Alternative latent structures

Alternative latent variable structures

I. Conventional simple structure

   A. each variable loads on one latent variable

   B. Orthogonal factors

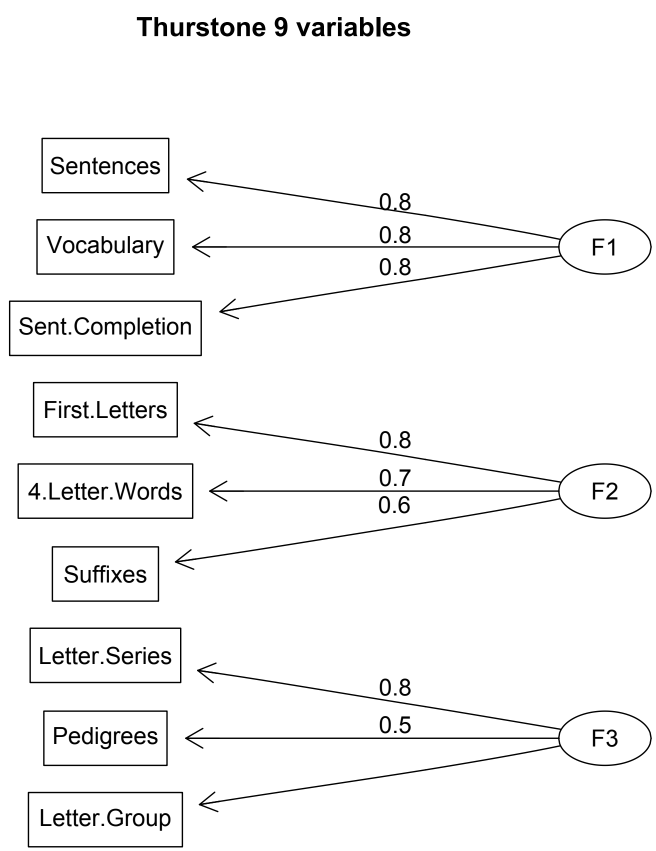
   C. Complexity >1 <=> variables load on more than one factor

