33 -0.31 -0.36 -0.36  0.02  0.01  0.05 -0.02  0.02  0.00
V19 -0.03 -0.01  0.00 -0.02 -0.05 -0.03 -0.27 -0.33 -0.27 -0.33 -0.32 -0.32
V20  0.03  0.04 -0.02 -0.01  0.02 -0.01 -0.33 -0.34 -0.36 -0.32 -0.31 -0.30
V21  0.00  0.04  0.02 -0.05  0.01  0.00 -0.31 -0.36 -0.38 -0.35 -0.31 -0.37
V22  0.02  0.06 -0.04 -0.04  0.01 -0.02 -0.34 -0.35 -0.34 -0.29 -0.32 -0.30
V23 -0.04  0.09 -0.06  0.03  0.03  0.01 -0.24 -0.33 -0.28 -0.33 -0.31 -0.33
V24  0.01 -0.02 -0.06 -0.01 -0.06 -0.04 -0.31 -0.40 -0.33 -0.29 -0.32 -0.34
```

Factor structure similar

```
> f2 <- factanal(cate,2)
> factor.plot(f2)
```



```
Call:
factanal(x = cate, factors = 2)
Uniquenesses:
   V1    V2    V3    V4    V5    V6    V7    V8    V9   V10   V11   V12   V13   V14   V15   V16   V17
V18   V19   V20   V21   V22  V23   V24
0.644 0.677 0.698 0.628 0.631 0.652 0.727 0.650 0.676 0.695 0.681 0.683 0.628 0.674 0.706 0.607 0.662
0.683 0.703 0.669 0.607 0.678  0.704 0.669
Loadings:
    Factor1 Factor2
V1   0.596
V2   0.564
V3   0.549
V4   0.609
V5   0.607
V6   0.588
V7           0.522
V8           0.591
V9           0.569
V10          0.549
V11          0.565
V12          0.563
V13 -0.610
V14 -0.567
V15 -0.542
V16 -0.626
V17 -0.580
V18 -0.562
V19         -0.544
V20         -0.575
V21         -0.627
V22         -0.567
V23         -0.544
V24         -0.575
               Factor1 Factor2
SS loadings      4.099   3.867
Proportion Var   0.171   0.161
Cumulative Var   0.171   0.332
Test of the hypothesis that 2 factors are sufficient.
The chi square statistic is 235.68 on 229 degrees of freedom.
The p-value is 0.367
```

Chi Squares are similar

Skewed items

I. Simulate 24 items representing two factors

II. 6 positive and negative on each factor

III. Items differ in skew

   A. skew created by truncating items to positive values

   B. items differing in base value (add .5 to y coordinate before cutting)

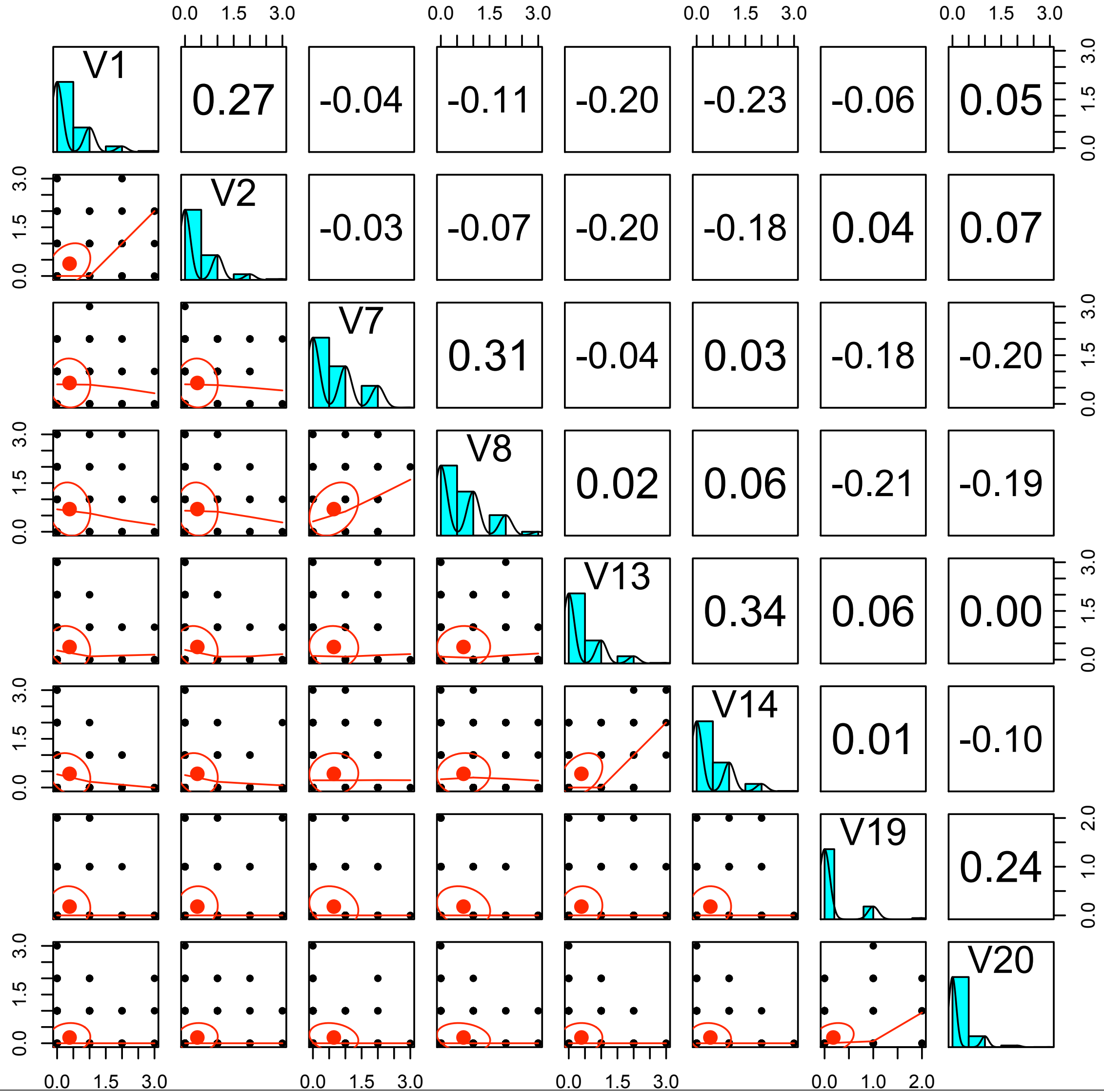
   C.

```
> set.seed(42)
> simp <- sim.item(24,ybias=.5,categorical=TRUE,low=0,truncate=TRUE)
> colnames(simp) <- paste("V",1:24,sep="")
```

Descriptive statistics

```
> describe(simp)
    var   n mean   sd median trimmed  mad min max range skew kurtosis   se
V1    1 500 0.38 0.64    0.0    0.26 0.00   0   3     3 1.65     2.37 0.03
V2    2 500 0.38 0.63    0.0    0.26 0.00   0   3     3 1.61     2.18 0.03
V3    3 500 0.38 0.64    0.0    0.25 0.00   0   3     3 1.63     2.09 0.03
V4    4 500 0.38 0.64    0.0    0.24 0.00   0   3     3 1.70     2.44 0.03
V5    5 500 0.36 0.60    0.0    0.25 0.00   0   3     3 1.62     2.29 0.03
V6    6 500 0.41 0.67    0.0    0.26 0.00   0   3     3 1.44     1.05 0.03
V7    7 500 0.64 0.76    0.0    0.55 0.00   0   3     3 0.72    -0.81 0.03
V8    8 500 0.70 0.82    0.0    0.59 0.00   0   3     3 0.91    -0.08 0.04
V9    9 500 0.69 0.81    0.0    0.58 0.00   0   3     3 0.92     0.01 0.04
V10  10 500 0.67 0.77    0.5    0.56 0.74   0   3     3 0.89     0.00 0.03
V11  11 500 0.62 0.80    0.0    0.49 0.00   0   3     3 1.18     0.77 0.04
V12  12 500 0.65 0.77    0.0    0.54 0.00   0   3     3 0.95     0.12 0.03
V13  13 500 0.39 0.65    0.0    0.26 0.00   0   3     3 1.54     1.62 0.03
V14  14 500 0.42 0.64    0.0    0.30 0.00   0   3     3 1.33     0.96 0.03
V15  15 500 0.41 0.64    0.0    0.28 0.00   0   3     3 1.45     1.45 0.03
V16  16 500 0.40 0.67    0.0    0.26 0.00   0   3     3 1.65     2.14 0.03
V17  17 500 0.38 0.64    0.0    0.26 0.00   0   3     3 1.51     1.42 0.03
V18  18 500 0.41 0.65    0.0    0.29 0.00   0   3     3 1.38     1.03 0.03
V19  19 500 0.18 0.42    0.0    0.08 0.00   0   2     2 2.21     4.21 0.02
V20  20 500 0.18 0.45    0.0    0.07 0.00   0   3     3 2.65     7.34 0.02
V21  21 500 0.18 0.47    0.0    0.06 0.00   0   3     3 2.67     7.16 0.02
V22  22 500 0.21 0.50    0.0    0.10 0.00   0   3     3 2.39     5.43 0.02
V23  23 500 0.19 0.47    0.0    0.07 0.00   0   3     3 2.63     6.87 0.02
V24  24 500 0.17 0.44    0.0    0.06 0.00   0   3     3 2.70     7.67 0.02
```

Skew differentially affects r



correlations with skew

```
> round(cor(simp)[,1:12],2)
       V1    V2    V3    V4    V5    V6    V7    V8    V9   V10   V11   V12
V1   1.00  0.27  0.26  0.30  0.33  0.29 -0.04 -0.11 -0.08 -0.01 -0.02 -0.05
V2   0.27  1.00  0.28  0.25  0.28  0.33 -0.03 -0.07 -0.07  0.01 -0.05 -0.06
V3   0.26  0.28  1.00  0.27  0.31  0.26  0.01  0.01  0.10  0.07  0.09 -0.07
V4   0.30  0.25  0.27  1.00  0.21  0.29 -0.05 -0.05  0.06  0.05 -0.02 -0.05
V5   0.33  0.28  0.31  0.21  1.00  0.30  0.05  0.01  0.00  0.03  0.03  0.01
V6   0.29  0.33  0.26  0.29  0.30  1.00  0.05  0.05  0.01 -0.01  0.07 -0.01
V7  -0.04 -0.03  0.01 -0.05  0.05  0.05  1.00  0.31  0.26  0.24  0.26  0.32
V8  -0.11 -0.07  0.01 -0.05  0.01  0.05  0.31  1.00  0.34  0.31  0.26  0.33
V9  -0.08 -0.07  0.10  0.06  0.00  0.01  0.26  0.34  1.00  0.25  0.32  0.36
V10 -0.01  0.01  0.07  0.05  0.03 -0.01  0.24  0.31  0.25  1.00  0.28  0.27
V11 -0.02 -0.05  0.09 -0.02  0.03  0.07  0.26  0.26  0.32  0.28  1.00  0.30
V12 -0.05 -0.06 -0.07 -0.05  0.01 -0.01  0.32  0.33  0.36  0.27  0.30  1.00
V13 -0.20 -0.20 -0.23 -0.24 -0.24 -0.19 -0.04  0.02  0.01 -0.02  0.01  0.00
V14 -0.23 -0.18 -0.21 -0.20 -0.22 -0.17  0.03  0.06  0.06  0.07  0.01  0.01
V15 -0.19 -0.19 -0.20 -0.18 -0.12 -0.23 -0.04 -0.07  0.02 -0.07  0.02 -0.03
V16 -0.18 -0.18 -0.24 -0.18 -0.23 -0.23 -0.08 -0.08 -0.02 -0.01 -0.05  0.03
V17 -0.17 -0.22 -0.16 -0.25 -0.22 -0.19 -0.04  0.00  0.01 -0.01  0.02  0.03
V18 -0.17 -0.18 -0.22 -0.20 -0.21 -0.23 -0.03 -0.03  0.08 -0.04  0.03 -0.03
V19 -0.06  0.04 -0.01 -0.04 -0.06  0.00 -0.18 -0.21 -0.15 -0.20 -0.11 -0.20
V20  0.05  0.07 -0.01  0.03  0.05  0.00 -0.20 -0.19 -0.16 -0.18 -0.16 -0.17
V21  0.04 -0.02 -0.02 -0.01 -0.03 -0.01 -0.19 -0.20 -0.22 -0.16 -0.12 -0.20
V22  0.04  0.00 -0.02 -0.01  0.03  0.02 -0.16 -0.23 -0.21 -0.23 -0.14 -0.23
V23 -0.03  0.08 -0.02  0.02  0.02 -0.02 -0.22 -0.22 -0.18 -0.22 -0.22 -0.19
V24  0.00  0.04  0.00 -0.04 -0.02 -0.05 -0.19 -0.19 -0.17 -0.22 -0.18 -0.18
```

Alternative models

I. Factor model (2-4 factors)

II. Cluster model (most appropriate for items)

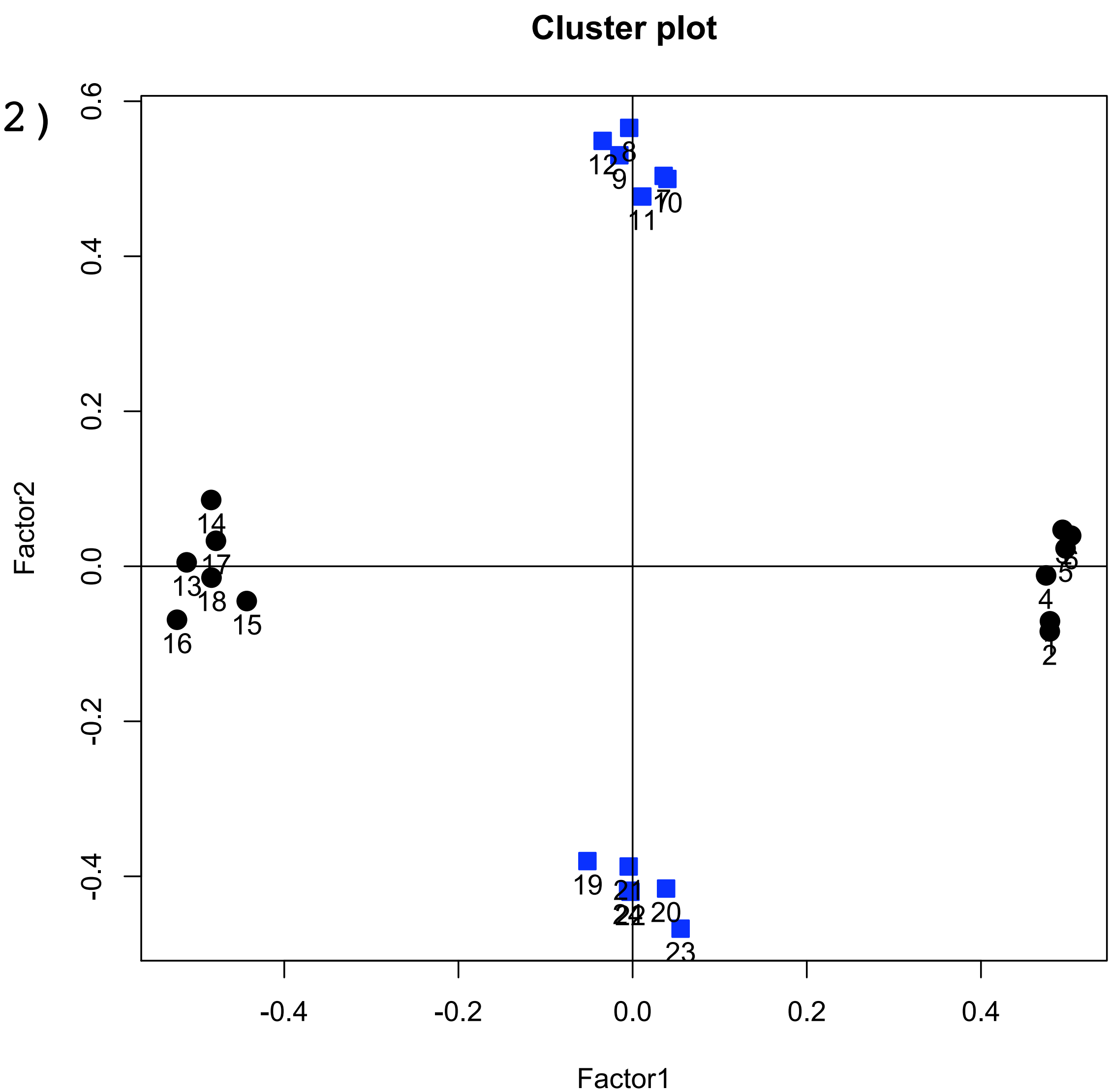
III. sem model based upon factor model

IV. sem model with correlated factors

V. sem model with bi-factor solution

Clear 2 dimensional structure

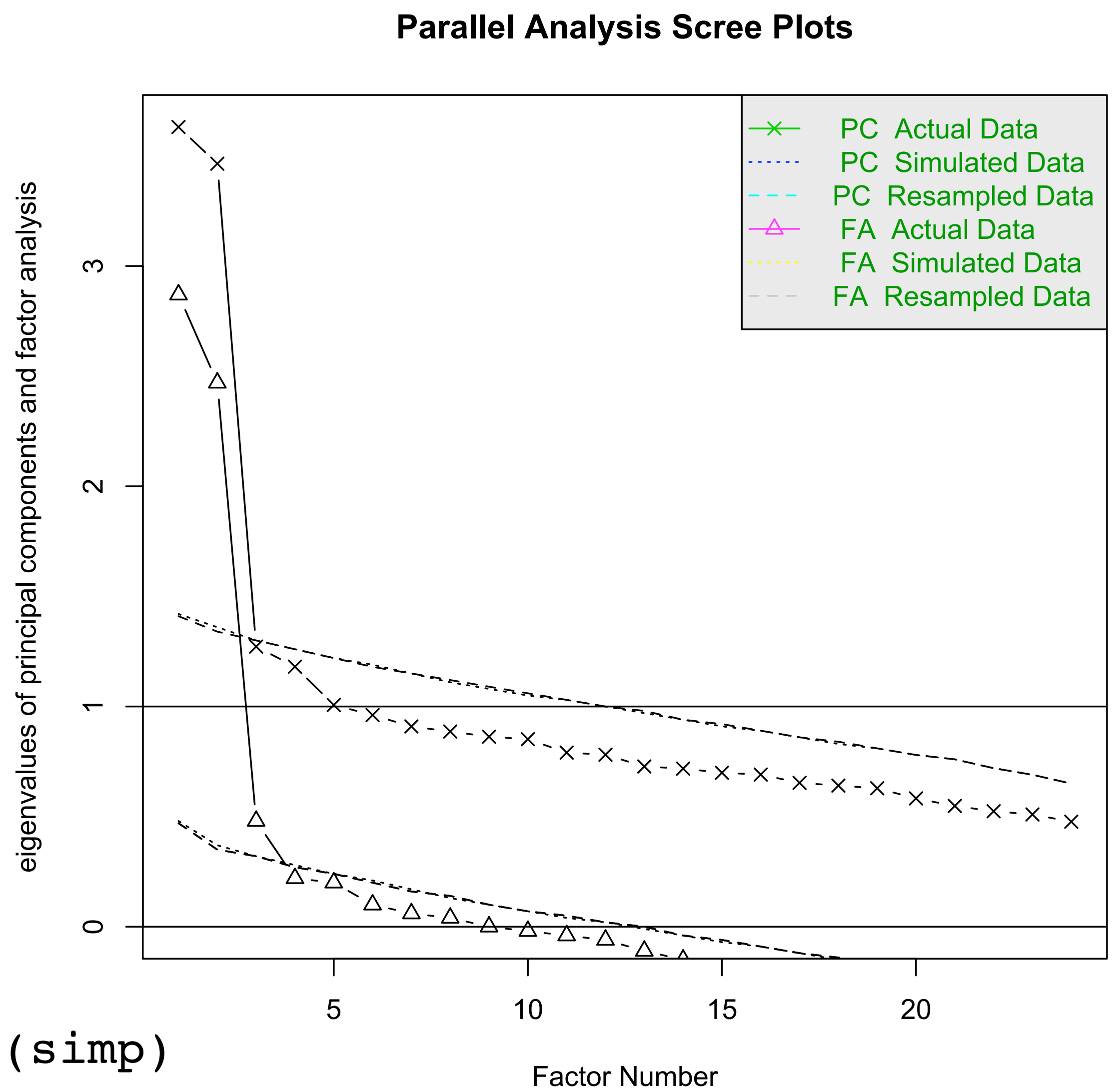
```
> f2 <- factanal(simp,2)
> factor.plot(f2)
```



But chi square is poor