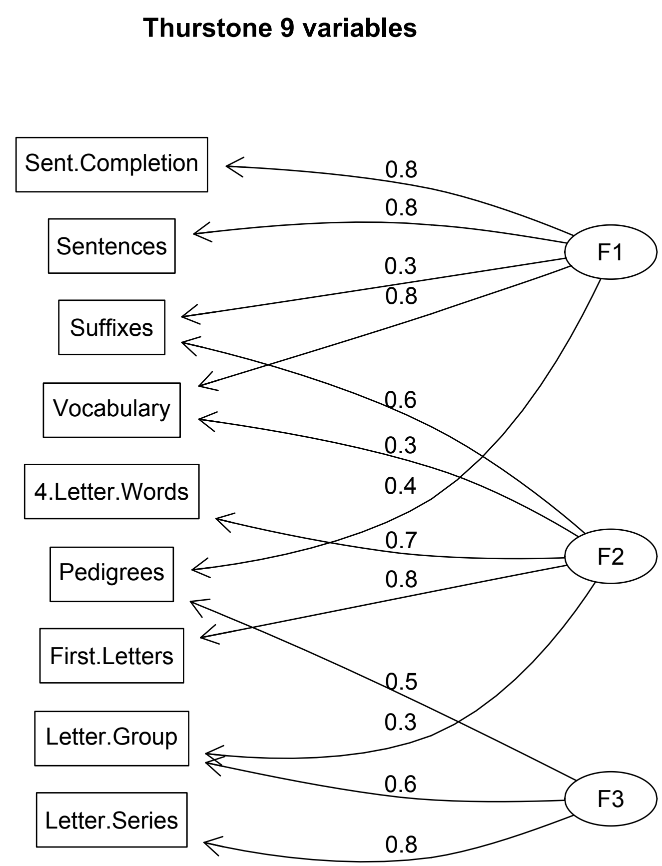
II. Oblique simple structure

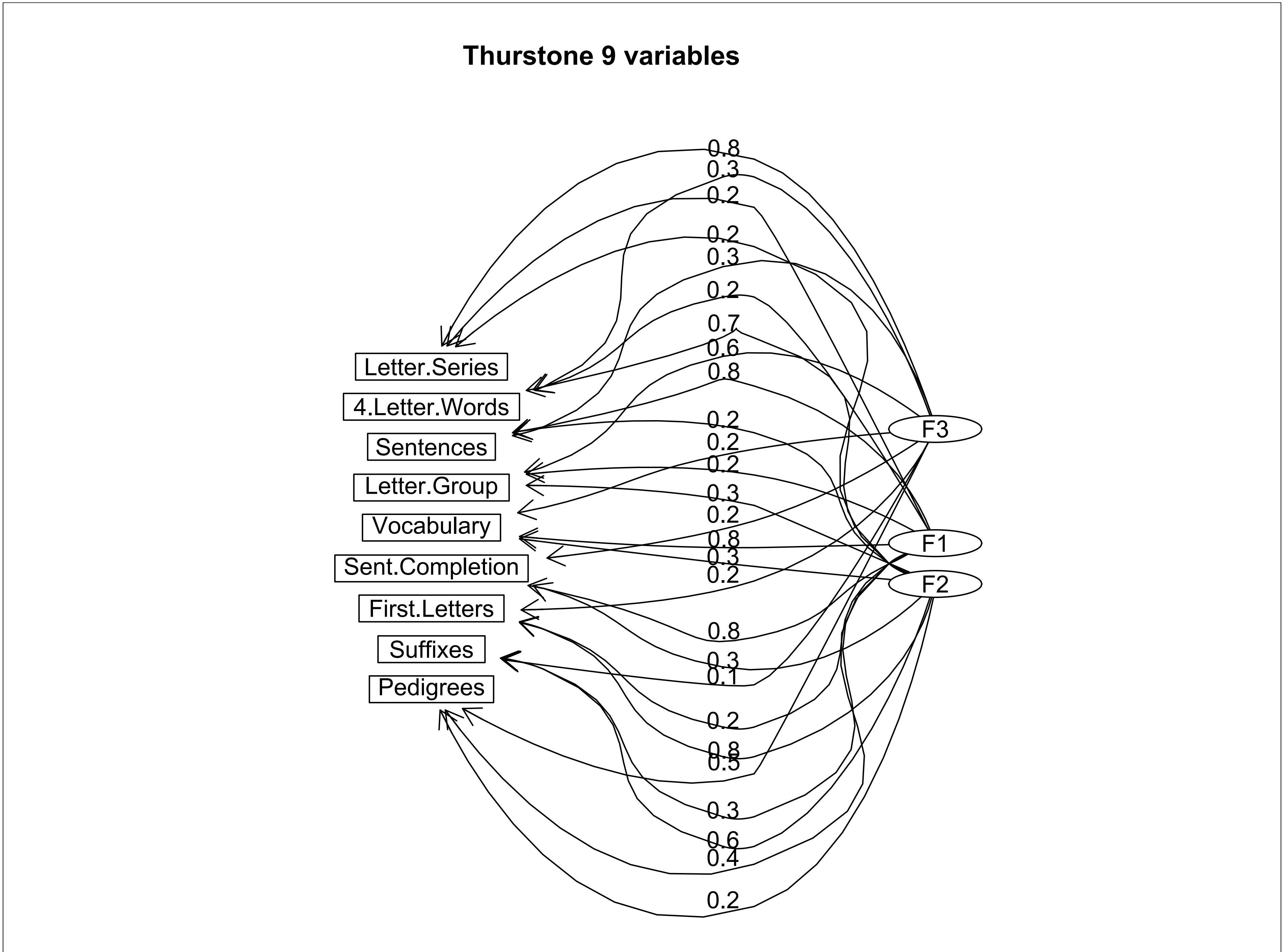
   A. Variables are simple structured

   B. Factors are correlated

Simple and not so simple structure

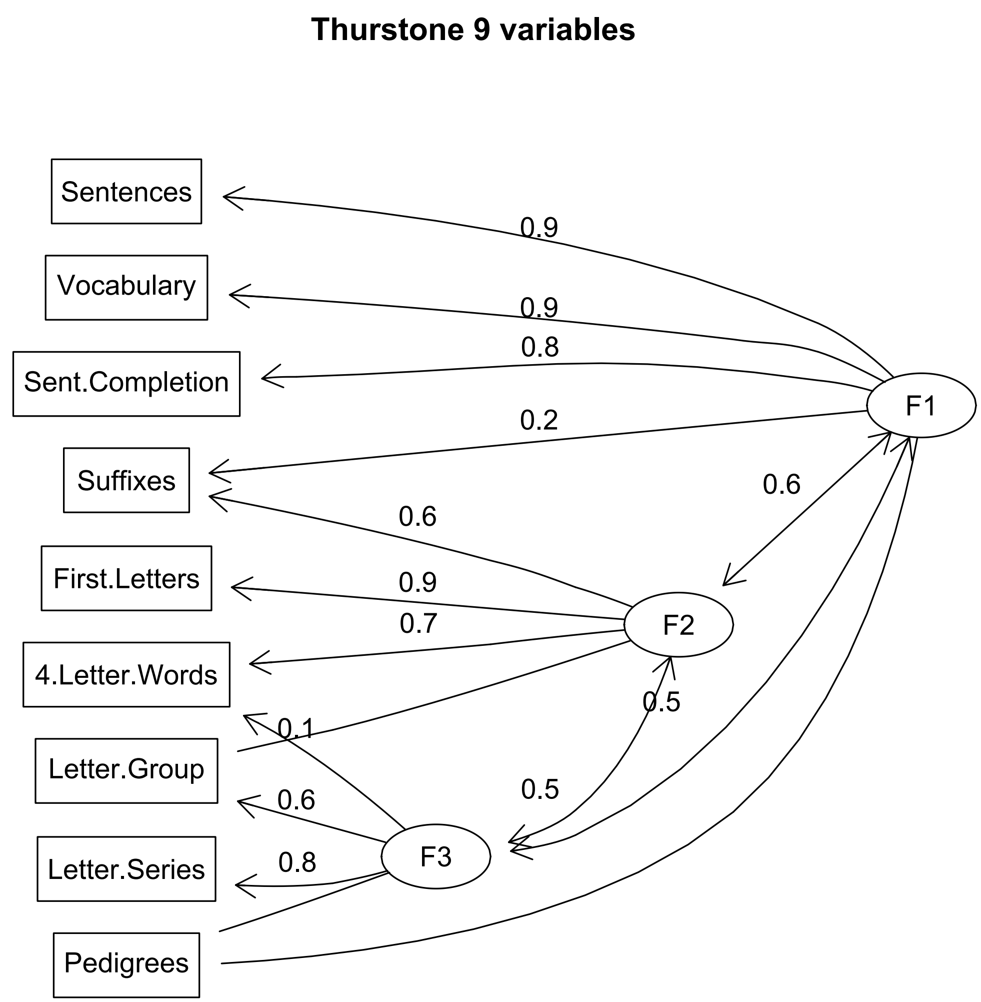






Thurstone 9 variables
Letter.Series
4.Letter.Words
Sentences
Letter.Group
Vocabulary
Sent.Completion
First.Letters
Suffixes
Pedigrees
F3
F1
F2
0.8
0.3
0.2
0.2
0.3
0.2
0.7
0.6
0.8
0.2
0.2
0.2
0.3
0.2
0.8
0.3
0.2
0.8
0.3
0.1
0.2
0.8
0.5
0.3
0.6
0.4
0.2