```
Call:
factanal(x = simp, factors = 2)

Uniquenesses:
   V1     V2     V3     V4     V5     V6     V7     V8     V9    V10    V11
V12   V13   V14   V15   V16   V17   V18   V19   V20   V21   V22
0.765 0.763 0.754 0.774 0.752 0.745 0.745 0.680 0.719 0.749 0.772
0.698 0.738 0.758 0.802 0.722 0.770 0.766 0.853 0.826 0.850 0.824
  V23   V24
0.778 0.825

Loadings:
    Factor1 Factor2
V1   0.479
V2   0.479
V3   0.494
V4   0.475
V5   0.497
V6   0.504
V7           0.504
V8           0.566
V9           0.530
V10          0.500
V11          0.477
V12          0.549
V13 -0.512
V14 -0.484
V15 -0.443
V16 -0.523
V17 -0.478
V18 -0.484
V19         -0.380
V20         -0.416
V21         -0.387
V22         -0.420
V23         -0.468
V24         -0.419

               Factor1 Factor2
SS loadings       2.87   2.703
Proportion Var    0.12   0.113
Cumulative Var    0.12   0.232

Test of the hypothesis that
2 factors are sufficient.
The chi square statistic is
350.52 on 229 degrees of
freedom.
The p-value is 4.06e-07
```

Maybe 3 factors?




```
> fa.parallel(simp)
```

3 factors

```
Call:
factanal(x = simp, factors = 3)
Uniquenesses:
   V1    V2    V3    V4    V5    V6    V7    V8    V9   V10   V11   V12   V13   V14   V15   V16   V17
V18   V19   V20   V21   V22    V23   V24
0.666 0.733 0.725 0.747 0.719 0.708 0.736 0.656 0.721 0.749 0.771 0.690 0.712 0.740 0.763 0.649 0.744
0.703 0.849 0.823 0.848 0.823 0.735 0.805
Loadings:
    Factor1 Factor2 Factor3
V1          -0.143   0.557
V2          -0.219   0.462
V3          -0.238   0.463
V4          -0.223   0.452
V5          -0.234   0.475
V6          -0.234   0.484
V7   0.500  -0.102
V8   0.563  -0.109  -0.123
V9   0.528
V10  0.500
V11  0.478
V12  0.543          -0.110
V13          0.478  -0.245
V14          0.439  -0.244
V15          0.452  -0.177
V16          0.556  -0.195
V17          0.454  -0.220
V18          0.515  -0.178
V19 -0.383
V20 -0.418
V21 -0.389
V22 -0.418
V23 -0.482  -0.161
V24 -0.427
                Factor1 Factor2 Factor3
SS loadings       2.711   1.751   1.722
Proportion Var    0.113   0.073   0.072
Cumulative Var    0.113   0.186   0.258
```

```
Test of the hypothesis that 3 factors are sufficient.
The chi square statistic is 262.01 on 207 degrees of freedom.
The p-value is 0.00574
```

```
> f4 <- factanal(simp,4)
> f4
Call:
factanal(x = simp, factors = 4)
Uniquenesses:
   V1    V2    V3    V4    V5    V6    V7    V8    V9   V10   V11   V12   V13   V14   V15   V16   V17
V18   V19   V20   V21   V22  V23   V24
0.667 0.731 0.712 0.747 0.709 0.706 0.740 0.647 0.598 0.755 0.731 0.660 0.716 0.747 0.745 0.650 0.750
0.674 0.806 0.731 0.843 0.809 0.649 0.758
Loadings:
    Factor1 Factor2 Factor3 Factor4
V1   0.541  -0.129  -0.143
V2   0.472          -0.199
V3   0.492          -0.201
V4   0.461          -0.203
V5   0.499          -0.200
V6   0.497          -0.211
V7           0.421          -0.272
V8           0.523          -0.254
V9           0.615          -0.127
V10          0.388          -0.304
V11          0.477          -0.184
V12          0.537          -0.214
V13 -0.269           0.459
V14 -0.272           0.413
V15 -0.174           0.471
V16 -0.219           0.546
V17 -0.252           0.427
V18 -0.172           0.544
V19         -0.158           0.407
V20         -0.139           0.495
V21         -0.242           0.314
V22         -0.251           0.350
V23         -0.176  -0.129   0.549
V24         -0.174           0.456
               Factor1 Factor2 Factor3 Factor4
SS loadings      1.818   1.757   1.655   1.492
Proportion Var   0.076   0.073   0.069   0.062
Cumulative Var   0.076   0.149   0.218   0.280
```

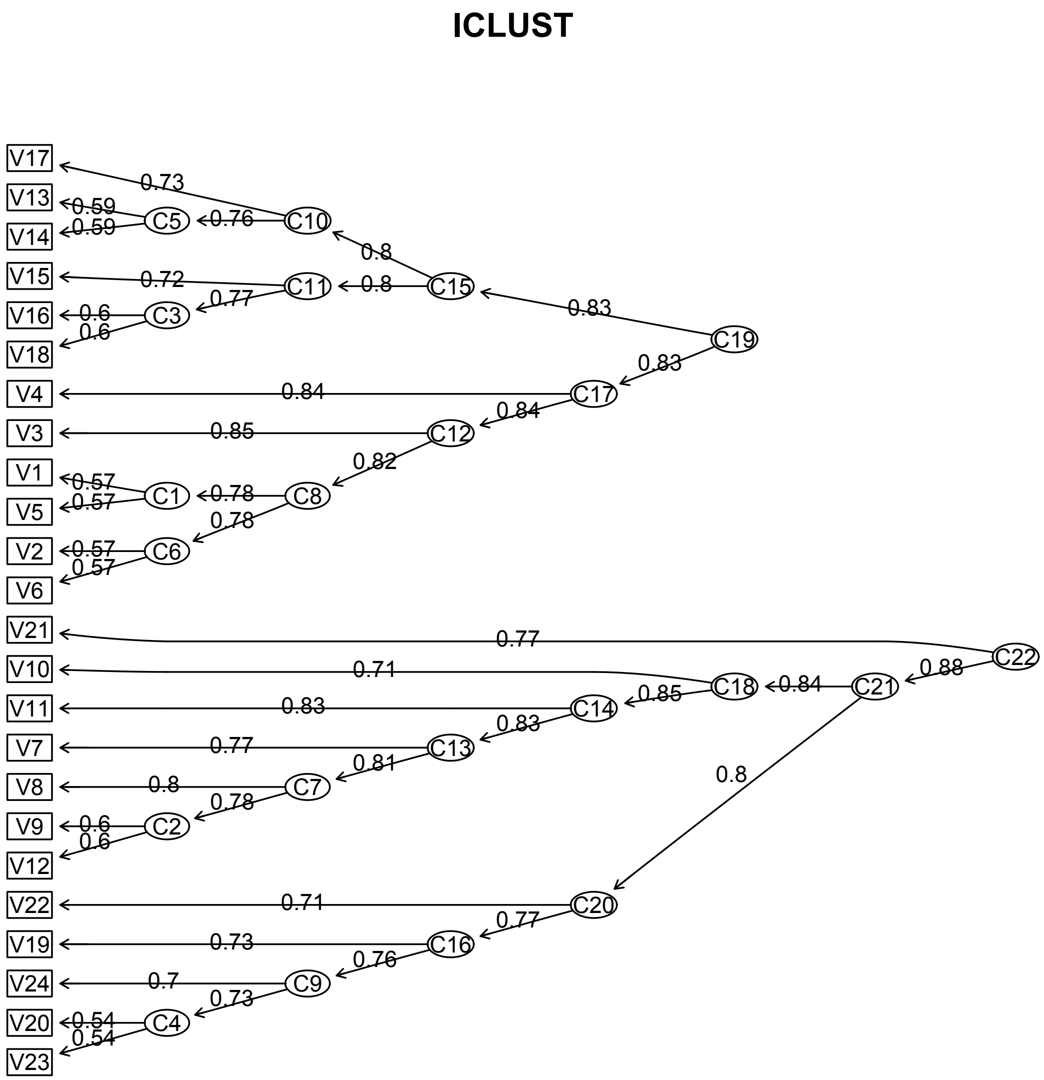
Four factors are messy

Test of the hypothesis that 4 factors are sufficient.
The chi square statistic is 196.54 on 186 degrees of freedom.
The p-value is 0.284

Item Cluster analysis (ICLUST)

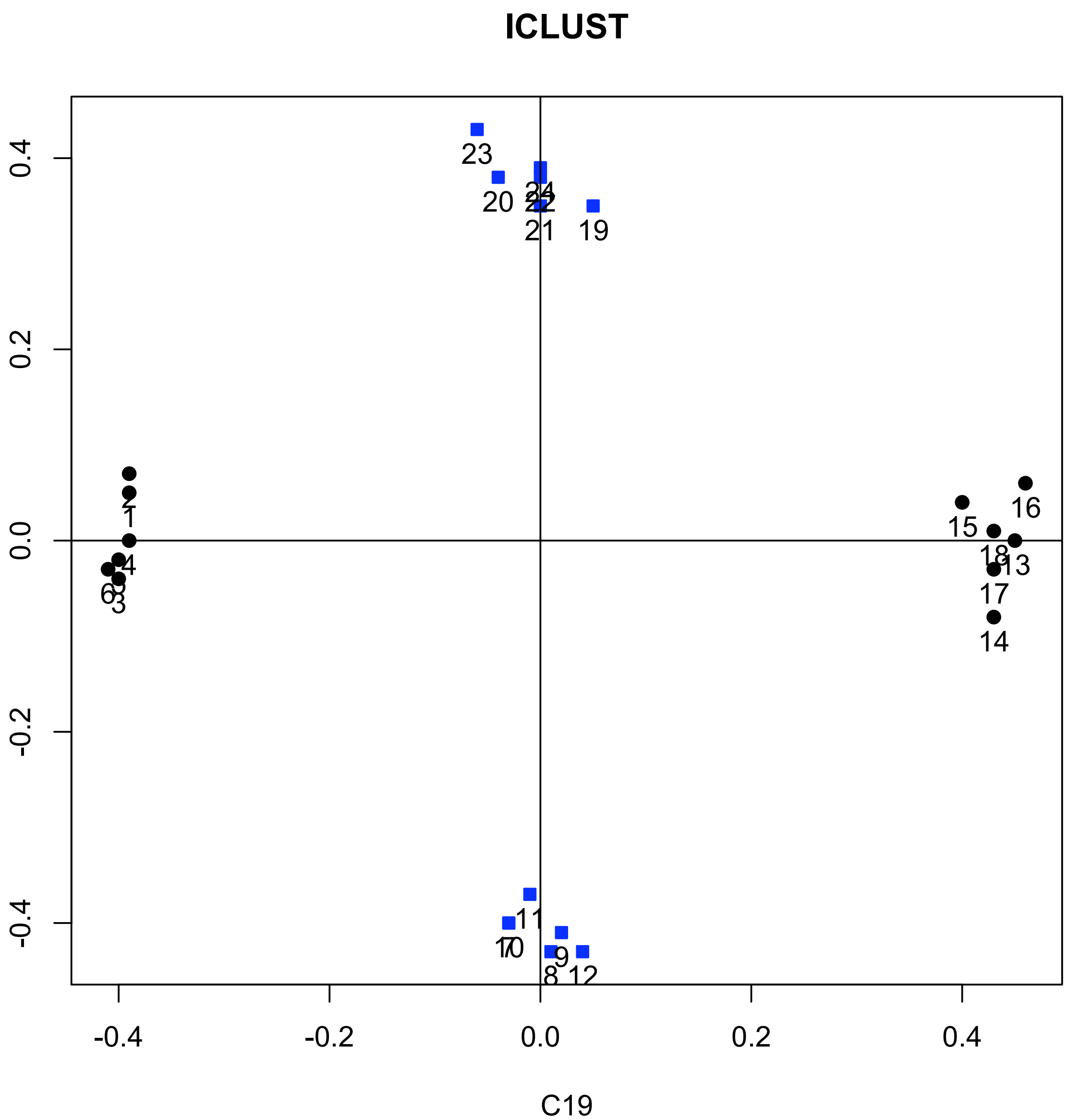
I. Hierarchical cluster analysis meant for items
   A. Find most similar item pair
   B. Combine them
   C. Repeat steps A,B until coefficients alpha and beta do not increase

ICLUST shows 2 with sub structure




```
> ic <- ICLUST(simp)
```

Items match factoring

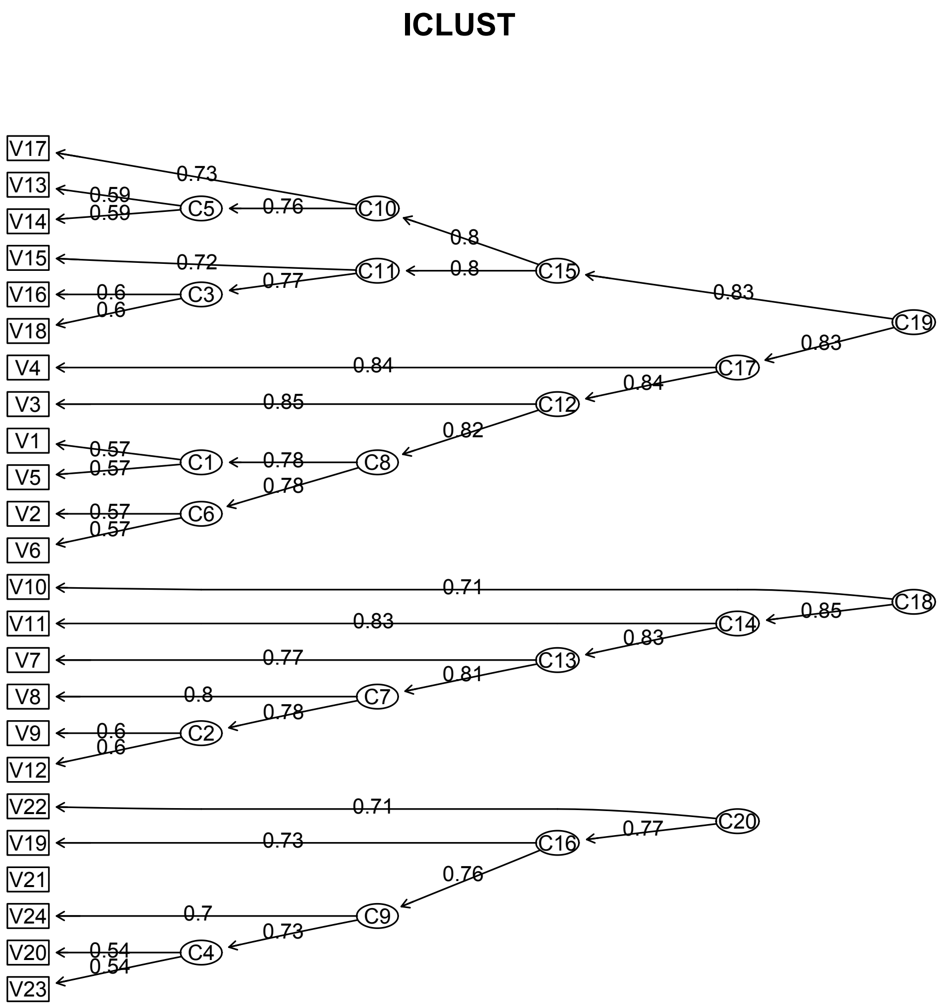