Oblique solution to Thurstone



Alternative structures

I. Additional conventional “simple” structures

   A. Hierarchical structure

   B. Bifactor structure

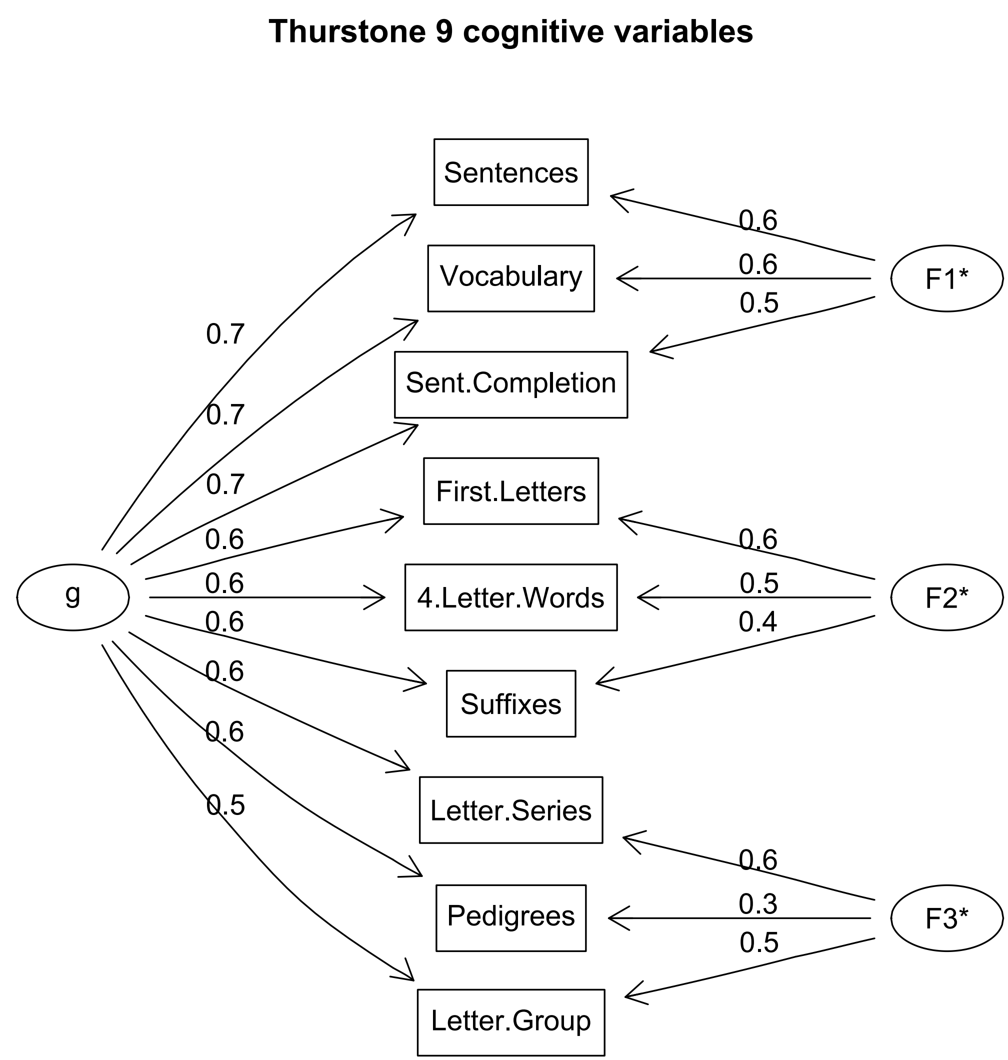
II. Non simple structures

   A. Circumplex

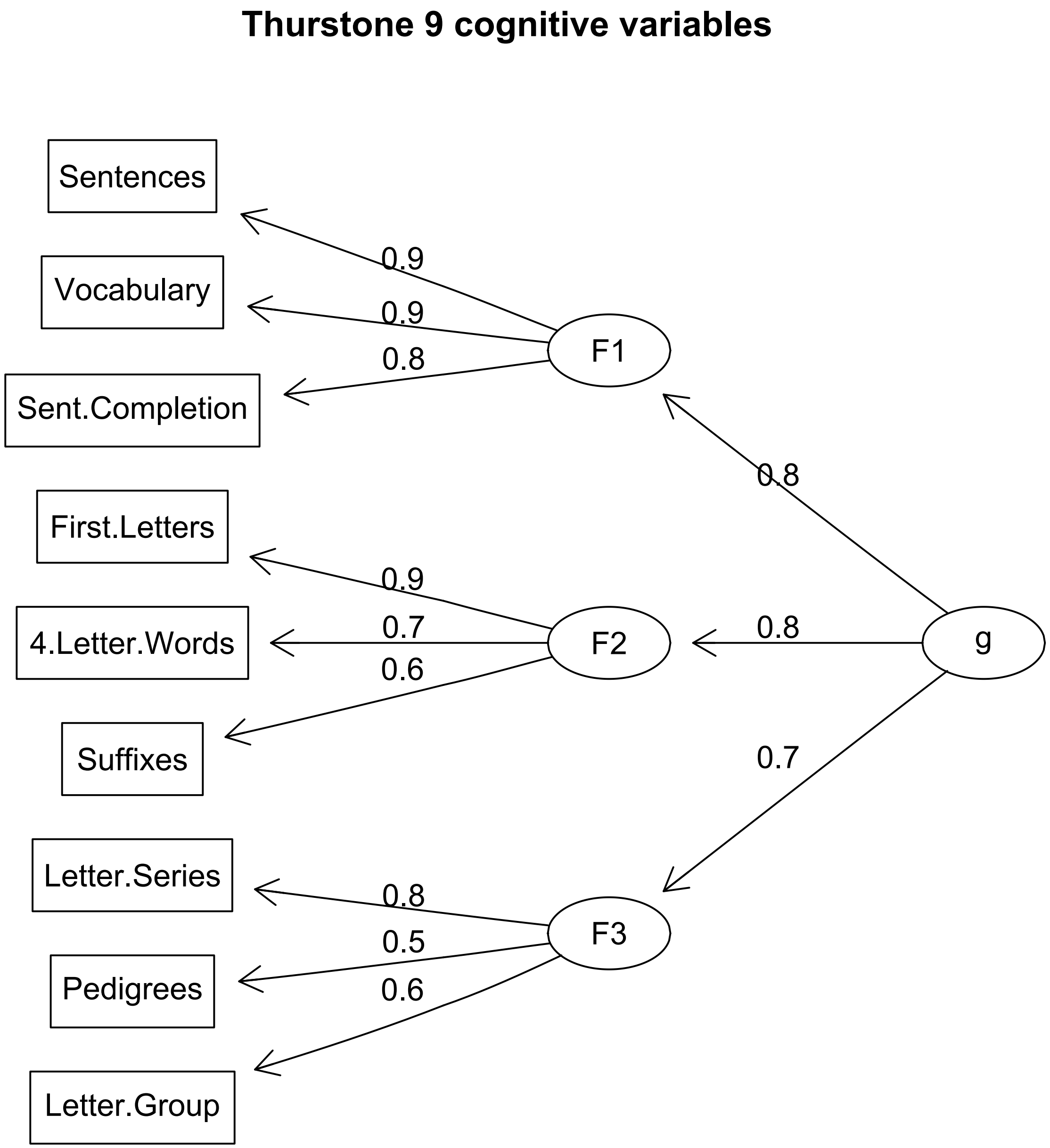
   B. Simplex

   C. Radex

Bifactor using Schmid Leiman



Hierarchical EFA



Circumplex structures

I. Most variables load on two factors, variables are equally spaced around the circle

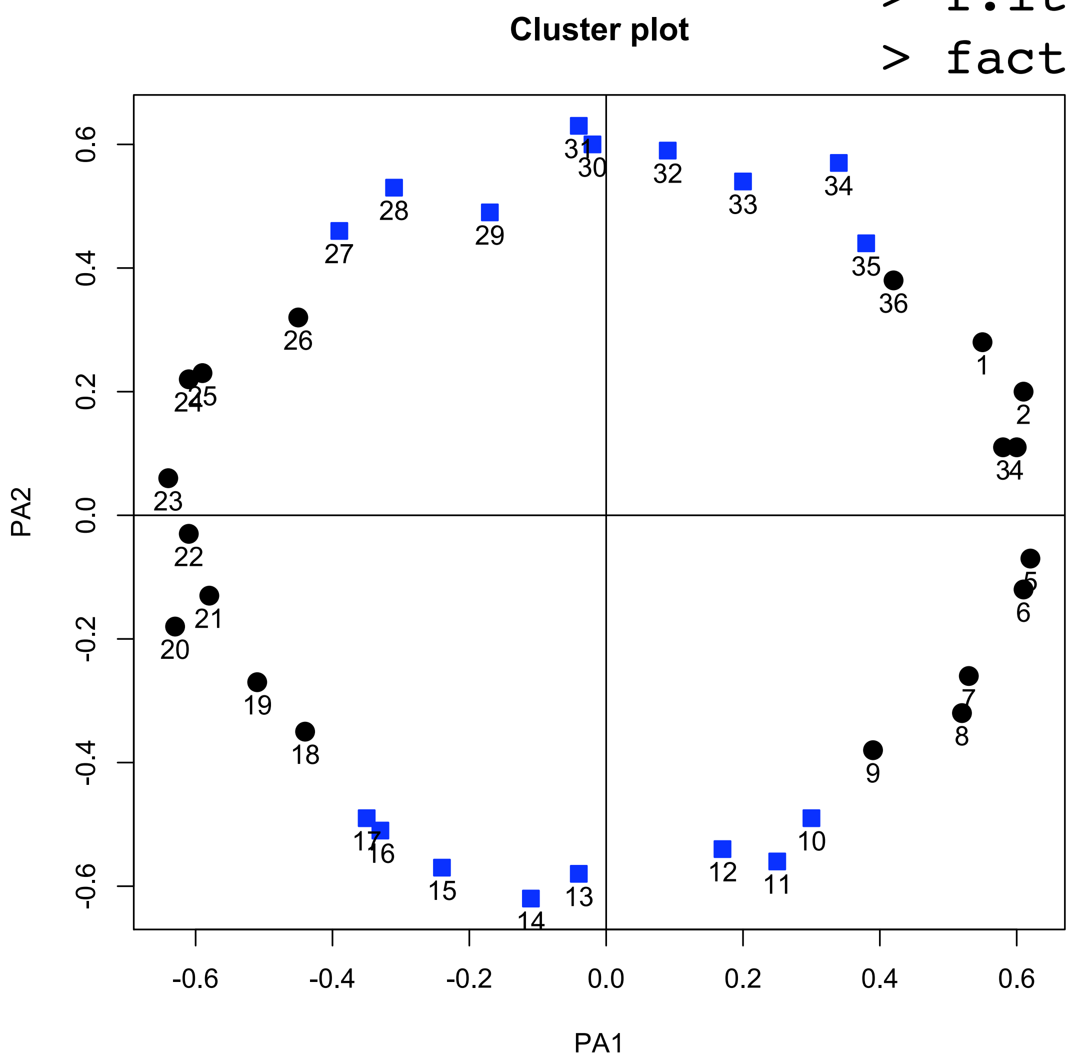
   A. Structure of affect (PA and NA), or EA and TA

   B. Interpersonal circumplex (Agency and Communion) or E x A

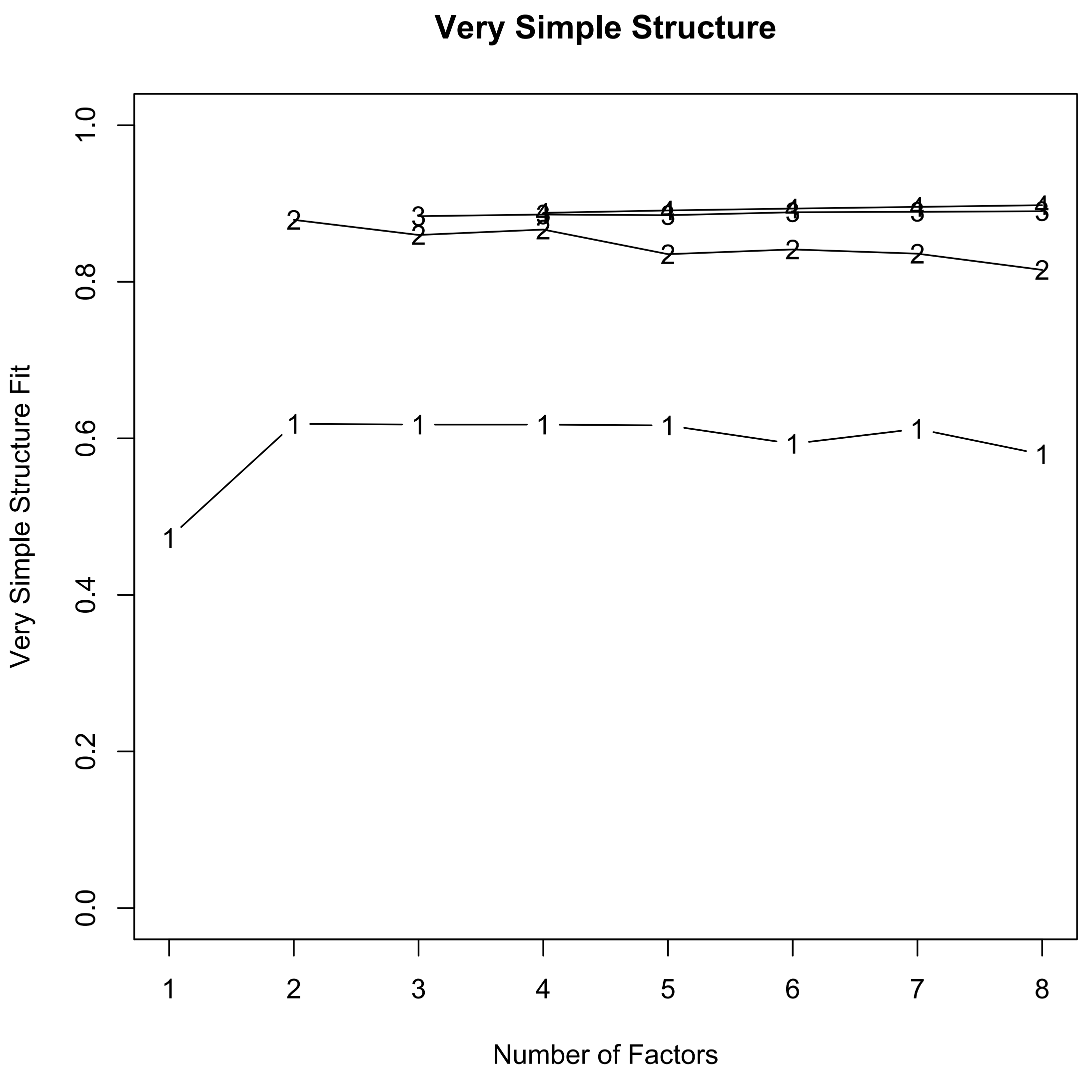
   C. Abridged Big 5 Circumplex (AB5C)

Simulated circumplex

```
> items <- sim.circ(36)
> f.items <- factor.pa(items,2)
> factor.plot(f.items)
```



VSS of circumplex data



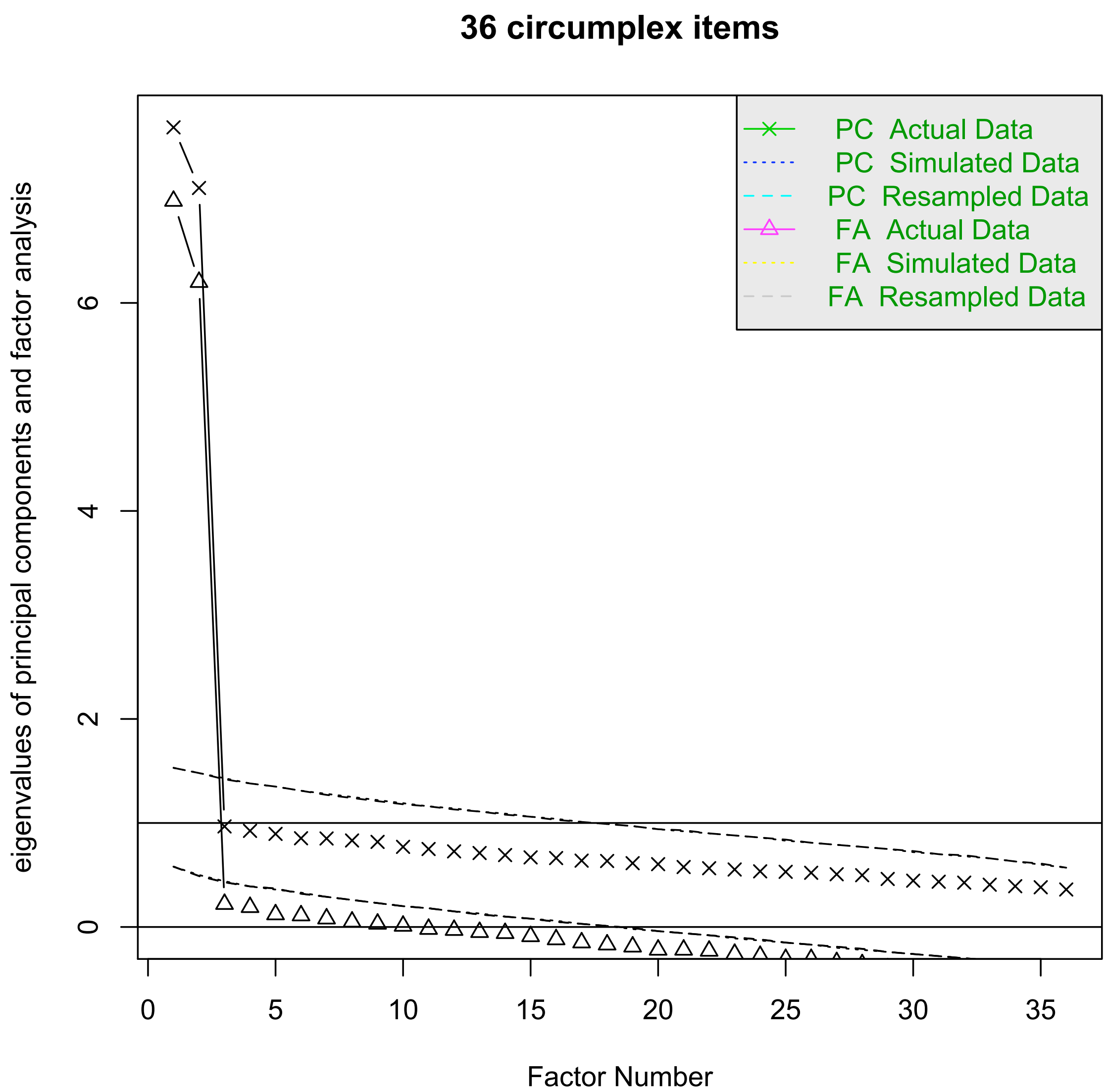
VSS of circumplex

```
> vss.circ <- VSS(items,pc="mle")
> vss.circ

Very Simple Structure
VSS complexity 1 achieves a maximimum of 0.62  with  2
factors
VSS complexity 2 achieves a maximimum of 0.88  with  2
factors

The Velicer MAP criterion achieves a minimum of 0.04  with
2  factors
 Velicer MAP
[1] 0.04 0.00 0.00 0.01 0.01 0.01 0.01 0.01

Very Simple Structure Complexity 1
[1] 0.47 0.62 0.62 0.62 0.62 0.59 0.61 0.58
Very Simple Structure Complexity 2
[1] 0.00 0.88 0.86 0.87 0.84 0.84 0.84 0.82
```