```
> plot(ic)
```

2 clusters

```
> summary(ic)
ICLUST

Purified Alpha:
 C19  C22
0.79 0.77

Original Beta:
 C19  C22
0.67 0.51

Cluster size:
C19 C22
 12  12

Purified scale intercorrelations:
      C19   C22
C19  1.00 -0.01
C22 -0.01  1.00
```

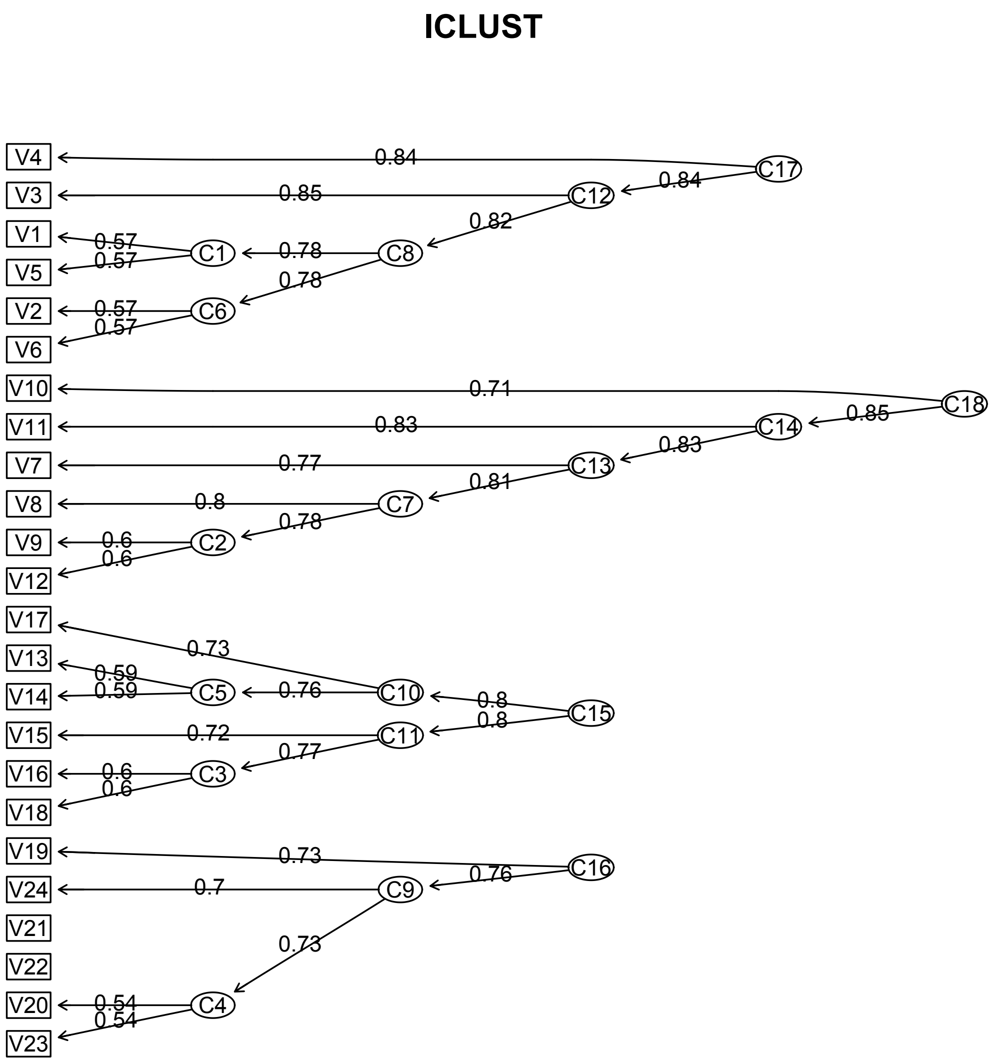
4 clusters




```
ic4 <- ICLUST(simp,4)
```

Note how item 21
did not cluster

6 clusters



ICLUST
V4
V3
V1
V5
V2
V6
V10
V11
V7
V8
V9
V12
V17
V13
V14
V15
V16
V18
V19
V24
V21
V22
V20
V23
C1
C2
C3
C4
C5
C6
C7
C8
C9
C10
C11
C12
C13
C14
C15
C16
C17
C18
0.84
0.85
0.84
0.82
0.57
0.57
0.78
0.78
0.57
0.57
0.71
0.85
0.83
0.83
0.77
0.81
0.8
0.78
0.6
0.6
0.73
0.59
0.59
0.76
0.8
0.8
0.72
0.77
0.6
0.6
0.73
0.76
0.7
0.73
0.54
0.54

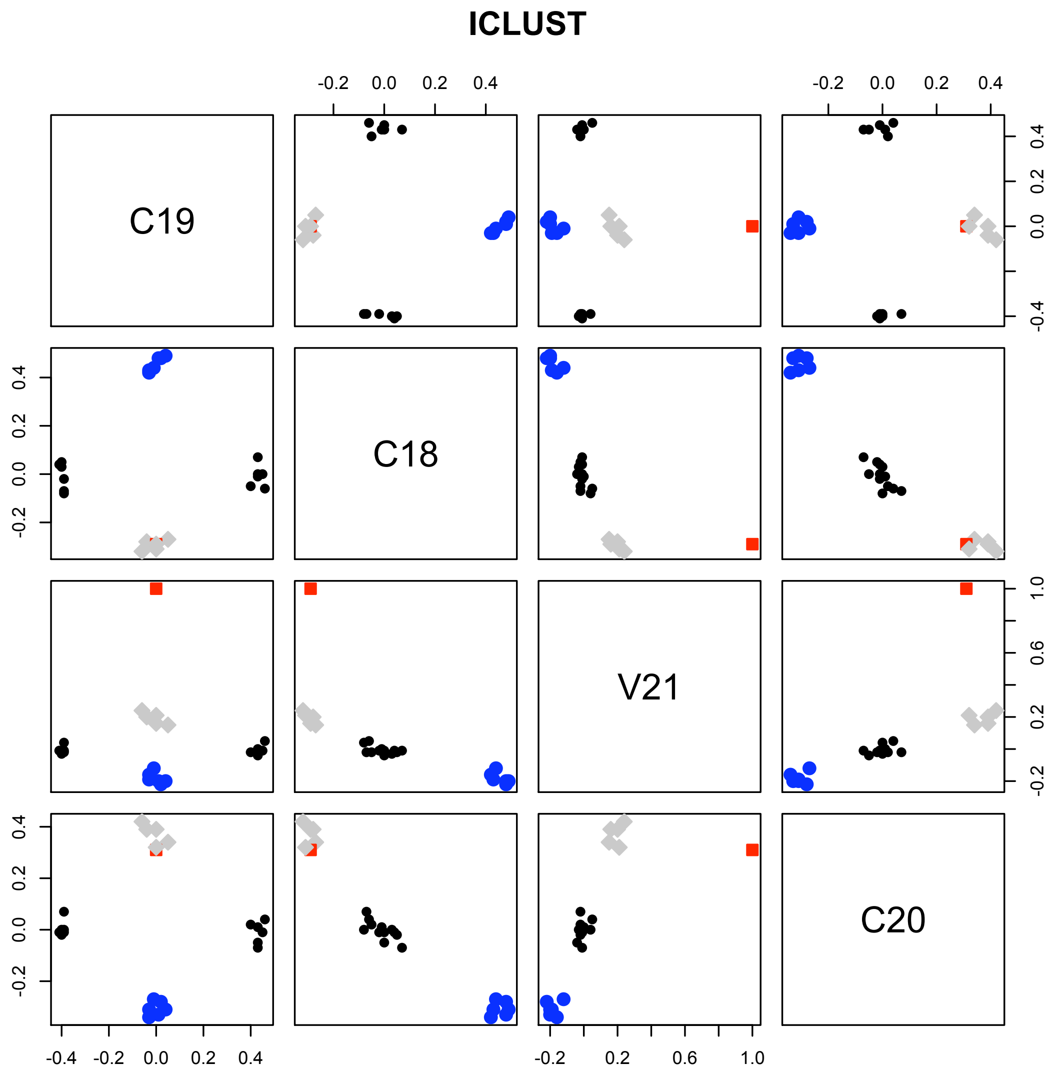
4 clusters
+ 2 items

```
> ic6 <- ICLUST(simp,6)
> summary(ic6)
ICLUST
Purified Alpha:
 C15  C17  C18  V22  V21  C16
0.70 0.70 0.71 1.00 1.00 0.58
Original Beta:
 C15  C17  C18  V22  V21  C16
0.63 0.57 0.57   NA   NA 0.48

Custer size:
C15 C17 C18 V22 V21 C16
  6   6   6   1   1   4
Purified scale intercorrelations:
      C15   C17   C18   V22   V21   C16
C15  1.00 -0.50 -0.01  0.02 -0.01 -0.03
C17 -0.50  1.00 -0.01  0.02 -0.01  0.00
C18 -0.01 -0.01  1.00 -0.31 -0.29 -0.44
V22  0.02  0.02 -0.31  1.00  0.21  0.30
V21 -0.01 -0.01 -0.29  0.21  1.00  0.28
C16 -0.03  0.00 -0.44  0.30  0.28  1.00
```

4 clusters

```
> ic4 <- ICLUST(simp,4)
> summary(ic4)
ICLUST

Purified Alpha:
 C19  C20  V21  C13
0.79 0.71 1.00 0.47

Original Beta:
 C19  C20  V21  C13
0.64 0.53   NA 0.43

Cluster size:
C19 C20 V21 C13
 12   8   1   3

Purified scale intercorrelations:
      C19  C20   V21  C13
C19  1.00 0.07 -0.03 0.10
C20  0.07 1.00  0.28 0.42
V21 -0.03 0.28  1.00 0.18
C13  0.10 0.42  0.18 1.00
```

Clusters are overlapping

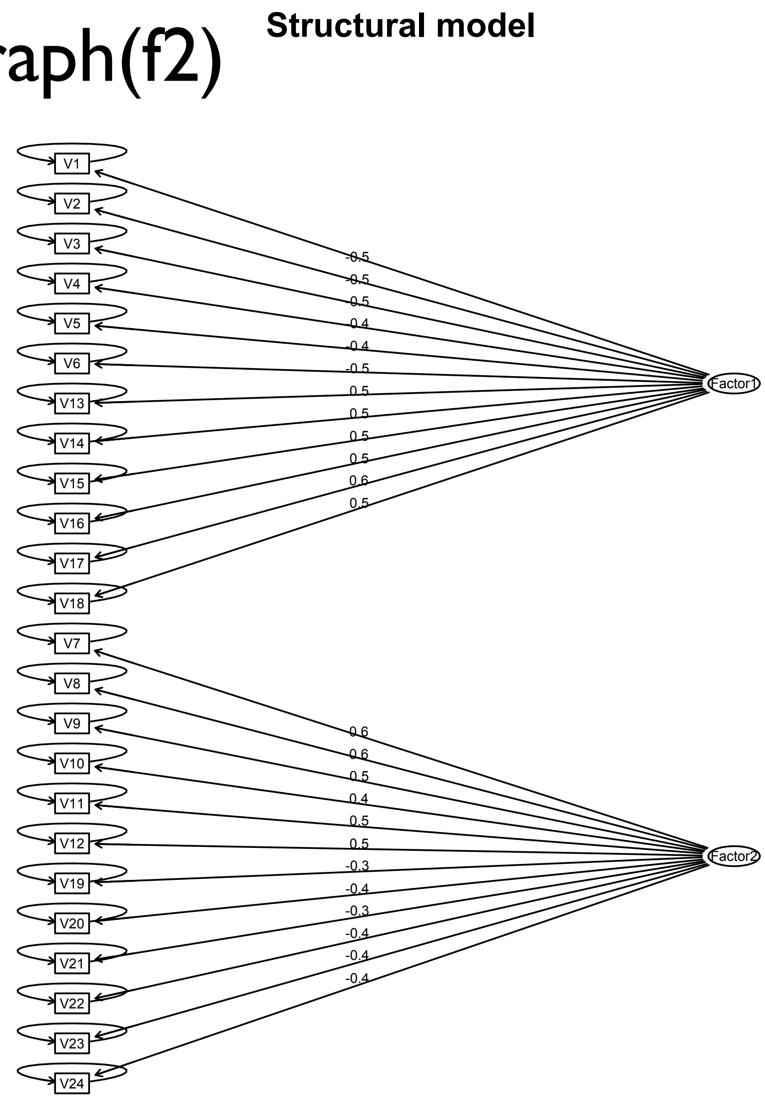


Sem for alternative sets

I. First do it with the continuous data set
II. Then the categorical
III. Then the skewed categorical

Try sem for 2 factors

mod2 <- structure.graph(f2)



Model

```
> mod2                                               [25,] "V1<->V1"            "x1e"     NA
      Path                 Parameter Value          [26,] "V2<->V2"            "x2e"     NA
 [1,] "Factor1->V1"        "F1V1"    NA             [27,] "V3<->V3"            "x3e"     NA
 [2,] "Factor1->V2"        "F1V2"    NA             [28,] "V4<->V4"            "x4e"     NA
 [3,] "Factor1->V3"        "F1V3"    NA             [29,] "V5<->V5"            "x5e"     NA
 [4,] "Factor1->V4"        "F1V4"    NA             [30,] "V6<->V6"            "x6e"     NA
 [5,] "Factor1->V5"        "F1V5"    NA             [31,] "V7<->V7"            "x7e"     NA
 [6,] "Factor1->V6"        "F1V6"    NA             [32,] "V8<->V8"            "x8e"     NA
 [7,] "Factor2->V7"        "F2V7"    NA             [33,] "V9<->V9"            "x9e"     NA
 [8,] "Factor2->V8"        "F2V8"    NA             [34,] "V10<->V10"          "x10e"    NA
 [9,] "Factor2->V9"        "F2V9"    NA             [35,] "V11<->V11"          "x11e"    NA
[10,] "Factor2->V10"       "F2V10"   NA             [36,] "V12<->V12"          "x12e"    NA
[11,] "Factor2->V11"       "F2V11"   NA             [37,] "V13<->V13"          "x13e"    NA
[12,] "Factor2->V12"       "F2V12"   NA             [38,] "V14<->V14"          "x14e"    NA
[13,] "Factor1->V13"       "F1V13"   NA             [39,] "V15<->V15"          "x15e"    NA
[14,] "Factor1->V14"       "F1V14"   NA             [40,] "V16<->V16"          "x16e"    NA
[15,] "Factor1->V15"       "F1V15"   NA             [41,] "V17<->V17"          "x17e"    NA
[16,] "Factor1->V16"       "F1V16"   NA             [42,] "V18<->V18"          "x18e"    NA
[17,] "Factor1->V17"       "F1V17"   NA             [43,] "V19<->V19"          "x19e"    NA
[18,] "Factor1->V18"       "F1V18"   NA             [44,] "V20<->V20"          "x20e"    NA
[19,] "Factor2->V19"       "F2V19"   NA             [45,] "V21<->V21"          "x21e"    NA
[20,] "Factor2->V20"       "F2V20"   NA             [46,] "V22<->V22"          "x22e"    NA
[21,] "Factor2->V21"       "F2V21"   NA             [47,] "V23<->V23"          "x23e"    NA
[22,] "Factor2->V22"       "F2V22"   NA             [48,] "V24<->V24"          "x24e"    NA
[23,] "Factor2->V23"       "F2V23"   NA             [49,] "Factor1<->Factor1" NA         "1"
[24,] "Factor2->V24"       "F2V24"   NA             [50,] "Factor2<->Factor2" NA         "1"
>
```

Continuous two factor

```
> summary(sem2,digits=2)

 Model Chisquare =  235   Df =  252 Pr(>Chisq) = 0.78
 Chisquare (null model) =  3568   Df =  276
 Goodness-of-fit index =  0.96
 Adjusted goodness-of-fit index =  0.96
 RMSEA index =  0   90% CI: (NA, 0.013)
 Bentler-Bonnett NFI =  0.93
 Tucker-Lewis NNFI =  1
 Bentler CFI =  1
 SRMR =  0.029
 BIC =  -1331

 Normalized Residuals
    Min.  1st Qu.   Median     Mean  3rd Qu.     Max.
-1.6e+00 -4.1e-01 -3.1e-05  8.8e-03  3.9e-01  2.2e+00
```

Relevant paths

Parameter Estimates

	Estimate	Std Error	z value	Pr(>|z|)	
F1V1	0.63	0.043	15	0	V1 <--- Factor1
F1V2	0.61	0.043	14	0	V2 <--- Factor1
F1V3	0.57	0.044	13	0	V3 <--- Factor1
F1V4	0.63	0.042	15	0	V4 <--- Factor1
F1V5	0.64	0.042	15	0	V5 <--- Factor1
F1V6	0.61	0.043	14	0	V6 <--- Factor1
F2V7	0.55	0.044	12	0	V7 <--- Factor2
F2V8	0.63	0.043	15	0	V8 <--- Factor2
F2V9	0.58	0.044	13	0	V9 <--- Factor2
F2V10	0.58	0.044	13	0	V10 <--- Factor2
F2V11	0.59	0.043	14	0	V11 <--- Factor2
F2V12	0.61	0.043	14	0	V12 <--- Factor2
F1V13	-0.63	0.042	-15	0	V13 <--- Factor1
F1V14	-0.59	0.043	-14	0	V14 <--- Factor1
F1V15	-0.57	0.043	-13	0	V15 <--- Factor1
F1V16	-0.64	0.042	-15	0	V16 <--- Factor1
F1V17	-0.63	0.043	-15	0	V17 <--- Factor1
F1V18	-0.59	0.043	-14	0	V18 <--- Factor1
F2V19	-0.57	0.044	-13	0	V19 <--- Factor2
F2V20	-0.60	0.043	-14	0	V20 <--- Factor2
F2V21	-0.62	0.043	-15	0	V21 <--- Factor2
F2V22	-0.57	0.044	-13	0	V22 <--- Factor2
F2V23	-0.58	0.044	-13	0	V23 <--- Factor2
F2V24	-0.60	0.043	-14	0	V24 <--- Factor2

Categorical 2 factor

I. Original model does not converge

II. Reset some paths to give initial estimates closer to the factor solution

III. Use the edit command

Modified paths in model

```
> mod2.c <- edit(mod2)
> mod2.c
      Path                    Parameter Value
 [1,] "Factor1->V1"           "F1V1"    ".6"
 [2,] "Factor1->V2"           "F1V2"    ".6"
 [3,] "Factor1->V3"           "F1V3"    ".6"
 [4,] "Factor1->V4"           "F1V4"    ".6"
 [5,] "Factor1->V5"           "F1V5"    ".6"
 [6,] "Factor1->V6"           "F1V6"    ".6"
 [7,] "Factor2->V7"           "F2V7"    ".6"
 [8,] "Factor2->V8"           "F2V8"    ".6"
 [9,] "Factor2->V9"           "F2V9"    ".6"
[10,] "Factor2->V10"          "F2V10"   ".6"
[11,] "Factor2->V11"          "F2V11"   ".6"
[12,] "Factor2->V12"          "F2V12"   ".6"
[13,] "Factor1->V13"          "F1V13"   "-.6"
[14,] "Factor1->V14"          "F1V14"   "-.6"
[15,] "Factor1->V15"          "F1V15"   "-.6"
[16,] "Factor1->V16"          "F1V16"   NA
[17,] "Factor1->V17"          "F1V17"   NA
[18,] "Factor1->V18"          "F1V18"   NA
[19,] "Factor2->V19"          "F2V19"   NA
[20,] "Factor2->V20"          "F2V20"   NA
[21,] "Factor2->V21"          "F2V21"   NA
[22,] "Factor2->V22"          "F2V22"   NA
[23,] "Factor2->V23"          "F2V23"   NA
[24,] "Factor2->V24"          "F2V24"   "-.6"
[25,] "V1<->V1"               "x1e"     NA
[26,] "V2<->V2"               "x2e"     NA
...
[49,] "Factor1<->Factor1" NA            "1"
[50,] "Factor2<->Factor2" NA            "1"
```

Fit is very good

```
>  summary(sem.c,digits=2)

 Model Chisquare =  255   Df =  252 Pr(>Chisq) = 0.44
 Chisquare (null model) =  3143   Df =  276
 Goodness-of-fit index =  0.96
 Adjusted goodness-of-fit index =  0.95
 RMSEA index =  0.0049   90% CI: (NA, 0.019)
 Bentler-Bonnett NFI =  0.92
 Tucker-Lewis NNFI =  1
 Bentler CFI =  1
 SRMR =  0.032
 BIC =  -1311

 Normalized Residuals
    Min.  1st Qu.   Median     Mean  3rd Qu.     Max.
-2.2e+00 -4.3e-01  2.2e-05  4.1e-02  5.4e-01  2.1e+00
```

Path coefficients are fine

Parameter Estimates

	Estimate	Std Error	z value	Pr(>|z|)	
F1V1	0.60	0.043	14	0	V1 <--- Factor1
F1V2	0.56	0.044	13	0	V2 <--- Factor1
F1V3	0.55	0.044	12	0	V3 <--- Factor1
F1V4	0.61	0.043	14	0	V4 <--- Factor1
F1V5	0.61	0.043	14	0	V5 <--- Factor1
F1V6	0.59	0.044	13	0	V6 <--- Factor1
F2V7	0.52	0.045	12	0	V7 <--- Factor2
F2V8	0.59	0.044	13	0	V8 <--- Factor2
F2V9	0.57	0.044	13	0	V9 <--- Factor2
F2V10	0.55	0.045	12	0	V10 <--- Factor2
F2V11	0.56	0.044	13	0	V11 <--- Factor2
F2V12	0.56	0.044	13	0	V12 <--- Factor2
F1V13	-0.61	0.043	-14	0	V13 <--- Factor1
F1V14	-0.57	0.044	-13	0	V14 <--- Factor1
F1V15	-0.54	0.044	-12	0	V15 <--- Factor1
F1V16	-0.63	0.043	-15	0	V16 <--- Factor1
F1V17	-0.58	0.044	-13	0	V17 <--- Factor1
F1V18	-0.56	0.044	-13	0	V18 <--- Factor1
F2V19	-0.55	0.045	-12	0	V19 <--- Factor2
F2V20	-0.58	0.044	-13	0	V20 <--- Factor2

Now try skewed

I. Once again, the initial model does not work (with a weird diagnostic), but the model with roughly the right answers (taken from the exploratory factor analysis) does.

II. However, the model does not fit by some criteria (i.e., chi square), but does by other (RMSEA)

Fit statistics

```
> sem.sk <- sem(mod2.c,cor(simp),500)
> summary(sem.sk,digits=2)

 Model Chisquare =  380   Df =  252 Pr(>Chisq) = 3.2e-07
 Chisquare (null model) =  2002   Df =  276
 Goodness-of-fit index =  0.94
 Adjusted goodness-of-fit index =  0.93
 RMSEA index =  0.032   90% CI: (0.025, 0.038)
 Bentler-Bonnett NFI =  0.81
 Tucker-Lewis NNFI =  0.92
 Bentler CFI =  0.93
 SRMR =  0.043
 BIC =  -1186

 Normalized Residuals
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
  -2.47   -0.26    0.30    0.31    1.02    2.51
```

Path coefficients

```
 Parameter Estimates
      Estimate Std Error z value Pr(>|z|)
F1V1    0.48    0.048      10.1   0.0e+00  V1 <--- Factor1
F1V2    0.48    0.048      10.0   0.0e+00  V2 <--- Factor1
F1V3    0.49    0.047      10.4   0.0e+00  V3 <--- Factor1
F1V4    0.48    0.048      10.0   0.0e+00  V4 <--- Factor1
F1V5    0.50    0.047      10.5   0.0e+00  V5 <--- Factor1
F1V6    0.51    0.047      10.7   0.0e+00  V6 <--- Factor1
F2V7    0.50    0.047      10.6   0.0e+00  V7 <--- Factor2
F2V8    0.56    0.047      12.0   0.0e+00  V8 <--- Factor2
F2V9    0.53    0.047      11.2   0.0e+00  V9 <--- Factor2
F2V10   0.50    0.047      10.5   0.0e+00  V10 <--- Factor2
F2V11   0.48    0.048       9.9   0.0e+00  V11 <--- Factor2
F2V12   0.55    0.047      11.8   0.0e+00  V12 <--- Factor2
F1V13  -0.51    0.047     -10.8   0.0e+00  V13 <--- Factor1
F1V14  -0.48    0.048     -10.2   0.0e+00  V14 <--- Factor1
F1V15  -0.44    0.048      -9.2   0.0e+00  V15 <--- Factor1
F1V16  -0.52    0.047     -11.1   0.0e+00  V16 <--- Factor1
F1V17  -0.48    0.048     -10.0   0.0e+00  V17 <--- Factor1
F1V18  -0.48    0.048     -10.1   0.0e+00  V18 <--- Factor1
F2V19  -0.38    0.049      -7.8   5.1e-15  V19 <--- Factor2
F2V20  -0.41    0.049      -8.5   0.0e+00  V20 <--- Factor2
F2V21  -0.39    0.049      -8.0   1.6e-15  V21 <--- Factor2
F2V22  -0.42    0.049      -8.7   0.0e+00  V22 <--- Factor2
F2V23  -0.47    0.048      -9.7   0.0e+00  V23 <--- Factor2
```

Alternative models

I. What about 4 unipolar factors

II. Correlated in pairs to get the polarity

III. Create the path model using symbolic notation with the structure.list and phi.list functions

   A. `fx <- structure.list(24,list(F1p=c(1:6),F2p=c(7:12),F1n=c(13:18),F2n=c(19:24)))`

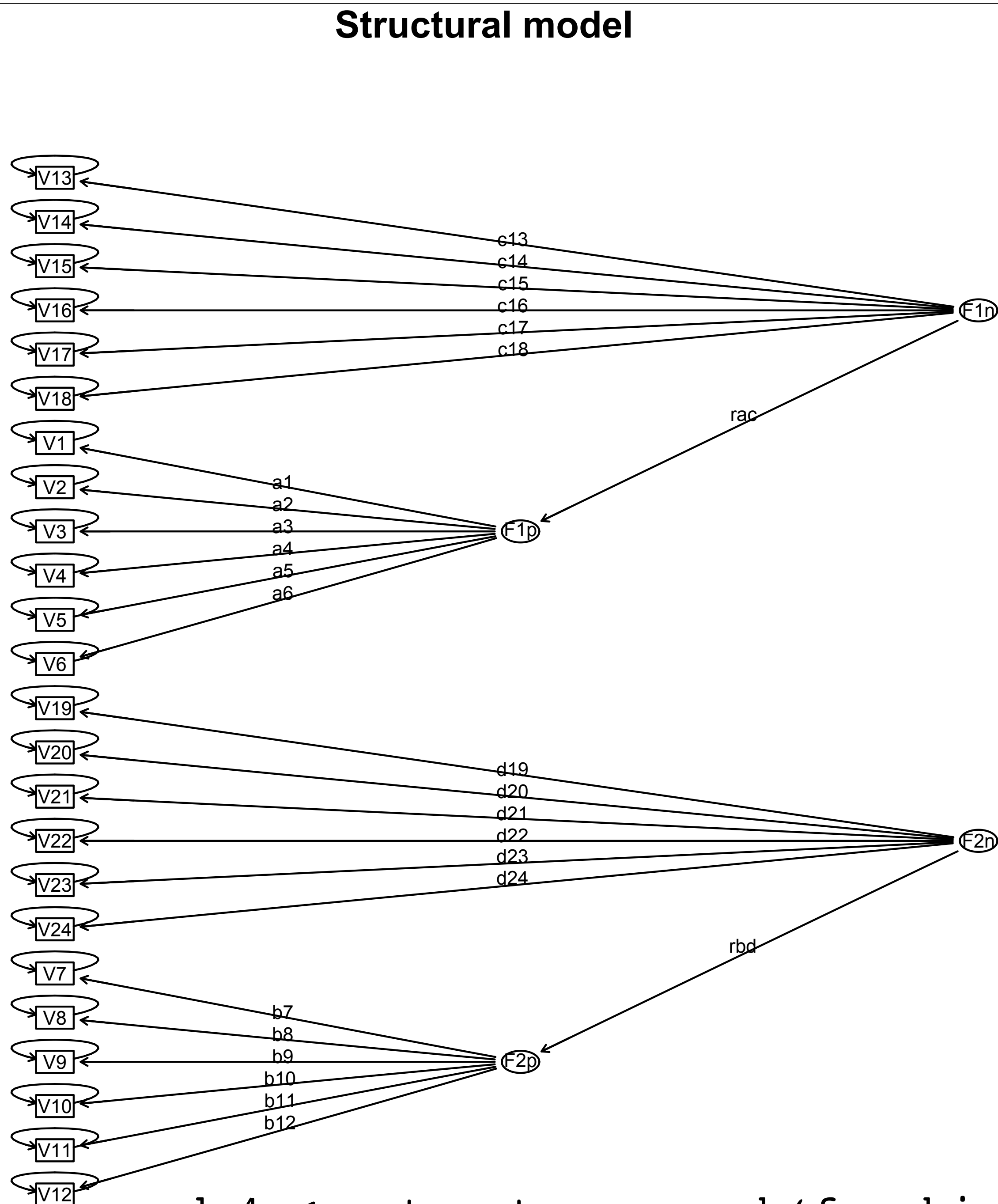
   B. `phi<- phi.list(4,list(F1=c(3),F2=c(4)))`

   C. `mod.4 <- structure.graph(fx,phi)`

Symbolic structure

```
> fx <- structure.list(24,list(F1p=c(1:6),F2p=c(7:12),
F1n=c(13:18),F2n=c(19:24)))
> fx
      F1p  F2p   F1n   F2n
 [1,] "a1" "0"   "0"   "0"
 [2,] "a2" "0"   "0"   "0"
 [3,] "a3" "0"   "0"   "0"
 [4,] "a4" "0"   "0"   "0"
 [5,] "a5" "0"   "0"   "0"
 [6,] "a6" "0"   "0"   "0"
 [7,] "0"  "b7"  "0"   "0"
 [8,] "0"  "b8"  "0"   "0"
 [9,] "0"  "b9"  "0"   "0"
[10,] "0"  "b10" "0"   "0"
[11,] "0"  "b11" "0"   "0"
[12,] "0"  "b12" "0"   "0"
[13,] "0"  "0"   "c13" "0"
[14,] "0"  "0"   "c14" "0"
[15,] "0"  "0"   "c15" "0"
[16,] "0"  "0"   "c16" "0"
[17,] "0"  "0"   "c17" "0"
[18,] "0"  "0"   "c18" "0"
[19,] "0"  "0"   "0"   "d19"
[20,] "0"  "0"   "0"   "d20"
[21,] "0"  "0"   "0"   "d21"
[22,] "0"  "0"   "0"   "d22"
[23,] "0"  "0"   "0"   "d23"
```

```
>  phi<- phi.list(4,list(F1=c(3),
      F2=c(4)))
> phi
   F1    F2    F3  F4
F1 "1"   "0"   "0" "0"
F2 "0"   "1"   "0" "0"
F3 "rac" "0"   "1" "0"
F4 "0"   "rbd" "0" "1"
```



Create the model

```
mod.4 <- structure.graph(fx,phi,labels=colnames(simp))
```

Fit is fine

```
> mod.4c <- edit(mod.4) #make the paths bidirectional
> sem.4 <- sem(mod.4c,cor(simp),500)
> summary(sem.4,digits=2)

 Model Chisquare =  265   Df =  250 Pr(>Chisq) = 0.25
 Chisquare (null model) =  2002   Df =  276
 Goodness-of-fit index =  0.96
 Adjusted goodness-of-fit index =  0.95
 RMSEA index =  0.011   90% CI: (NA, 0.021)
 Bentler-Bonnett NFI =  0.87
 Tucker-Lewis NNFI =  1
 Bentler CFI =  1
 SRMR =  0.036
 BIC =  -1289

 Normalized Residuals
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
 -2.470  -0.608  -0.069  -0.052   0.449   2.330
```

Paths