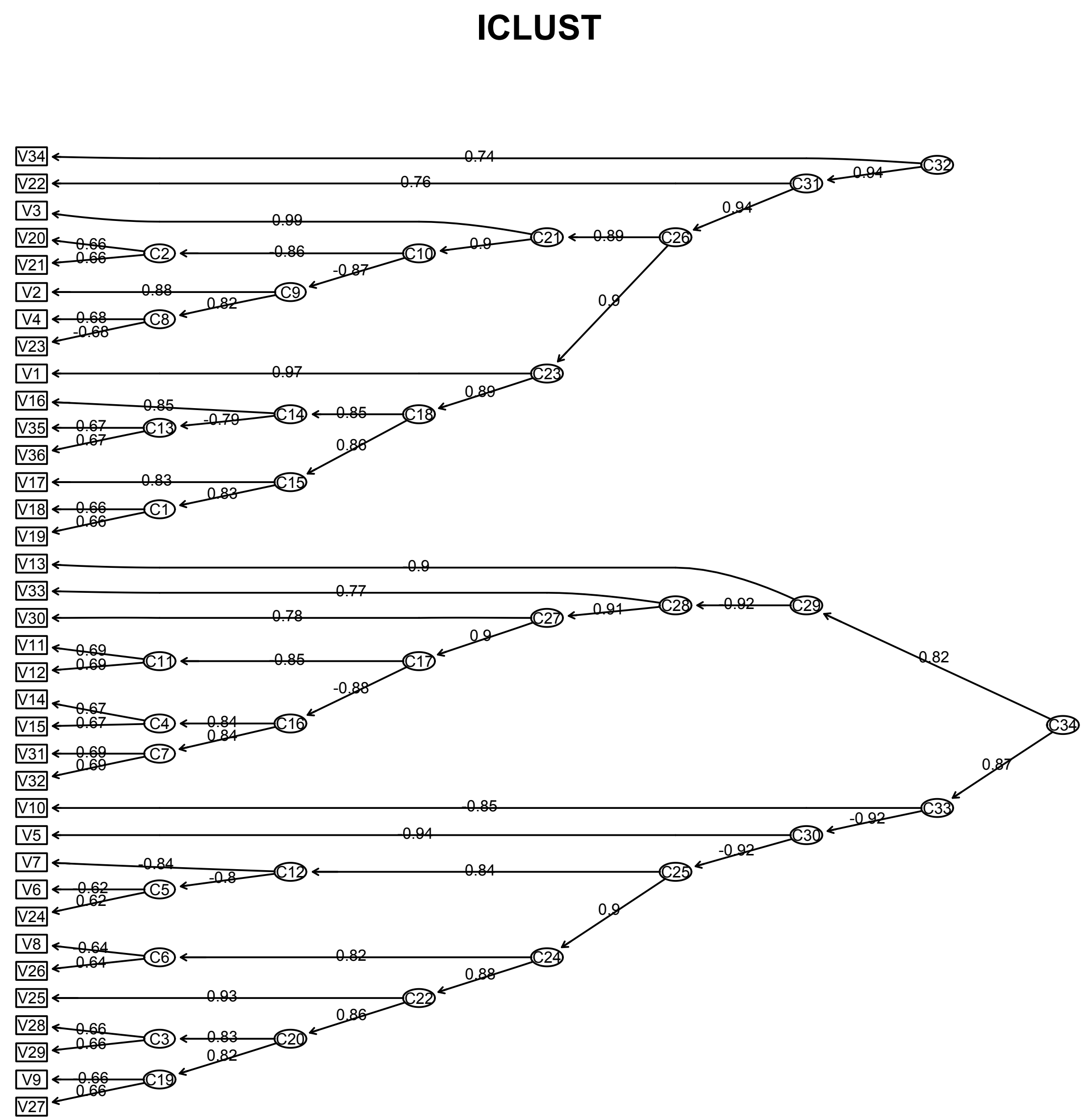
Chi Square of circumplex

```
> vss.circ$vss.stats[,1:3]
  dof     chisq      prob
1 594 3583.3960 0.0000000
2 559  576.4697 0.2956277
3 525  516.2642 0.5988992
4 492  466.6593 0.7883722
5 460  420.3704 0.9072375
6 429  376.5568 0.9675557
7 399  341.4850 0.9829587
8 370  308.3503 0.9913705
```

Parallel analysis -- scree



Cluster analysis of circumplex



Simplex structures

I. Described by Guttman (1950) as one of several alternatives to simple structure

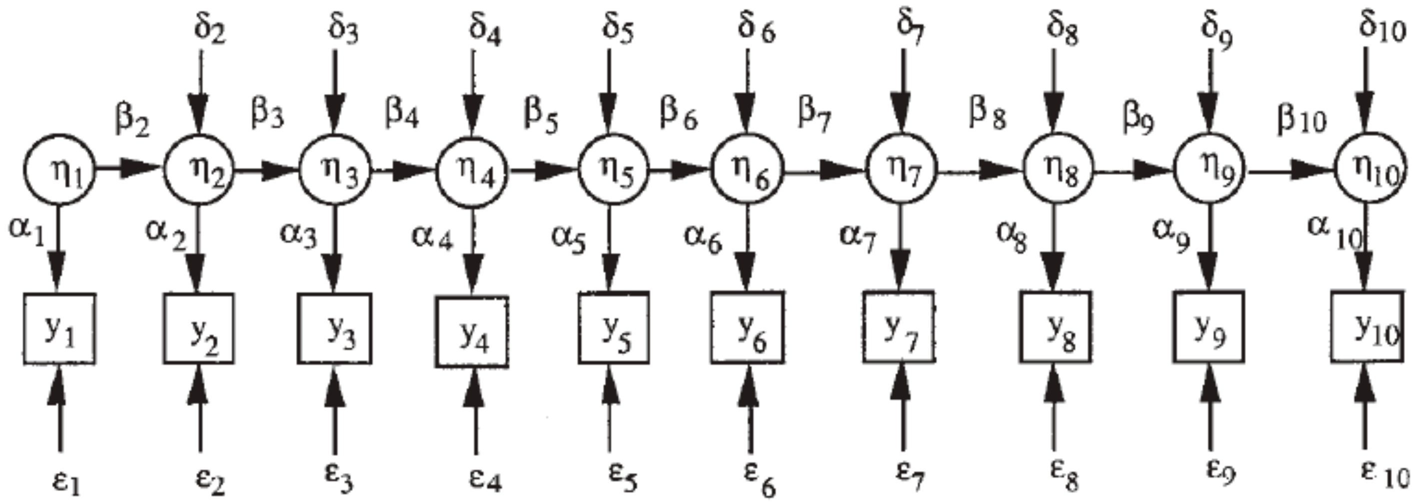
II. Appropriate for growth/development models

III. Also known as quasi-Markov simplex

   A. Latent at time x+1 = Latent at time x + error

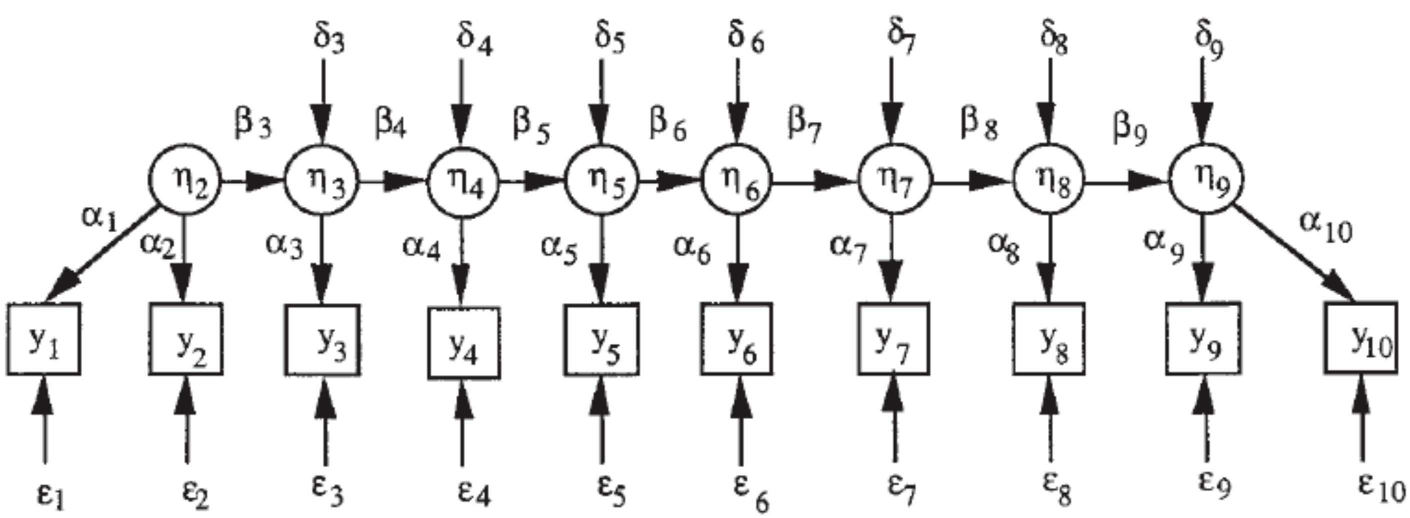
   B. Produces a particular correlation pattern

Simplex structures



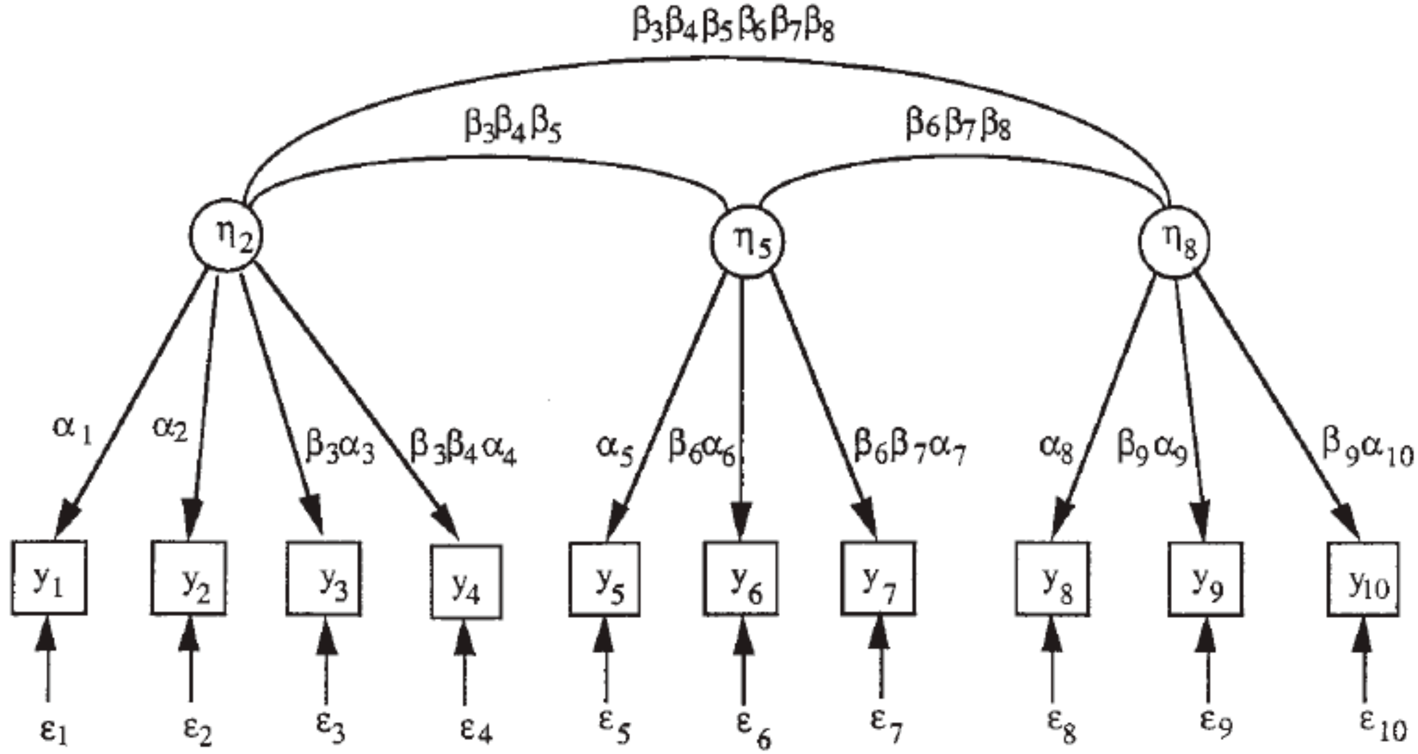
Mulaik and Millsap, 2000

Alternative parameterization



Mulaik and Millsap, 2000

3 factors or 10?

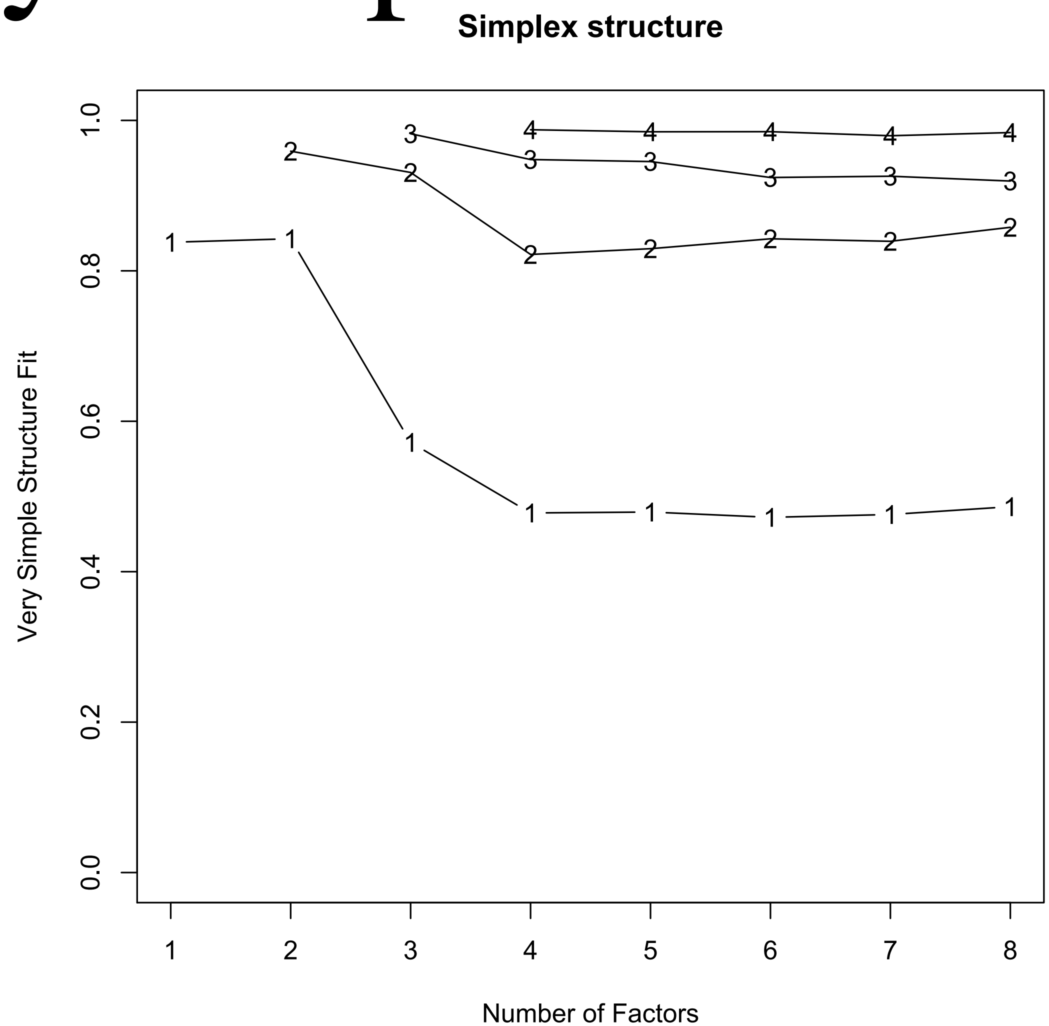


Mulaik and Millsap, 2000

10 variable simplex

```
> mat <- diag(1,10)
> mat <- r^abs(row(mat) - col(mat))
> colnames(mat) <- rownames(mat) <- paste("V",1:10,sep="")
> round(mat,2)
      V1   V2   V3   V4   V5   V6   V7   V8   V9  V10
V1  1.00 0.80 0.64 0.51 0.41 0.33 0.26 0.21 0.17 0.13
V2  0.80 1.00 0.80 0.64 0.51 0.41 0.33 0.26 0.21 0.17
V3  0.64 0.80 1.00 0.80 0.64 0.51 0.41 0.33 0.26 0.21
V4  0.51 0.64 0.80 1.00 0.80 0.64 0.51 0.41 0.33 0.26
V5  0.41 0.51 0.64 0.80 1.00 0.80 0.64 0.51 0.41 0.33
V6  0.33 0.41 0.51 0.64 0.80 1.00 0.80 0.64 0.51 0.41
V7  0.26 0.33 0.41 0.51 0.64 0.80 1.00 0.80 0.64 0.51
V8  0.21 0.26 0.33 0.41 0.51 0.64 0.80 1.00 0.80 0.64
V9  0.17 0.21 0.26 0.33 0.41 0.51 0.64 0.80 1.00 0.80
V10 0.13 0.17 0.21 0.26 0.33 0.41 0.51 0.64 0.80 1.00
```