```
  Parameter Estimates
      Estimate Std Error z value Pr(>|z|)
a1      0.53    0.048       11.0   0.0e+00  V1 <--- F1p
a2      0.53    0.049       10.8   0.0e+00  V2 <--- F1p
...
a6      0.56    0.048       11.5   0.0e+00  V6 <--- F1p
b7      0.52    0.048       10.7   0.0e+00  V7 <--- F2p
b8      0.58    0.047       12.3   0.0e+00  V8 <--- F2p
...
c13     0.55    0.048       11.4   0.0e+00  V13 <--- F1n
..
c18     0.52    0.049       10.7   0.0e+00  V18 <--- F1n
d19     0.43    0.051        8.3   2.2e-16  V19 <--- F2n
..
d24     0.48    0.051        9.5   0.0e+00  V24 <--- F2n
x1e     0.72    0.053       13.6   0.0e+00  V1 <--> V1
x2e     0.72    0.053       13.7   0.0e+00  V2 <--> V2
...
x7e     0.73    0.053       13.9   0.0e+00  V7 <--> V7
x8e     0.66    0.050       13.1   0.0e+00  V8 <--> V8
...
rF3F1 -0.72     0.044      -16.4   0.0e+00  F1p <--> F1n
rF4F2 -0.73     0.046      -15.7   0.0e+00  F2p <--> F2n
```

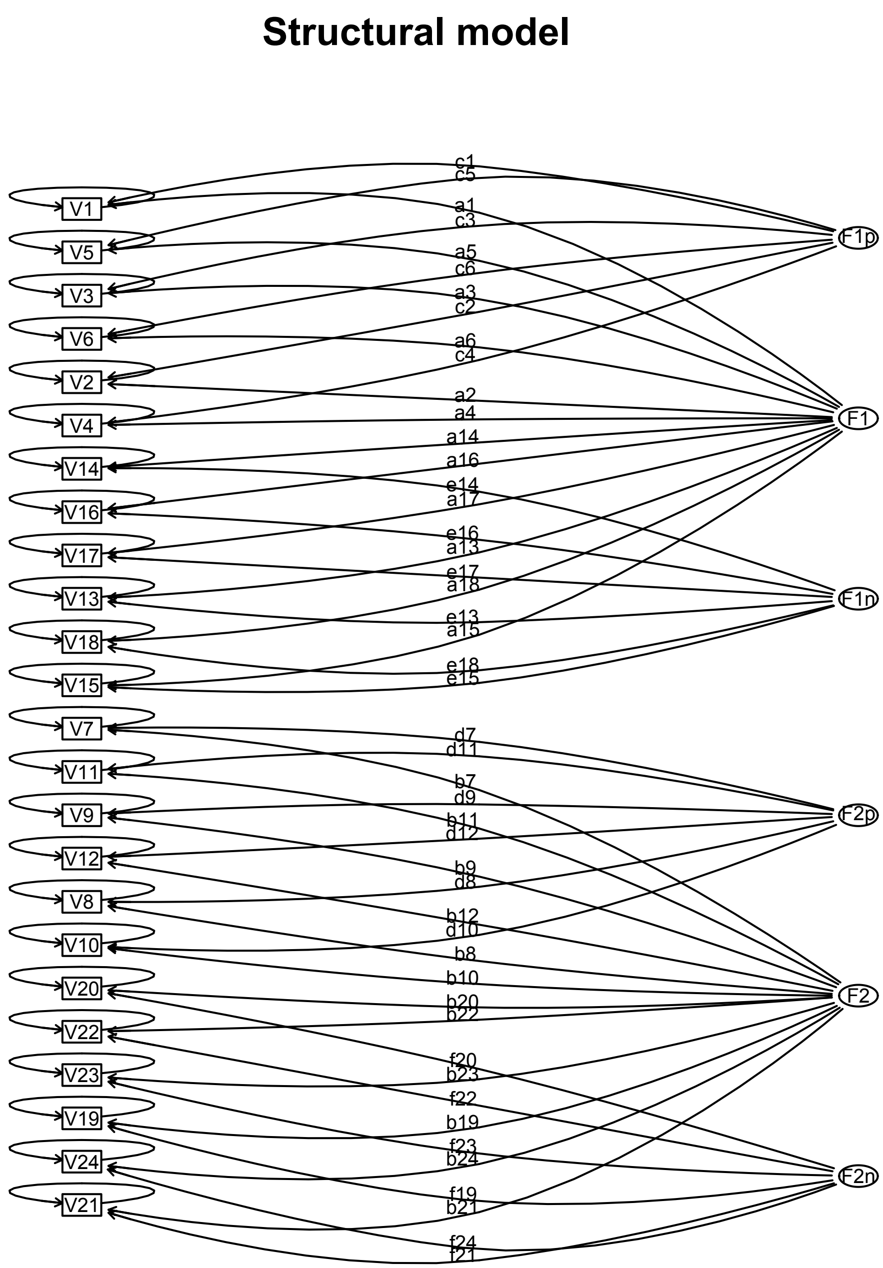
Consider a different model

I. Let the factors be bipolar, but add a residual factor at each end to account for skew differences

II. Basically a bifactor solution, but applied to each of the two main dimensions

```
> fxb <-
structure.list(24,list(F1=c(1:6,13:18),F2=c(7:12,19:24),F1p=c(1:6),F2p=c(7:12),F1n
(13:18),F2n=c(19:24)))
> fxb
      F1    F2    F1p  F2p   F1n   F2n
 [1,] "a1"  "0"   "c1" "0"   "0"   "0"
 [2,] "a2"  "0"   "c2" "0"   "0"   "0"
 [3,] "a3"  "0"   "c3" "0"   "0"   "0"
 [4,] "a4"  "0"   "c4" "0"   "0"   "0"
 [5,] "a5"  "0"   "c5" "0"   "0"   "0"
 [6,] "a6"  "0"   "c6" "0"   "0"   "0"
 [7,] "0"   "b7"  "0"  "d7"  "0"   "0"
 [8,] "0"   "b8"  "0"  "d8"  "0"   "0"
 [9,] "0"   "b9"  "0"  "d9"  "0"   "0"
[10,] "0"   "b10" "0"  "d10" "0"   "0"
[11,] "0"   "b11" "0"  "d11" "0"   "0"
[12,] "0"   "b12" "0"  "d12" "0"   "0"
[13,] "a13" "0"   "0"  "0"   "e13" "0"
[14,] "a14" "0"   "0"  "0"   "e14" "0"
[15,] "a15" "0"   "0"  "0"   "e15" "0"
[16,] "a16" "0"   "0"  "0"   "e16" "0"
[17,] "a17" "0"   "0"  "0"   "e17" "0"
[18,] "a18" "0"   "0"  "0"   "e18" "0"
[19,] "0"   "b19" "0"  "0"   "0"   "f19"
[20,] "0"   "b20" "0"  "0"   "0"   "f20"
[21,] "0"   "b21" "0"  "0"   "0"   "f21"
[22,] "0"   "b22" "0"  "0"   "0"   "f22"
[23,] "0"   "b23" "0"  "0"   "0"   "f23"
[24,] "0"   "b24" "0"  "0"   "0"   "f24"
> mod.2b <- structure.graph(fxb,labels=colnames(simp))
```

Create the structure symbolically



Structural model
V1
V5
V3
V6
V2
V4
V14
V16
V17
V13
V18
V15
V7
V11
V9
V12
V8
V10
V20
V22
V23
V19
V24
V21
F1p
F1
F1n
F2p
F2
F2n
c1
c5
a1
c3
a5
c6
a3
c2
a6
c4
a2
a4
a14
a16
e14
a17
e16
a13
e17
a18
e13
a15
e18
e15
d7
d11
b7
d9
b11
d12
b9
d8
b12
d10
b8
b10
b20
b22
f20
b23
f22
b19
f23
b24
f19
b21
f24
f21

Path model

```
> sem.2b <- sem(mod.2b,cor(simp),500)
> summary(sem.2b,digits=2)

 Model Chisquare =  228   Df =  228 Pr(>Chisq) = 0.49
 Chisquare (null model) =  2002   Df =  276
 Goodness-of-fit index =  0.96
 Adjusted goodness-of-fit index =  0.95
 RMSEA index =  0   90% CI: (NA, 0.019)
 Bentler-Bonnett NFI =  0.89
 Tucker-Lewis NNFI =  1
 Bentler CFI =  1
 SRMR =  0.034
 BIC =  -1189

 Normalized Residuals
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
 -2.470  -0.481  -0.002  -0.040   0.380   2.330
```

Paths

```
 Parameter Estimates
     Estimate Std Error z value Pr(>|z|)
a1     0.3530  0.051        6.884 5.8e-12  V1 <--- F1
c1     0.4170  0.064        6.475 9.5e-11  V1 <--- F1p
a2     0.3583  0.051        7.019 2.2e-12  V2 <--- F1
c2     0.3924  0.063        6.195 5.8e-10  V2 <--- F1p
...
c6     0.4179  0.063        6.598 4.2e-11  V6 <--- F1p
b7    -0.5069  0.077       -6.580 4.7e-11  V7 <--- F2
d7     0.0800  0.227        0.353 7.2e-01  V7 <--- F2p
b8    -0.5632  0.063       -8.974 0.0e+00  V8 <--- F2
...
d12    0.2523  0.238        1.059 2.9e-01  V12 <--- F2p
a13   -0.5628  0.050      -11.250 0.0e+00  V13 <--- F1
e13   -0.0985  0.087       -1.129 2.6e-01  V13 <--- F1n
a14   -0.5524  0.051      -10.847 0.0e+00  V14 <--- F1
e14   -0.1679  0.121       -1.383 1.7e-01  V14 <--- F1n
...
a18   -0.5413  0.066       -8.140 4.4e-16  V18 <--- F1
e18    0.5160  0.248        2.079 3.8e-02  V18 <--- F1n
b19    0.3435  0.059        5.816 6.0e-09  V19 <--- F2
f19    0.2525  0.081        3.101 1.9e-03  V19 <--- F2n
b20    0.3495  0.061        5.730 1.0e-08  V20 <--- F2
f20    0.3791  0.085        4.460 8.2e-06  V20 <--- F2n
b21    0.3566  0.060        5.965 2.4e-09  V21 <--- F2
...
b24    0.3664  0.062        5.937 2.9e-09  V24 <--- F2
f24    0.3304  0.085        3.909 9.3e-05  V24 <--- F2n
x1e    0.7015  0.057       12.322 0.0e+00  V1 <--> V1
x2e    0.7177  0.056       12.852 0.0e+00  V2 <--> V2
...
x24e   0.7566  0.060       12.582 0.0e+00  V24 <--> V24
```

Do the models differ?

```
> anova(sem.2b,sem.4)
LR Test for Difference Between Models

        Model Df Model Chisq  Df LR Chisq Pr(>Chisq)
Model 1      228     227.960
Model 2      250     264.517  22   36.557    0.02644 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 '
' 1
>
```

But they are not nested models

The bipolar model has a smaller chi square, but is penalized for 22 degrees of freedom (compare the BICs)

`BIC =  -1189   vs.   BIC =  -1289  vs. BIC =  -1186  (for orig)`

Comparisons of models and data

data	model	chi sq	df	BIC	RMSEA
Continuous	2 f	235	252	-1331	0.0000
Categorical	2 f	255	252	-1311	0.0049
Skewed	2 f	380	252	-1186	0.0320
	4 f	265	250	-1289	0.0110
	2 bi	228	228	-1189	0.0000

Consider Circumplex Structure

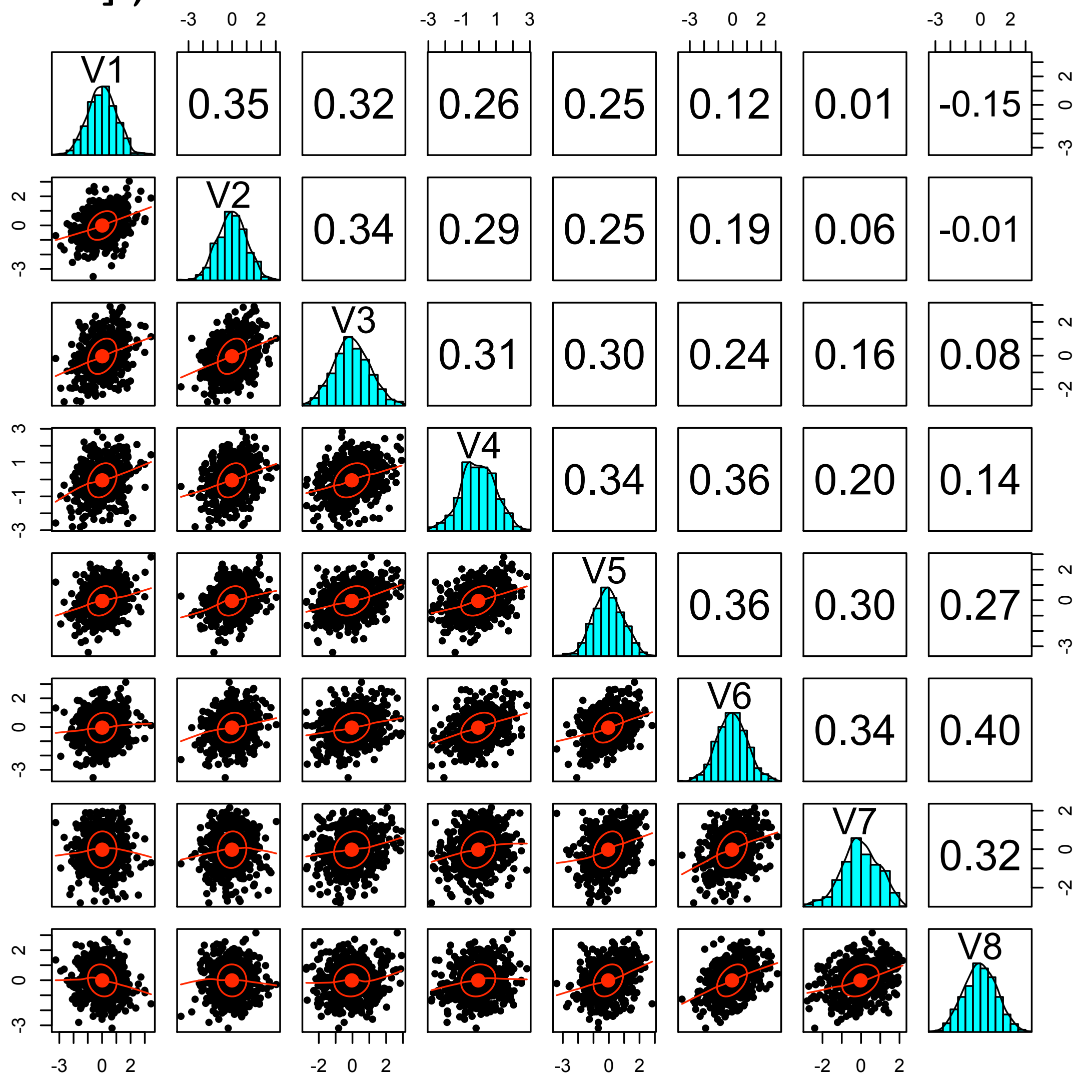
I. Two dimensional model of data, with and without skew

The data

```
> set.seed(42)
> circ <- sim.item(24,circum=TRUE)
> describe(circ)
    var   n  mean   sd median trimmed  mad   min  max range  skew kurtosis   se
V1    1 500  0.01 1.01   0.03    0.01 0.97 -3.26 3.44  6.69  0.05     0.13 0.04
V2    2 500 -0.01 0.99  -0.01   -0.01 1.02 -3.52 3.04  6.56 -0.03    -0.03 0.04
V3    3 500 -0.04 1.05  -0.07   -0.05 1.04 -2.75 2.92  5.66  0.12    -0.18 0.05
V4    4 500 -0.05 1.01  -0.06   -0.04 1.06 -2.82 2.83  5.64 -0.05    -0.17 0.05
V5    5 500 -0.04 0.96  -0.07   -0.05 0.95 -3.40 2.82  6.22 -0.02    -0.04 0.04
V6    6 500 -0.05 1.05  -0.05   -0.06 1.04 -3.55 3.12  6.67  0.03     0.09 0.05
V7    7 500 -0.03 0.95  -0.04   -0.01 0.93 -2.79 2.16  4.95 -0.19    -0.17 0.04
V8    8 500 -0.01 1.07  -0.01   -0.01 1.10 -3.19 3.15  6.35  0.01    -0.28 0.05
V9    9 500  0.01 1.02   0.04    0.02 1.07 -2.58 3.54  6.12  0.01    -0.28 0.05
V10  10 500  0.01 0.96  -0.04    0.01 0.94 -2.45 3.10  5.55  0.02    -0.02 0.04
V11  11 500 -0.03 0.98  -0.09   -0.05 0.99 -3.45 3.06  6.51  0.15     0.27 0.04
V12  12 500 -0.03 1.01  -0.04   -0.04 1.08 -3.36 3.26  6.62  0.03    -0.10 0.05
V13  13 500 -0.05 1.07  -0.08   -0.07 1.11 -2.93 3.74  6.66  0.13    -0.01 0.05
V14  14 500  0.08 0.97   0.09    0.08 0.99 -2.82 2.64  5.45 -0.07    -0.28 0.04
V15  15 500  0.03 1.01  -0.03    0.02 1.02 -2.64 3.26  5.90  0.13    -0.06 0.05
V16  16 500  0.01 1.02  -0.06    0.00 1.10 -2.90 2.99  5.89  0.08    -0.18 0.05
V17  17 500 -0.01 1.00   0.04   -0.01 1.09 -2.63 2.94  5.58 -0.01    -0.36 0.04
V18  18 500  0.04 1.00   0.04    0.04 1.03 -3.71 2.83  6.54 -0.05     0.09 0.04
V19  19 500 -0.01 0.97  -0.02   -0.01 1.02 -2.99 2.62  5.62 -0.01    -0.23 0.04
V20  20 500  0.03 0.98  -0.01    0.02 0.94 -2.96 2.94  5.90  0.05     0.25 0.04
V21  21 500 -0.03 1.04  -0.09   -0.04 1.05 -3.27 3.34  6.61  0.11    -0.03 0.05
V22  22 500  0.04 1.02  -0.03    0.03 1.02 -3.31 3.68  6.99  0.09     0.18 0.05
V23  23 500  0.01 1.00   0.00    0.00 1.01 -2.95 3.16  6.10  0.06    -0.09 0.04
V24  24 500 -0.01 1.00   0.07   -0.01 0.92 -2.71 3.11  5.82  0.01     0.06 0.04
```

SPLOM

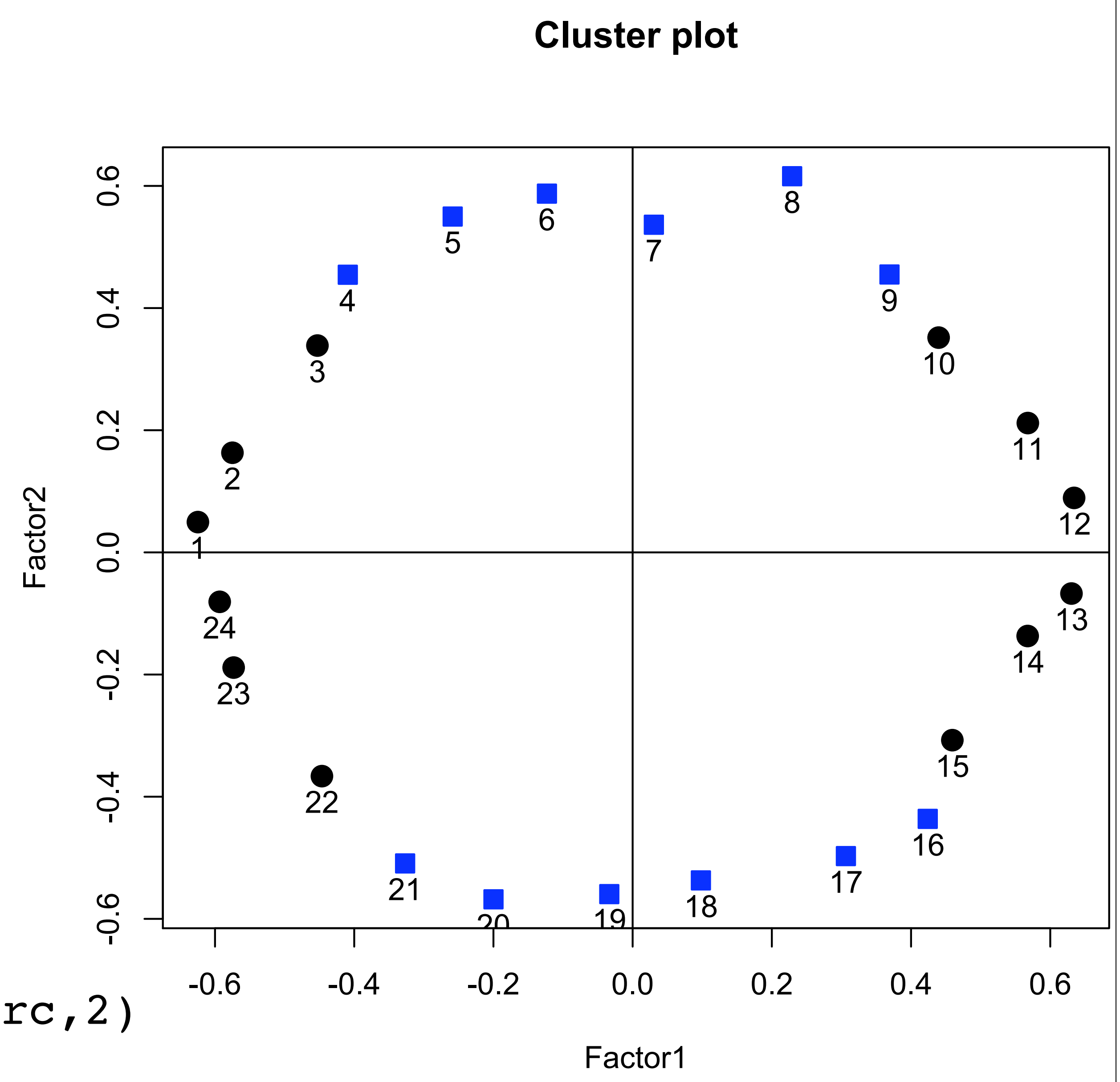
```
pairs.panels(circ[,1:8])
```



Circumplex correlations