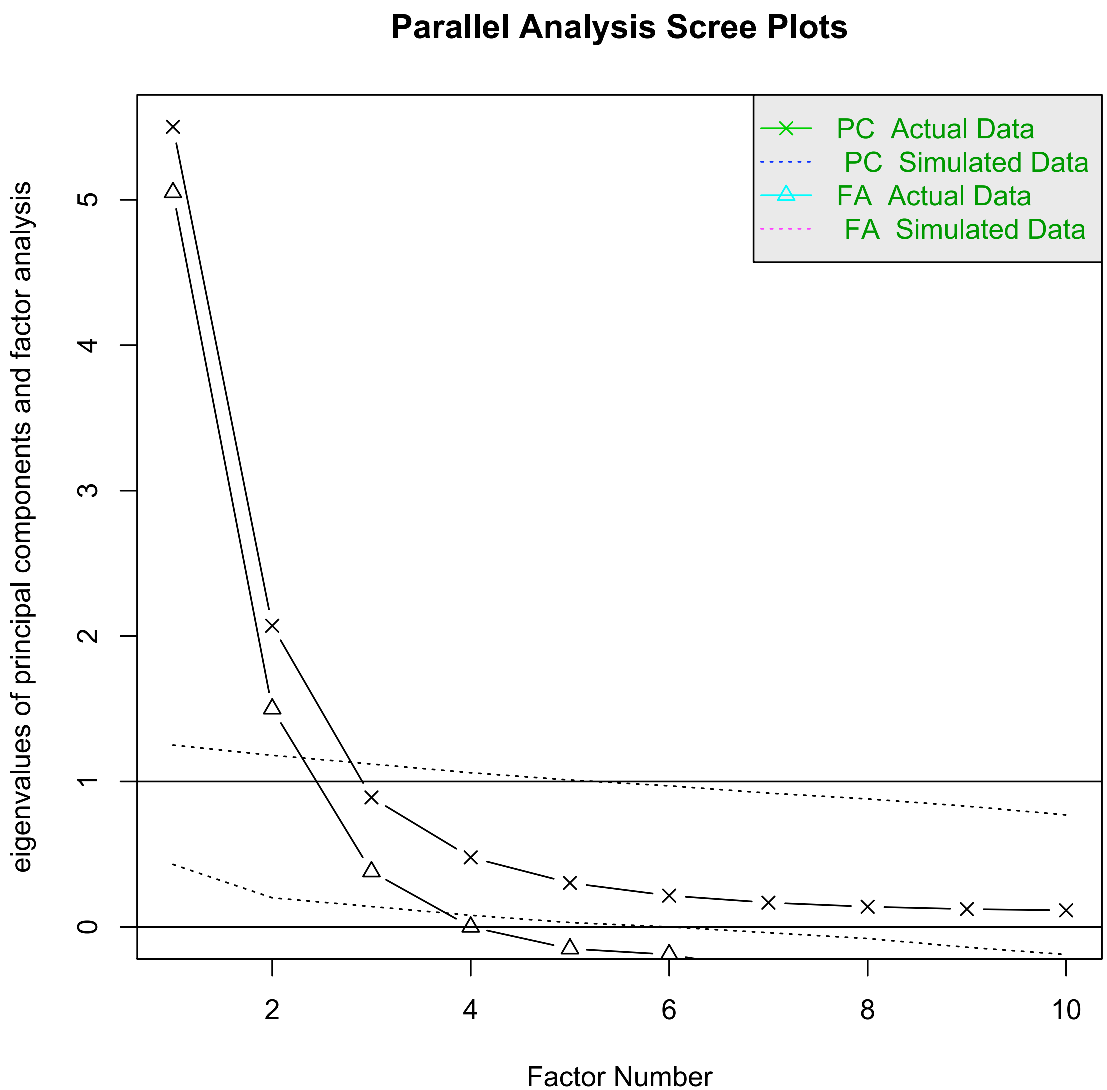
Very Simple Structure



VSS stats

```
> vss <- VSS(mat,n.obs=400,title="Simplex structure")
> vss
Very Simple Structure of  Simplex structure
VSS complexity 1 achieves a maximimum of 0.84  with  2  factors
VSS complexity 2 achieves a maximimum of 0.96  with  2  factors
The Velicer MAP criterion achieves a minimum of 0.45  with  3  factors
 Velicer MAP
[1] 0.17 0.11 0.08 0.10 0.13 0.18 0.27 0.45

Very Simple Structure Complexity 1
[1] 0.84 0.84 0.57 0.48 0.48 0.47 0.48 0.49
Very Simple Structure Complexity 2
[1] 0.00 0.96 0.93 0.82 0.83 0.84 0.84 0.86

 > print(vss$vss.stats[,1:3],digits=3)
   dof    chisq      prob
 1  35 1667.304  0.00e+00
 2  26  703.626 1.26e-131
 3  18  284.328  7.96e-50
 4  11   73.339  2.82e-11
 5   5   18.475  2.41e-03
 6   0    6.535        NA
```

Parallel analysis



Regression with simplex

```
> mat.regress(mat,c(1:5),c(6:10))
$beta
    V6   V7   V8   V9  V10
V1 0.0 0.00 0.00 0.00 0.00
V2 0.0 0.00 0.00 0.00 0.00
V3 0.0 0.00 0.00 0.00 0.00
V4 0.0 0.00 0.00 0.00 0.00
V5 0.8 0.64 0.51 0.41 0.33

$R
  V6   V7   V8   V9  V10
0.80 0.64 0.51 0.41 0.33

$R2
  V6   V7   V8   V9  V10
0.64 0.41 0.26 0.17 0.11
```

Just the last predictor in the chain has any effect. V5 ‘mediates’ the effect of the prior variables.

Compare with congeneric

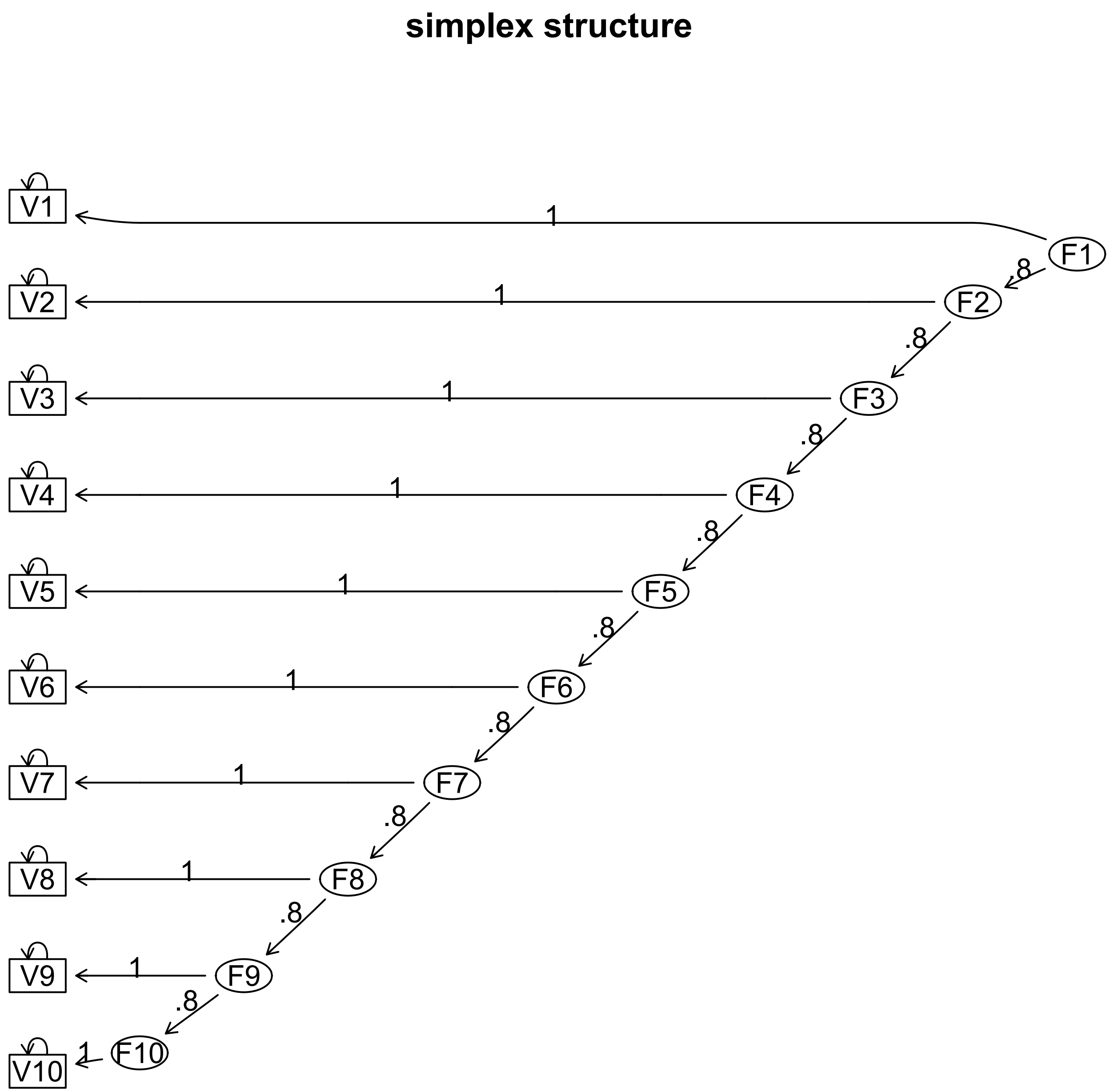
```
>  cong <- sim.congeneric(rep(.8,10))
> round(cong,2)
      V1   V2   V3   V4   V5   V6   V7   V8   V9  V10
V1  1.00 0.64 0.64 0.64 0.64 0.64 0.64 0.64 0.64 0.64
V2  0.64 1.00 0.64 0.64 0.64 0.64 0.64 0.64 0.64 0.64
V3  0.64 0.64 1.00 0.64 0.64 0.64 0.64 0.64 0.64 0.64
V4  0.64 0.64 0.64 1.00 0.64 0.64 0.64 0.64 0.64 0.64
V5  0.64 0.64 0.64 0.64 1.00 0.64 0.64 0.64 0.64 0.64
V6  0.64 0.64 0.64 0.64 0.64 1.00 0.64 0.64 0.64 0.64
V7  0.64 0.64 0.64 0.64 0.64 0.64 1.00 0.64 0.64 0.64
V8  0.64 0.64 0.64 0.64 0.64 0.64 0.64 1.00 0.64 0.64
V9  0.64 0.64 0.64 0.64 0.64 0.64 0.64 0.64 1.00 0.64
V10 0.64 0.64 0.64 0.64 0.64 0.64 0.64 0.64 0.64 1.00
```