```
> round(cor(circ)[,1:12],2)
       V1    V2    V3    V4    V5    V6    V7    V8    V9   V10   V11   V12
V1   1.00  0.35  0.32  0.26  0.25  0.12  0.01 -0.15 -0.25 -0.25 -0.34 -0.37
V2   0.35  1.00  0.34  0.29  0.25  0.19  0.06 -0.01 -0.14 -0.20 -0.32 -0.36
V3   0.32  0.34  1.00  0.31  0.30  0.24  0.16  0.08  0.04 -0.07 -0.12 -0.33
V4   0.26  0.29  0.31  1.00  0.34  0.36  0.20  0.14  0.07  0.00 -0.15 -0.20
V5   0.25  0.25  0.30  0.34  1.00  0.36  0.30  0.27  0.16  0.11 -0.02 -0.08
V6   0.12  0.19  0.24  0.36  0.36  1.00  0.34  0.40  0.22  0.10  0.08 -0.03
V7   0.01  0.06  0.16  0.20  0.30  0.34  1.00  0.32  0.23  0.17  0.14  0.08
V8  -0.15 -0.01  0.08  0.14  0.27  0.40  0.32  1.00  0.38  0.29  0.21  0.21
V9  -0.25 -0.14  0.04  0.07  0.16  0.22  0.23  0.38  1.00  0.29  0.32  0.24
V10 -0.25 -0.20 -0.07  0.00  0.11  0.10  0.17  0.29  0.29  1.00  0.38  0.32
V11 -0.34 -0.32 -0.12 -0.15 -0.02  0.08  0.14  0.21  0.32  0.38  1.00  0.40
V12 -0.37 -0.36 -0.33 -0.20 -0.08 -0.03  0.08  0.21  0.24  0.32  0.40  1.00
V13 -0.38 -0.37 -0.33 -0.29 -0.21 -0.09  0.00  0.06  0.21  0.24  0.35  0.38
V14 -0.36 -0.31 -0.34 -0.35 -0.25 -0.10 -0.02  0.08  0.16  0.20  0.27  0.31
V15 -0.33 -0.32 -0.28 -0.34 -0.24 -0.22 -0.16 -0.10  0.06  0.06  0.22  0.25
V16 -0.28 -0.28 -0.35 -0.38 -0.35 -0.28 -0.25 -0.18 -0.06  0.06  0.13  0.25
V17 -0.19 -0.26 -0.27 -0.38 -0.34 -0.33 -0.26 -0.24 -0.11 -0.06  0.09  0.17
V18 -0.09 -0.16 -0.27 -0.26 -0.34 -0.33 -0.29 -0.35 -0.15 -0.16 -0.07 -0.01
V19 -0.04 -0.08 -0.16 -0.25 -0.30 -0.32 -0.30 -0.34 -0.24 -0.24 -0.15 -0.09
V20  0.11  0.03 -0.12 -0.16 -0.25 -0.29 -0.32 -0.37 -0.37 -0.29 -0.23 -0.14
V21  0.17  0.09  0.00 -0.13 -0.18 -0.23 -0.29 -0.38 -0.37 -0.34 -0.24 -0.26
V22  0.31  0.21  0.05  0.00 -0.05 -0.15 -0.23 -0.32 -0.35 -0.30 -0.32 -0.30
V23  0.30  0.35  0.16  0.17  0.05 -0.01 -0.08 -0.26 -0.28 -0.36 -0.38 -0.40
V24  0.39  0.29  0.22  0.22  0.08  0.03 -0.05 -0.23 -0.25 -0.29 -0.37 -0.40
```

2 factor solution




```
> f2c <- factanal(circ,2)
> factor.plot(f2c)
```

2 factors are great

```
factanal(x = circ, factors = 2)
Uniquenesses:
   V1    V2    V3    V4    V5    V6    V7    V8    V9   V10   V11
V12   V13   V14   V15   V16   V17   V18   V19   V20   V21   V22
0.607 0.643 0.680 0.626 0.631 0.640 0.711 0.568 0.657 0.683 0.633
0.590 0.598 0.659 0.694 0.630 0.659 0.702 0.686 0.637 0.634 0.667
  V23   V24
0.636 0.641
Loadings:
    Factor1 Factor2
V1  -0.625
V2  -0.575   0.163
V3  -0.453   0.339
V4  -0.409   0.455
V5  -0.259   0.550
V6  -0.123   0.587
V7           0.536
V8   0.229   0.616
V9   0.369   0.455
V10  0.440   0.352
V11  0.568   0.212
V12  0.634
```

```
[V13  0.630
V14  0.568  -0.137
V15  0.459  -0.307
V16  0.424  -0.436
V17  0.306  -0.497
V18         -0.537
V19         -0.559
V20 -0.200  -0.568
V21 -0.327  -0.509
V22 -0.446  -0.366
V23 -0.573  -0.189
V24 -0.593
```

```
Test of the
hypothesis that
2 factors are
sufficient.
The chi square
statistic is
224.9 on 229
degrees of
freedom.
The p-value is
0.564
```

```
               Factor1 Factor2
SS loadings      4.524   3.963
Proportion Var   0.189   0.165
Cumulative Var   0.189   0.354
```

But, the simple structure model does not fit

```
> sem.c <- sem(mod2,cor(circ),500)
> summary(sem.c,digits=2)

 Model Chisquare =  1204   Df =  252 Pr(>Chisq) = 0
 Chisquare (null model) =  3449   Df =  276
 Goodness-of-fit index =  0.8
 Adjusted goodness-of-fit index =  0.75
 RMSEA index =  0.087   90% CI: (NA, NA)
 Bentler-Bonnett NFI =  0.65
 Tucker-Lewis NNFI =  0.67
 Bentler CFI =  0.7
 SRMR =  0.15
 BIC =  -362

 Normalized Residuals
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
 -8.440  -1.850  -0.036  -0.054   1.690   8.960
```

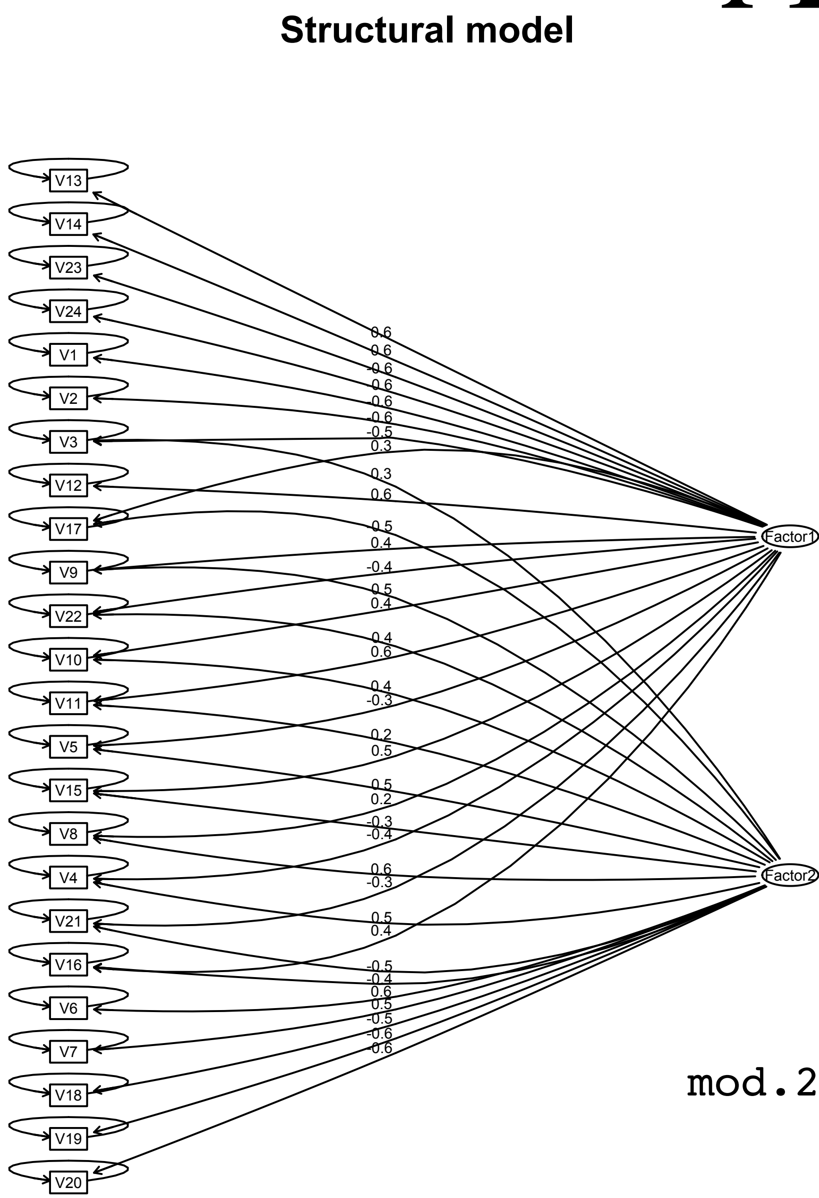
Parameters make sense

```
 Parameter Estimates
      Estimate Std Error z value Pr(>|z|)
F1V1    0.51    0.046     11.0   0.0e+00  V1 <--- Factor1
F1V2    0.54    0.045     11.8   0.0e+00  V2 <--- Factor1
F1V3    0.57    0.045     12.8   0.0e+00  V3 <--- Factor1
F1V4    0.61    0.044     13.8   0.0e+00  V4 <--- Factor1
F1V5    0.54    0.045     12.0   0.0e+00  V5 <--- Factor1
F1V6    0.44    0.047      9.3   0.0e+00  V6 <--- Factor1
F2V7    0.38    0.048      7.9   2.2e-15  V7 <--- Factor2
F2V8    0.57    0.045     12.7   0.0e+00  V8 <--- Factor2
F2V9    0.59    0.045     13.1   0.0e+00  V9 <--- Factor2
F2V10   0.57    0.045     12.7   0.0e+00  V10 <--- Factor2
F2V11   0.54    0.046     11.9   0.0e+00  V11 <--- Factor2
F2V12   0.50    0.047     10.6   0.0e+00  V12 <--- Factor2
F1V13 -0.52    0.046    -11.3   0.0e+00  V13 <--- Factor1
F1V14 -0.54    0.046    -11.8   0.0e+00  V14 <--- Factor1
F1V15 -0.55    0.045    -12.1   0.0e+00  V15 <--- Factor1
F1V16 -0.61    0.044    -13.8   0.0e+00  V16 <--- Factor1
F1V17 -0.54    0.045    -11.9   0.0e+00  V17 <--- Factor1
F1V18 -0.40    0.047     -8.5   0.0e+00  V18 <--- Factor1
F2V19 -0.41    0.047     -8.7   0.0e+00  V19 <--- Factor2
F2V20 -0.54    0.046    -11.7   0.0e+00  V20 <--- Factor2
F2V21 -0.61    0.045    -13.6   0.0e+00  V21 <--- Factor2
F2V22 -0.57    0.045    -12.6   0.0e+00  V22 <--- Factor2
F2V23 -0.54    0.046    -11.9   0.0e+00  V23 <--- Factor2
F2V24 -0.46    0.047     -9.9   0.0e+00  V24 <--- Factor2
```

Examine residuals

```
> round(residuals(sem.c)[,1:12],2)
       V1    V2    V3    V4    V5    V6    V7    V8    V9   V10   V11   V12
V1   0.00  0.08  0.03 -0.06 -0.03 -0.10  0.01 -0.15 -0.25 -0.25 -0.34 -0.37
V2   0.08  0.00  0.03 -0.04 -0.04 -0.05  0.06 -0.01 -0.14 -0.20 -0.32 -0.36
V3   0.03  0.03  0.00 -0.04 -0.01 -0.01  0.16  0.08  0.04 -0.07 -0.12 -0.33
V4  -0.06 -0.04 -0.04  0.00  0.01  0.09  0.20  0.14  0.07  0.00 -0.15 -0.20
V5  -0.03 -0.04 -0.01  0.01  0.00  0.12  0.30  0.27  0.16  0.11 -0.02 -0.08
V6  -0.10 -0.05 -0.01  0.09  0.12  0.00  0.34  0.40  0.22  0.10  0.08 -0.03
V7   0.01  0.06  0.16  0.20  0.30  0.34  0.00  0.11  0.01 -0.05 -0.06 -0.11
V8  -0.15 -0.01  0.08  0.14  0.27  0.40  0.11  0.00  0.04 -0.04 -0.10 -0.08
V9  -0.25 -0.14  0.04  0.07  0.16  0.22  0.01  0.04  0.00 -0.04  0.00 -0.05
V10 -0.25 -0.20 -0.07  0.00  0.11  0.10 -0.05 -0.04 -0.04  0.00  0.07  0.04
V11 -0.34 -0.32 -0.12 -0.15 -0.02  0.08 -0.06 -0.10  0.00  0.07  0.00  0.13
V12 -0.37 -0.36 -0.33 -0.20 -0.08 -0.03 -0.11 -0.08 -0.05  0.04  0.13  0.00
V13 -0.12 -0.09 -0.03  0.03  0.07  0.14  0.00  0.06  0.21  0.24  0.35  0.38
V14 -0.09 -0.03 -0.03 -0.02  0.04  0.13 -0.02  0.08  0.16  0.20  0.27  0.31
V15 -0.05 -0.02  0.03  0.00  0.06  0.02 -0.16 -0.10  0.06  0.06  0.22  0.25
V16  0.03  0.05  0.00  0.00 -0.02 -0.01 -0.25 -0.18 -0.06  0.06  0.13  0.25
V17  0.08  0.03  0.04 -0.05 -0.05 -0.09 -0.26 -0.24 -0.11 -0.06  0.09  0.17
V18  0.11  0.05 -0.04 -0.01 -0.12 -0.16 -0.29 -0.35 -0.15 -0.16 -0.07 -0.01
V19 -0.04 -0.08 -0.16 -0.25 -0.30 -0.32 -0.15 -0.11  0.00 -0.01  0.08  0.12
V20  0.11  0.03 -0.12 -0.16 -0.25 -0.29 -0.12 -0.07 -0.06  0.02  0.07  0.13
V21  0.17  0.09  0.00 -0.13 -0.18 -0.23 -0.06 -0.03 -0.02  0.01  0.09  0.04
V22  0.31  0.21  0.05  0.00 -0.05 -0.15 -0.02  0.00 -0.02  0.02 -0.01 -0.02
V23  0.30  0.35  0.16  0.17  0.05 -0.01  0.12  0.05  0.04 -0.05 -0.09 -0.13
V24  0.39  0.29  0.22  0.22  0.08  0.03  0.13  0.03  0.02 -0.02 -0.11 -0.17
```

Allow for cross loadings



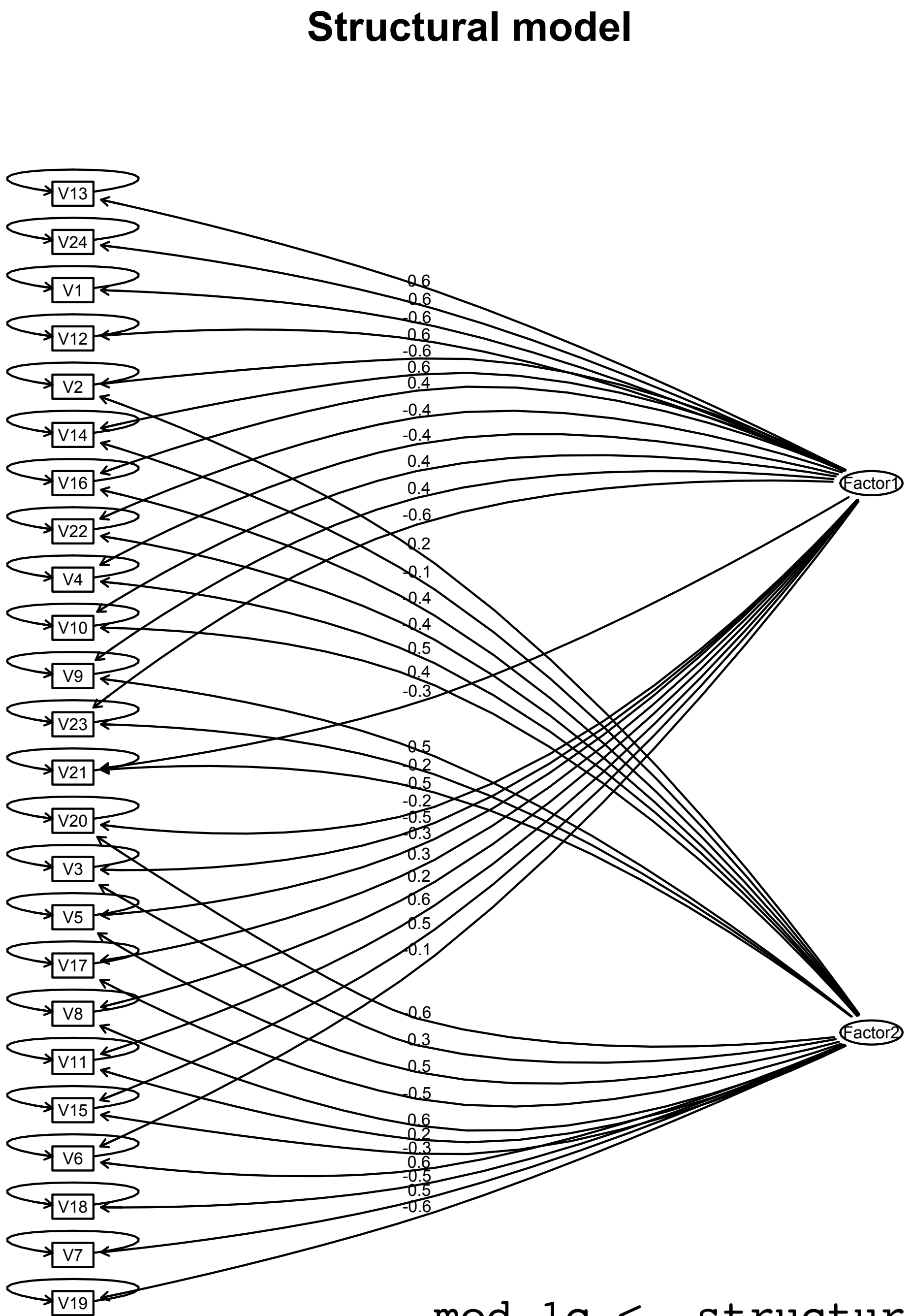