Multiple regression

```
> mat.regress(cong,c(1:5),c(6:10))
$beta
     V6   V7   V8   V9  V10
V1 0.18 0.18 0.18 0.18 0.18
V2 0.18 0.18 0.18 0.18 0.18
V3 0.18 0.18 0.18 0.18 0.18
V4 0.18 0.18 0.18 0.18 0.18
V5 0.18 0.18 0.18 0.18 0.18
$R
  V6   V7   V8   V9  V10
0.76 0.76 0.76 0.76 0.76
$R2
  V6   V7   V8   V9  V10
0.58 0.58 0.58 0.58 0.58
> mat.regress(cong,c(1:2),c(3:10))
$beta
     V3   V4   V5   V6   V7   V8   V9  V10
V1 0.39 0.39 0.39 0.39 0.39 0.39 0.39 0.39
V2 0.39 0.39 0.39 0.39 0.39 0.39 0.39 0.39
$R
  V3   V4   V5   V6   V7   V8   V9  V10
0.71 0.71 0.71 0.71 0.71 0.71 0.71 0.71
```

Each predictor has equal weight, although increasing the number of predictors reduces the predictive weight.

Fitting a Simplex



Simplex model

```
> mod.sim3
   Path       Parameter StartValue
1  F10->V10   <fixed>   1
2  F9->V9     <fixed>   1
3  F8->V8     <fixed>   1
...
9  F2->V2     <fixed>   1
10 F1->V1     <fixed>   1
11 V10<->V10 <fixed>   0
...
20 V1<->V1    <fixed>   0
21 F9 ->F10   rF2F1
22 F8 ->F9    rF3F2
23 F7 ->F8    rF4F3
24 F6 ->F7    rF5F4
25 F5 ->F6    rF6F5
26 F4 ->F5    rF7F6
27 F3 ->F4    rF8F7
28 F2 ->F3    rF9F8
29 F1 ->F2    rF10F9
30 F10<->F10 i         1
31 F9<->F9    h         1
32 F8<->F8    g         1
33 F7<->F7    f         1
34 F6<->F6    e         1
35 F5<->F5    d         1
36 F4<->F4    c         1
37 F3<->F3    b         1
38 F2<->F2    a         1
39 F1<->F1    <fixed>   1
```

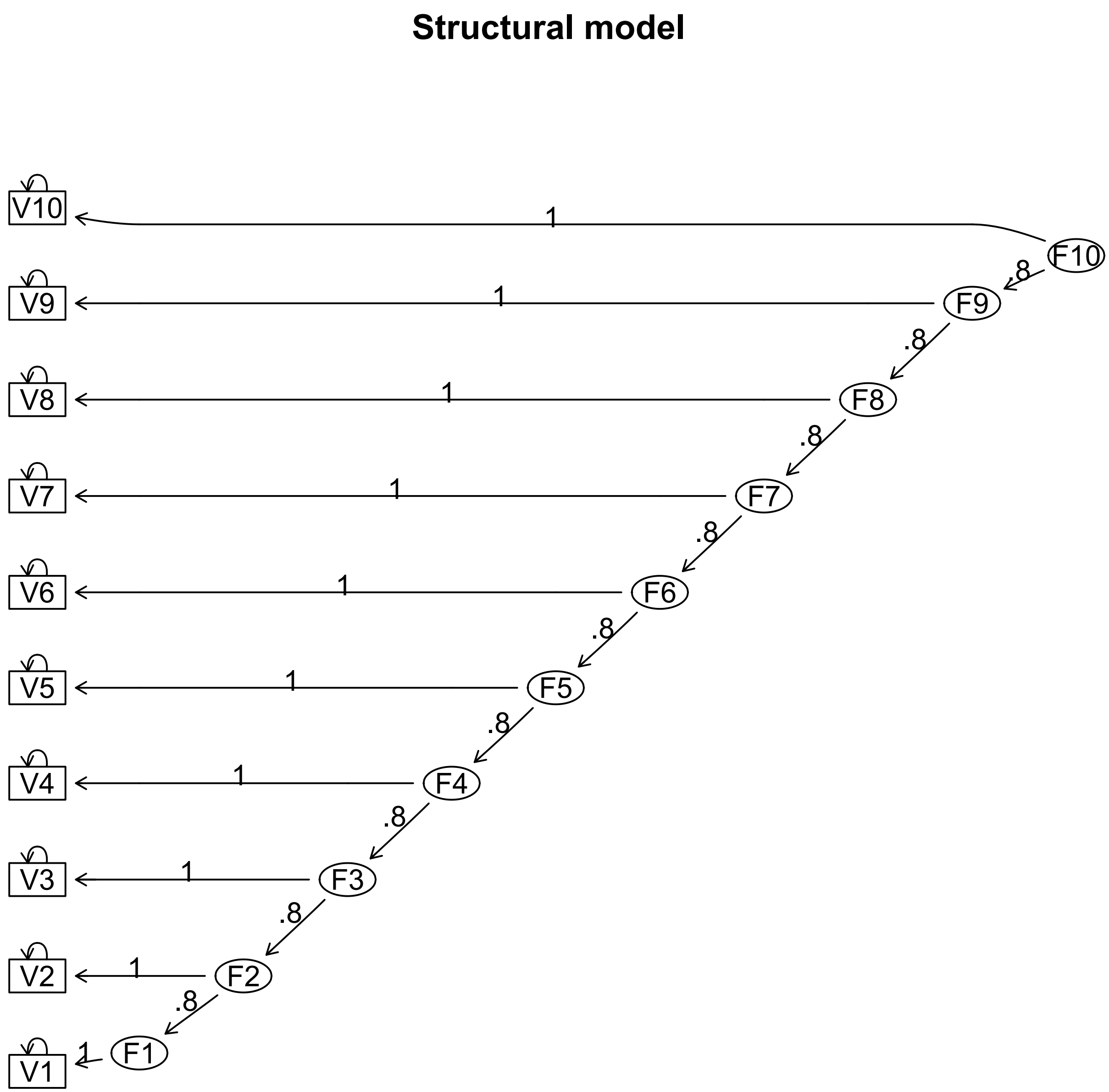
Simplex fits

```
> summary(sem.sim3)

 Model Chisquare =  7.0877e-13   Df =  37 Pr(>Chisq) = 1
 Chisquare (null model) =  3668.7   Df =  45
 Goodness-of-fit index =  1
 Adjusted goodness-of-fit index =  1
 RMSEA index =  0   90% CI: (NA, NA)
 Bentler-Bonnett NFI =  1
 Tucker-Lewis NNFI =  1.0124
 Bentler CFI =  1
 SRMR =  1.0654e-15
 BIC =  -221.68

 Normalized Residuals
     Min.   1st Qu.    Median      Mean   3rd Qu.      Max.
-4.48e-14 -1.82e-14 -1.08e-14 -9.45e-15  0.00e+00  3.14e-14
```

Perfect

```
 Parameter Estimates
       Estimate Std Error z value Pr(>|z|)
rF2F1  0.80     0.030038  26.633  0        F10 <--- F9
rF3F2  0.80     0.030038  26.633  0        F9 <--- F8
rF4F3  0.80     0.030038  26.633  0        F8 <--- F7
rF5F4  0.80     0.030038  26.633  0        F7 <--- F6
rF6F5  0.80     0.030038  26.633  0        F6 <--- F5
rF7F6  0.80     0.030038  26.633  0        F5 <--- F4
rF8F7  0.80     0.030038  26.633  0        F4 <--- F3
rF9F8  0.80     0.030038  26.633  0        F3 <--- F2
rF10F9 0.80     0.030038  26.633  0        F2 <--- F1
i      0.36     0.025502  14.117  0        F10 <--> F10
h      0.36     0.025502  14.117  0        F9 <--> F9
g      0.36     0.025502  14.117  0        F8 <--> F8
f      0.36     0.025502  14.117  0        F7 <--> F7
e      0.36     0.025502  14.117  0        F6 <--> F6
d      0.36     0.025502  14.117  0        F5 <--> F5
c      0.36     0.025502  14.117  0        F4 <--> F4
b      0.36     0.025502  14.117  0        F3 <--> F3
a      0.36     0.025502  14.117  0        F2 <--> F2
 Iterations =  1
```