```
mod.2c <- structure.graph(f2,cut=.
2,simple=FALSE)
```

Much better

```
Model Chisquare =  339.99   Df =  240 Pr(>Chisq) = 2.2571e-05
Chisquare (null model) =  3449.1   Df =  276
Goodness-of-fit index =  0.94666
Adjusted goodness-of-fit index =  0.93333
RMSEA index =  0.028894   90% CI: (0.021463, 0.035723)
Bentler-Bonnett NFI =  0.90143
Tucker-Lewis NNFI =  0.96376
Bentler CFI =  0.96849
SRMR =  0.054238
BIC =  -1151.5

Normalized Residuals
    Min.  1st Qu.   Median     Mean  3rd Qu.     Max.
-3.63000 -0.72200 -0.01100 -0.00459  0.66900  5.55000
```

Paths

```
 Parameter Estimates
      Estimate Std Error z value  Pr(>|z|)
F1V1  -0.62510 0.042679  -14.6464 0.0000e+00 V1 <--- Factor1
F1V2  -0.57215 0.043609  -13.1200 0.0000e+00 V2 <--- Factor1
F1V3  -0.45852 0.043319  -10.5848 0.0000e+00 V3 <--- Factor1
F2V3  -0.32955 0.042673   -7.7225 1.1324e-14 V3 <--- Factor2
F1V4  -0.41496 0.042243   -9.8232 0.0000e+00 V4 <--- Factor1
F2V4  -0.44892 0.042254  -10.6244 0.0000e+00 V4 <--- Factor2
F1V5  -0.26585 0.042014   -6.3277 2.4878e-10 V5 <--- Factor1
F2V5  -0.54198 0.043029  -12.5957 0.0000e+00 V5 <--- Factor2
F2V6  -0.58679 0.043969  -13.3455 0.0000e+00 V6 <--- Factor2
F2V7  -0.54103 0.044515  -12.1540 0.0000e+00 V7 <--- Factor2
F1V8   0.22373 0.040683    5.4994 3.8119e-08 V8 <--- Factor1
F2V8  -0.61794 0.042222  -14.6355 0.0000e+00 V8 <--- Factor2
F1V9   0.35981 0.042647    8.4368 0.0000e+00 V9 <--- Factor1
F2V9  -0.46352 0.042975  -10.7856 0.0000e+00 V9 <--- Factor2
F1V10  0.43260 0.043362    9.9764 0.0000e+00 V10 <--- Factor1
F2V10 -0.35543 0.043014   -8.2631 2.2204e-16 V10 <--- Factor2
F1V11  0.56574 0.042811   13.2148 0.0000e+00 V11 <--- Factor1
F2V11 -0.21849 0.041302   -5.2900 1.2231e-07 V11 <--- Factor2
F1V12  0.63382 0.042565   14.8906 0.0000e+00 V12 <--- Factor1
F1V13  0.63250 0.042544   14.8671 0.0000e+00 V13 <--- Factor1
F1V14  0.56924 0.043669   13.0353 0.0000e+00 V14 <--- Factor1
F1V15  0.46708 0.043475   10.7437 0.0000e+00 V15 <--- Factor1
F2V15  0.30006 0.042985    6.9806 2.9388e-12 V15 <--- Factor2
```



Allow for even finer resolution

```
mod.1c <- structure.graph(f2,cut=.1,simple=FALSE)
```

More cross loadings

```
> mod.1cr <- edit(mod.1c)  #specify a few to be correct
> sem.1cr <- sem(mod.1cr,cor(circ),500)
> summary(sem.1cr,digits=2)

 Model Chisquare =  251   Df =  235 Pr(>Chisq) = 0.22
 Chisquare (null model) =  3449   Df =  276
 Goodness-of-fit index =  0.96
 Adjusted goodness-of-fit index =  0.95
 RMSEA index =  0.012   90% CI: (NA, 0.022)
 Bentler-Bonnett NFI =  0.93
 Tucker-Lewis NNFI =  1
 Bentler CFI =  1
 SRMR =  0.033
 BIC =  -1209

 Normalized Residuals
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
-2.1100 -0.4460  0.0253  0.0095  0.4770  2.1000
```

Paths

```
 Parameter Estimates
      Estimate Std Error z value Pr(>|z|)
F1V1  -0.62    0.043     -14.6   0.0e+00  V1 <--- Factor1
F1V2  -0.57    0.043     -13.3   0.0e+00  V2 <--- Factor1
F2V2  -0.17    0.042      -4.1   4.0e-05  V2 <--- Factor2
F1V3  -0.45    0.044     -10.2   0.0e+00  V3 <--- Factor1
F2V3  -0.35    0.043      -8.0   8.9e-16  V3 <--- Factor2
F1V4  -0.40    0.043      -9.3   0.0e+00  V4 <--- Factor1
F2V4  -0.46    0.043     -10.8   0.0e+00  V4 <--- Factor2
F1V5  -0.25    0.043      -5.7   9.3e-09  V5 <--- Factor1
F2V5  -0.55    0.043     -12.8   0.0e+00  V5 <--- Factor2
F1V6  -0.11    0.043      -2.6   9.5e-03  V6 <--- Factor1
F2V6  -0.59    0.043     -13.6   0.0e+00  V6 <--- Factor2
F2V7  -0.54    0.045     -12.0   0.0e+00  V7 <--- Factor2
F1V8   0.24    0.042       5.7   1.2e-08  V8 <--- Factor1
F2V8  -0.61    0.042     -14.4   0.0e+00  V8 <--- Factor2
F1V9   0.38    0.044       8.7   0.0e+00  V9 <--- Factor1
F2V9  -0.45    0.043     -10.4   0.0e+00  V9 <--- Factor2
F1V10  0.45    0.044      10.2   0.0e+00  V10 <--- Factor1
F2V10 -0.34    0.043      -7.9   2.9e-15  V10 <--- Factor2
F1V11  0.57    0.043      13.3   0.0e+00  V11 <--- Factor1
F2V11 -0.20    0.042      -4.8   2.0e-06  V11 <--- Factor2
```

What about categorical?

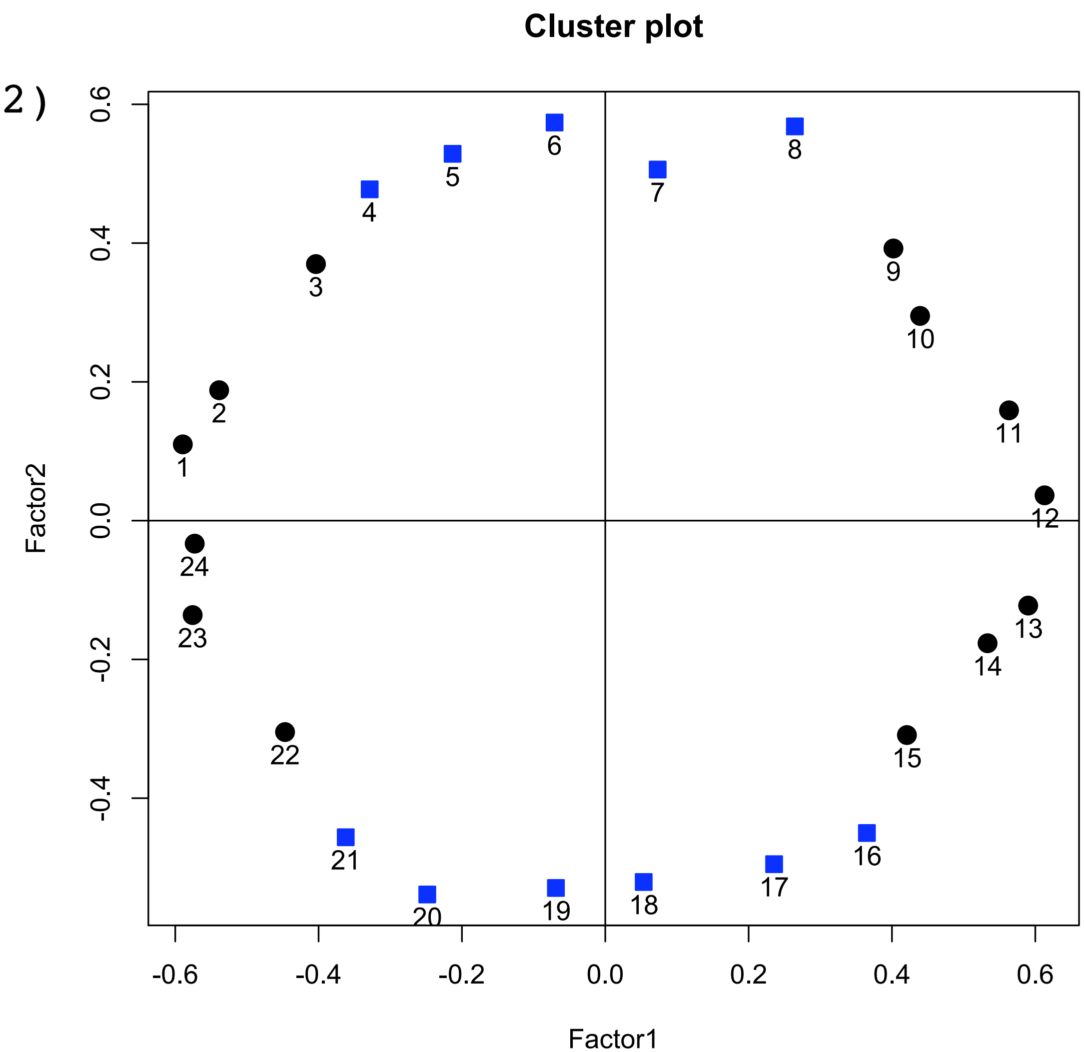
```
> set.seed(42)
> circ.cat <- sim.item(24,circum=TRUE,categorical=TRUE)
> colnames(circ.cat) <- paste("V",1:24,sep="")
> describe(circ.cat)
    var   n  mean   sd median trimmed  mad min max range  skew kurtosis   se
V1    1 500  0.00 1.05      0    0.00 1.48  -3   3     6  0.06     0.03 0.05
V2    2 500  0.02 1.03      0    0.01 1.48  -3   3     6  0.03    -0.02 0.05
V3    3 500 -0.03 1.10      0   -0.04 1.48  -3   3     6  0.11    -0.12 0.05
V4    4 500 -0.06 1.07      0   -0.06 1.48  -3   3     6 -0.02    -0.22 0.05
V5    5 500 -0.04 1.00      0   -0.03 1.48  -3   3     6 -0.09     0.05 0.04
V6    6 500 -0.05 1.08      0   -0.04 1.48  -3   3     6  0.02     0.08 0.05
V7    7 500 -0.02 0.99      0    0.01 1.48  -3   2     5 -0.21    -0.09 0.04
V8    8 500  0.00 1.10      0    0.01 1.48  -3   3     6 -0.03    -0.25 0.05
V9    9 500  0.01 1.06      0   -0.01 1.48  -3   3     6  0.06    -0.34 0.05
V10  10 500  0.03 0.98      0    0.04 1.48  -2   3     5 -0.05    -0.28 0.04
V11  11 500 -0.02 1.03      0   -0.05 1.48  -3   3     6  0.18     0.04 0.05
V12  12 500 -0.03 1.05      0   -0.05 1.48  -3   3     6  0.07    -0.22 0.05
V13  13 500 -0.04 1.09      0   -0.06 1.48  -3   3     6  0.03    -0.08 0.05
V14  14 500  0.06 1.03      0    0.06 1.48  -3   3     6 -0.05    -0.25 0.05
V15  15 500  0.02 1.07      0    0.03 1.48  -3   3     6  0.02    -0.25 0.05
V16  16 500  0.03 1.05      0    0.01 1.48  -3   3     6  0.10    -0.09 0.05
V17  17 500  0.02 1.05      0    0.02 1.48  -3   3     6  0.02    -0.31 0.05
V18  18 500  0.04 1.03      0    0.03 1.48  -3   3     6  0.03    -0.02 0.05
V19  19 500 -0.01 0.99      0    0.00 1.48  -3   3     6 -0.07    -0.15 0.04
V20  20 500  0.01 1.03      0   -0.01 1.48  -3   3     6  0.06     0.32 0.05
V21  21 500 -0.04 1.07      0   -0.05 1.48  -3   3     6  0.12     0.04 0.05
V22  22 500  0.03 1.05      0    0.02 1.48  -3   3     6  0.04     0.08 0.05
V23  23 500  0.03 1.05      0    0.02 1.48  -3   3     6  0.05    -0.13 0.05
V24  24 500 -0.01 1.04      0    0.01 1.48  -3   3     6 -0.02     0.10 0.05
```

Correlations are similar

```
> round(cor(circ.cat)[,1:12],2)
       V1    V2    V3    V4    V5    V6    V7    V8    V9   V10   V11   V12
V1   1.00  0.32  0.30  0.21  0.24  0.13  0.03 -0.13 -0.21 -0.22 -0.31 -0.35
V2   0.32  1.00  0.31  0.26  0.23  0.18  0.06 -0.03 -0.13 -0.18 -0.30 -0.32
V3   0.30  0.31  1.00  0.29  0.28  0.22  0.14  0.08  0.03 -0.07 -0.09 -0.31
V4   0.21  0.26  0.29  1.00  0.29  0.33  0.20  0.16  0.07  0.01 -0.11 -0.19
V5   0.24  0.23  0.28  0.29  1.00  0.32  0.26  0.23  0.13  0.11 -0.04 -0.08
V6   0.13  0.18  0.22  0.33  0.32  1.00  0.31  0.39  0.19  0.08  0.06 -0.02
V7   0.03  0.06  0.14  0.20  0.26  0.31  1.00  0.28  0.22  0.15  0.15  0.07
V8  -0.13 -0.03  0.08  0.16  0.23  0.39  0.28  1.00  0.35  0.25  0.20  0.19
V9  -0.21 -0.13  0.03  0.07  0.13  0.19  0.22  0.35  1.00  0.30  0.29  0.23
V10 -0.22 -0.18 -0.07  0.01  0.11  0.08  0.15  0.25  0.30  1.00  0.35  0.28
V11 -0.31 -0.30 -0.09 -0.11 -0.04  0.06  0.15  0.20  0.29  0.35  1.00  0.35
V12 -0.35 -0.32 -0.31 -0.19 -0.08 -0.02  0.07  0.19  0.23  0.28  0.35  1.00
V13 -0.36 -0.34 -0.30 -0.25 -0.18 -0.07  0.00  0.03  0.20  0.20  0.32  0.33
V14 -0.33 -0.29 -0.29 -0.31 -0.26 -0.11 -0.01  0.07  0.17  0.19  0.23  0.30
V15 -0.30 -0.30 -0.23 -0.28 -0.20 -0.20 -0.13 -0.09  0.07  0.04  0.22  0.26
V16 -0.26 -0.24 -0.33 -0.35 -0.31 -0.24 -0.21 -0.17 -0.04  0.05  0.14  0.21
V17 -0.18 -0.22 -0.25 -0.35 -0.30 -0.29 -0.23 -0.20 -0.08 -0.05  0.07  0.12
V18 -0.08 -0.15 -0.27 -0.24 -0.31 -0.32 -0.26 -0.32 -0.12 -0.15 -0.08 -0.01
V19 -0.03 -0.07 -0.15 -0.22 -0.30 -0.29 -0.27 -0.31 -0.21 -0.20 -0.12 -0.07
V20  0.11  0.05 -0.12 -0.15 -0.23 -0.27 -0.31 -0.34 -0.35 -0.27 -0.22 -0.13
V21  0.15  0.11  0.02 -0.13 -0.14 -0.21 -0.27 -0.35 -0.34 -0.31 -0.22 -0.25
V22  0.25  0.21  0.03 -0.03 -0.04 -0.13 -0.22 -0.28 -0.30 -0.24 -0.31 -0.30
V23  0.27  0.35  0.16  0.13  0.07 -0.03 -0.06 -0.22 -0.27 -0.34 -0.36 -0.37
V24  0.36  0.25  0.22  0.20  0.08  0.03 -0.04 -0.24 -0.23 -0.26 -0.35 -0.37
```

Loadings are slightly smaller

```
> f2c <- factanal(circ.cat,2)
> factor.plot(f2c)
```

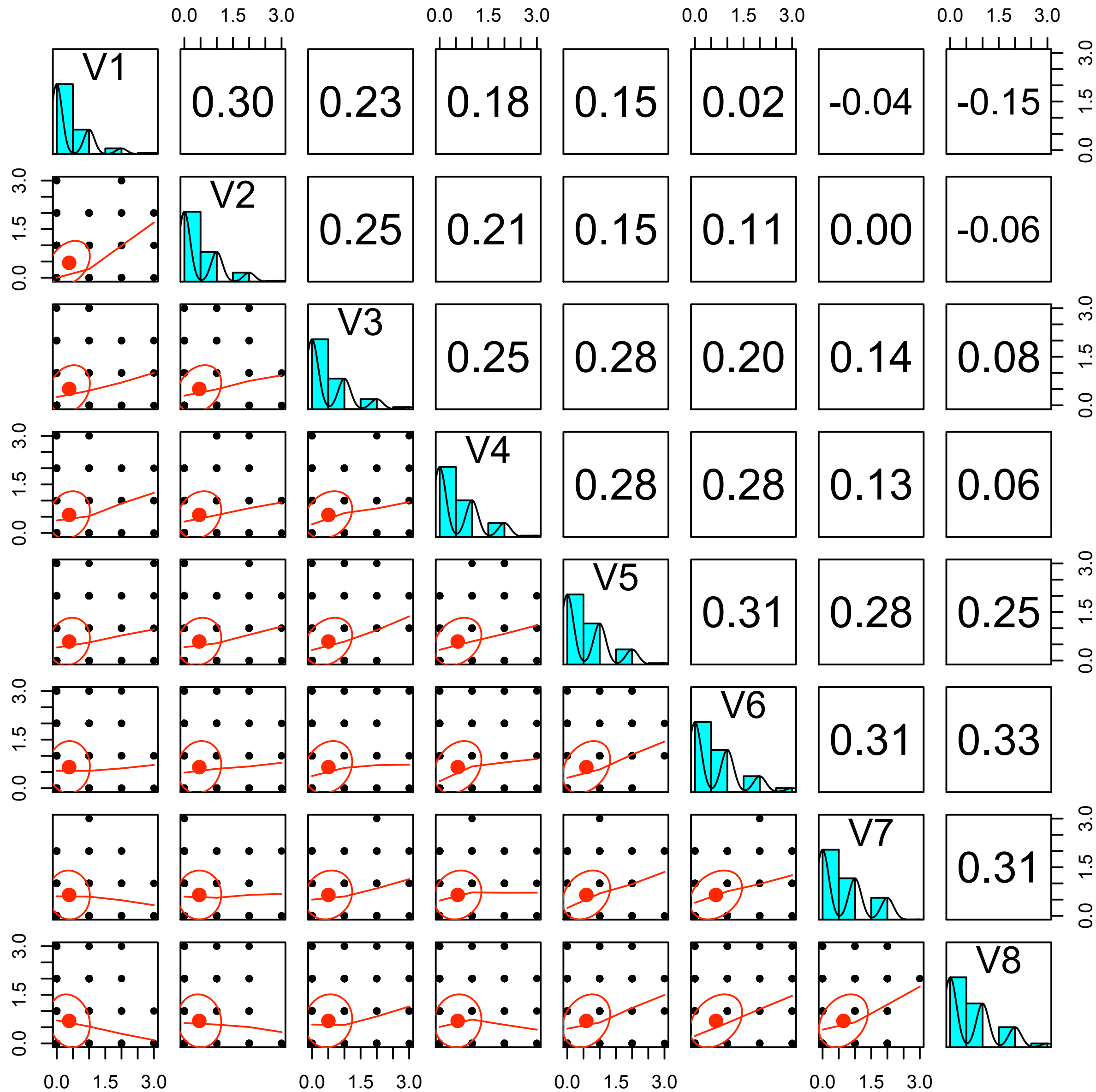


sem needs help

```
>  mod.1crc <-edit(mod.1crc) #starting with the fa values
>  summary(sem.2c,digits=2)

 Model Chisquare =  258   Df =  235 Pr(>Chisq) = 0.15
 Chisquare (null model) =  3021   Df =  276
 Goodness-of-fit index =  0.96
 Adjusted goodness-of-fit index =  0.95
 RMSEA index =  0.014   90% CI: (NA, 0.024)
 Bentler-Bonnett NFI =  0.91
 Tucker-Lewis NNFI =  1
 Bentler CFI =  1
 SRMR =  0.034
 BIC =  -1203

 Normalized Residuals
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
 -2.470  -0.427   0.045   0.025   0.463   2.190
```

skew categorical

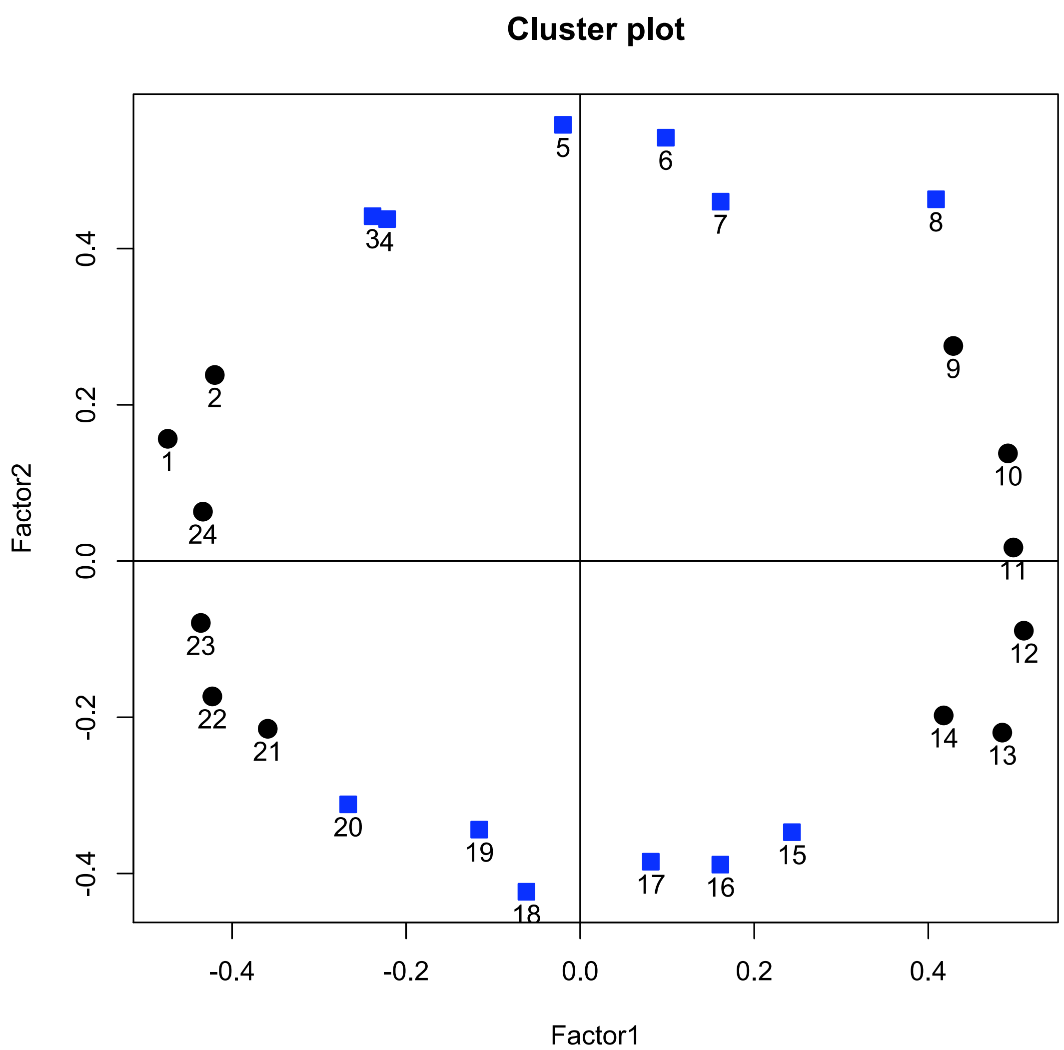
```
> set.seed(42)
> circ.skewed <- sim.item(24,circum=TRUE,ybias=.5,categorical=TRUE,truncat=TRUE)
> colnames(circ.skewed) <- paste("V",1:24,sep="")
> describe(circ.skewed)
    var   n mean   sd median trimmed mad min max range skew kurtosis   se
V1    1 500 0.38 0.64      0    0.26   0   0   3     3 1.65     2.37 0.03
V2    2 500 0.46 0.68      0    0.33   0   0   3     3 1.31     0.97 0.03
V3    3 500 0.51 0.73      0    0.36   0   0   3     3 1.34     1.14 0.03
V4    4 500 0.56 0.73      0    0.44   0   0   3     3 1.05     0.19 0.03
V5    5 500 0.59 0.73      0    0.47   0   0   3     3 0.97     0.03 0.03
V6    6 500 0.65 0.81      0    0.52   0   0   3     3 1.06     0.36 0.04
V7    7 500 0.64 0.76      0    0.55   0   0   3     3 0.72    -0.81 0.03
V8    8 500 0.69 0.82      0    0.58   0   0   3     3 0.92    -0.05 0.04
V9    9 500 0.67 0.77      0    0.57   0   0   3     3 0.82    -0.26 0.03
V10  10 500 0.54 0.72      0    0.40   0   0   3     3 1.20     0.86 0.03
V11  11 500 0.47 0.71      0    0.32   0   0   3     3 1.38     1.15 0.03
V12  12 500 0.44 0.67      0    0.31   0   0   3     3 1.33     0.96 0.03
V13  13 500 0.39 0.65      0    0.26   0   0   3     3 1.54     1.62 0.03
V14  14 500 0.36 0.59      0    0.25   0   0   3     3 1.50     1.45 0.03
V15  15 500 0.30 0.57      0    0.18   0   0   3     3 1.97     3.67 0.03
V16  16 500 0.25 0.53      0    0.14   0   0   3     3 2.18     4.70 0.02
V17  17 500 0.20 0.46      0    0.09   0   0   3     3 2.42     6.06 0.02
V18  18 500 0.20 0.46      0    0.08   0   0   2     2 2.33     4.78 0.02
V19  19 500 0.18 0.42      0    0.08   0   0   2     2 2.21     4.21 0.02
V20  20 500 0.19 0.46      0    0.08   0   0   2     2 2.42     5.24 0.02
V21  21 500 0.21 0.49      0    0.10   0   0   3     3 2.38     5.46 0.02
V22  22 500 0.24 0.51      0    0.14   0   0   3     3 2.20     4.94 0.02
V23  23 500 0.28 0.56      0    0.16   0   0   3     3 2.03     3.78 0.02
V24  24 500 0.31 0.58      0    0.19   0   0   3     3 2.05     4.41 0.03
>
```




```
> pairs.panels(circ.skewed[,1:8])
```

Loadings are reduced

Angular locations are preserved



Two factors works!

```
> f2cs

Call:
factanal(x = circ.skewed, factors = 2)

Uniquenesses:
   V1    V2    V3    V4    V5    V6    V7    V8    V9   V10   V11   V12   V13   V14
V15   V16   V17   V18   V19   V20   V21   V22
0.751 0.767 0.748 0.759 0.688 0.697 0.762 0.618 0.740 0.739 0.752 0.732 0.716 0.786
0.820 0.823 0.845 0.817 0.868 0.832 0.825 0.791
  V23   V24
0.804 0.808

Loadings:
    Factor1 Factor2
V1  -0.474   0.157
V2  -0.420   0.238
V3  -0.239   0.441
V4  -0.222   0.438
V5           0.558
V6           0.542
V7   0.161   0.460
V8   0.409   0.463
V9   0.429   0.275
V10  0.492   0.138
V11  0.498
V12  0.510
V13  0.485  -0.220
V14  0.418  -0.198
V15  0.243  -0.347
V16  0.161  -0.389
V17         -0.385
V18         -0.423
V19 -0.116  -0.344
V20 -0.267  -0.311
V21 -0.359  -0.215
V22 -0.423  -0.173
V23 -0.436
V24 -0.433

               Factor1 Factor2
SS loadings      2.919   2.590
Proportion Var   0.122   0.108
Cumulative Var   0.122   0.230

Test of the hypothesis that 2
factors are sufficient.
The chi square statistic is 238.55
on 229 degrees of freedom.
The p-value is 0.319
```

sem works as well

```
> sem.cs <- sem(mod.1crc,cor(circ.skewed),500)
> summary(sem.cs,digits=2)

 Model Chisquare =  252   Df =  235 Pr(>Chisq) = 0.21
 Chisquare (null model) =  1864   Df =  276
 Goodness-of-fit index =  0.96
 Adjusted goodness-of-fit index =  0.95
 RMSEA index =  0.012   90% CI: (NA, 0.023)
 Bentler-Bonnett NFI =  0.86
 Tucker-Lewis NNFI =  0.99
 Bentler CFI =  0.99
 SRMR =  0.034
 BIC =  -1208

 Normalized Residuals
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
  -1.57   -0.23    0.25    0.27    0.80    2.31
```

Cross loadings helped

Parameter Estimates

	Estimate	Std Error	z value	Pr(>|z|)	
F1V1	-0.498	0.047	-10.5	0.0e+00	V1 <--- Factor1
F1V2	-0.468	0.048	-9.9	0.0e+00	V2 <--- Factor1
F2V2	0.114	0.048	2.4	1.8e-02	V2 <--- Factor2
F1V3	-0.349	0.048	-7.2	4.4e-13	V3 <--- Factor1
F2V3	0.359	0.048	7.5	5.7e-14	V3 <--- Factor2
F1V4	-0.333	0.048	-6.9	5.0e-12	V4 <--- Factor1
F2V4	0.360	0.048	7.5	6.8e-14	V4 <--- Factor2
F1V5	-0.172	0.048	-3.5	3.9e-04	V5 <--- Factor1
F2V5	0.530	0.047	11.3	0.0e+00	V5 <--- Factor2
F1V6	-0.054	0.049	-1.1	2.6e-01	V6 <--- Factor1
F2V6	0.550	0.047	11.7	0.0e+00	V6 <--- Factor2
F2V7	0.488	0.048	10.2	0.0e+00	V7 <--- Factor2
F1V8	0.267	0.048	5.6	2.0e-08	V8 <--- Factor1
F2V8	0.557	0.046	12.1	0.0e+00	V8 <--- Factor2
F1V9	0.337	0.048	7.0	3.1e-12	V9 <--- Factor1
F2V9	0.382	0.048	8.0	1.1e-15	V9 <--- Factor2
F1V10	0.436	0.047	9.2	0.0e+00	V10 <--- Factor1
F2V10	0.266	0.048	5.6	2.6e-08	V10 <--- Factor2
F1V11	0.475	0.047	10.0	0.0e+00	V11 <--- Factor1
F2V11	0.155	0.048	3.2	1.3e-03	V11 <--- Factor2
F1V12	0.515	0.047	11.0	0.0e+00	V12 <--- Factor1
F1V13	0.526	0.047	11.2	0.0e+00	V13 <--- Factor1
F1V14	0.456	0.048	9.6	0.0e+00	V14 <--- Factor1
F2V14	-0.074	0.049	-1.5	1.3e-01	V14 <--- Factor2
F1V15	0.327	0.049	6.7	1.6e-11	V15 <--- Factor1
F2V15	-0.267	0.049	-5.5	4.6e-08	V15 <--- Factor2
F1V16	0.260	0.049	5.3	8.9e-08	V16 <--- Factor1

Conclusions

I. Characteristics of items will affect solutions

II. In general, the multivariate methods will recover structure, but sometimes need significant help in starting values