Another simplex



Paths are reversed

```
> sim.rev.1
      Path          Parameter Value
[1,] "F1->V1"      NA        "1"
[2,] "F2->V2"      NA        "1"
[3,] "F3->V3"      NA        "1"
[4,] "F4->V4"      NA        "1"
[5,] "F5->V5"      NA        "1"
[6,] "F6->V6"      NA        "1"
[7,] "F7->V7"      NA        "1"
[8,] "F8->V8"      NA        "1"
[9,] "F9->V9"      NA        "1"
[10,] "F10->V10"   NA        "1"
[11,] "V1<->V1"    NA        "0"
[12,] "V2<->V2"    NA        "0"
[13,] "V3<->V3"    NA        "0"
[14,] "V4<->V4"    NA        "0"
[15,] "V5<->V5"    NA        "0"
[16,] "V6<->V6"    NA        "0"
[17,] "V7<->V7"    NA        "0"
[18,] "V8<->V8"    NA        "0"
[19,] "V9<->V9"    NA        "0"
[20,] "V10<->V10" NA         "0"
[21,] "F2 ->F1"    "rF2F1"   NA
[22,] "F3 ->F2"    "rF3F2"   NA
[23,] "F4 ->F3"    "rF4F3"   NA
[24,] "F5 ->F4"    "rF5F4"   NA
[25,] "F6 ->F5"    "rF6F5"   NA
[26,] "F7 ->F6"    "rF7F6"   NA
[27,] "F8 ->F7"    "rF8F7"   NA
[28,] "F9 ->F8"    "rF9F8"   NA
[29,] "F10 ->F9"   "rF10F9"  NA
[30,] "F1<->F1"    "a"       "1"
[31,] "F2<->F2"    "b"       "1"
[32,] "F3<->F3"    "c"       "1"
[33,] "F4<->F4"    "d"       "1"
[34,] "F5<->F5"    "e"       "1"
[35,] "F6<->F6"    "f"       "1"
[36,] "F7<->F7"    "g"       "1"
[37,] "F8<->F8"    "h"       "1"
[38,] "F9<->F9"    "i"       "1"
[39,] "F10<->F10" NA         "1"
```

Fit is the same!

```
> sem.rev.1 <- sem(sim.rev.1,mat,400)
> summary(sem.rev.1)

 Model Chisquare =  7.0877e-13   Df =  37 Pr(>Chisq) = 1
 Chisquare (null model) =  3668.7   Df =  45
 Goodness-of-fit index =  1
 Adjusted goodness-of-fit index =  1
 RMSEA index =  0   90% CI: (NA, NA)
 Bentler-Bonnett NFI =  1
 Tucker-Lewis NNFI =  1.0124
 Bentler CFI =  1
 SRMR =  9.5145e-16
 BIC =  -221.68

 Normalized Residuals
     Min.    1st Qu.    Median      Mean   3rd Qu.      Max.
-2.82e-14 -6.44e-15  6.53e-15  4.98e-15  1.37e-14  4.70e-14
```

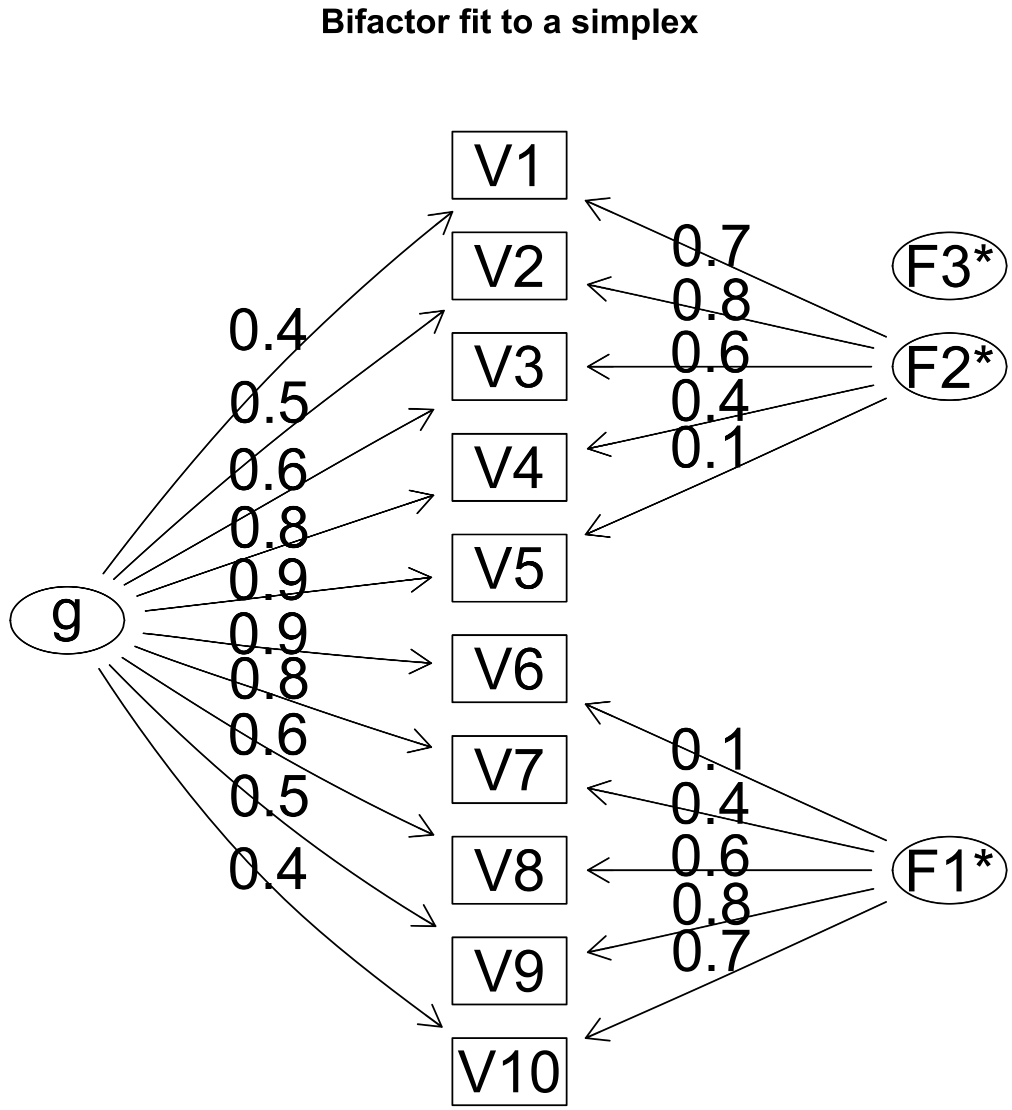
Parameters

Parameter Estimates

	Estimate	Std Error	z value	Pr(>|z|)	
rF2F1	0.80	0.030038	26.633	0	F1 <--- F2
rF3F2	0.80	0.030038	26.633	0	F2 <--- F3
rF4F3	0.80	0.030038	26.633	0	F3 <--- F4
rF5F4	0.80	0.030038	26.633	0	F4 <--- F5
rF6F5	0.80	0.030038	26.633	0	F5 <--- F6
rF7F6	0.80	0.030038	26.633	0	F6 <--- F7
rF8F7	0.80	0.030038	26.633	0	F7 <--- F8
rF9F8	0.80	0.030038	26.633	0	F8 <--- F9
rF10F9	0.80	0.030038	26.633	0	F9 <--- F10
a	0.36	0.025502	14.117	0	F1 <--> F1
b	0.36	0.025502	14.117	0	F2 <--> F2
c	0.36	0.025502	14.117	0	F3 <--> F3
d	0.36	0.025502	14.117	0	F4 <--> F4
e	0.36	0.025502	14.117	0	F5 <--> F5
f	0.36	0.025502	14.117	0	F6 <--> F6
g	0.36	0.025502	14.117	0	F7 <--> F7
h	0.36	0.025502	14.117	0	F8 <--> F8
i	0.36	0.025502	14.117	0	F9 <--> F9

Iterations = 1

Fitting a bifactor model



Model specification

```
> om.sl$model
      Path          Parameter Initial Value
 [1,] "g->V1"       "V1"      NA
 [2,] "g->V2"       "V2"      NA
 [3,] "g->V3"       "V3"      NA
 [4,] "g->V4"       "V4"      NA
 [5,] "g->V5"       "V5"      NA
 [6,] "g->V6"       "V6"      NA
 [7,] "g->V7"       "V7"      NA
 [8,] "g->V8"       "V8"      NA
 [9,] "g->V9"       "V9"      NA
[10,] "g->V10"      "V10"     NA
[11,] "F2*->V1"     "F2*V1"   NA
[12,] "F2*->V2"     "F2*V2"   NA
[13,] "F2*->V3"     "F2*V3"   NA
[14,] "F2*->V4"     "F2*V4"   NA
[15,] "F2*->V5"     "F2*V5"   NA
[16,] "F1*->V6"     "F1*V6"   NA
[17,] "F1*->V7"     "F1*V7"   NA
[18,] "F1*->V8"     "F1*V8"   NA
[19,] "F1*->V9"     "F1*V9"   NA
[20,] "F1*->V10"    "F1*V10"  NA
[21,] "V1<->V1"     "e1"      NA
[22,] "V2<->V2"     "e2"      NA
[23,] "V3<->V3"     "e3"      NA
[24,] "V4<->V4"     "e4"      NA
[25,] "V5<->V5"     "e5"      NA
[26,] "V6<->V6"     "e6"      NA
[27,] "V7<->V7"     "e7"      NA
[28,] "V8<->V8"     "e8"      NA
[29,] "V9<->V9"     "e9"      NA
[30,] "V10<->V10"   "e10"     NA
[31,] "F1*<->F1*"   NA        "1"
[32,] "F2*<->F2*"   NA        "1"
[33,] "F3*<->F3*"   NA        "1"
[34,] "g <->g"      NA        "1"
```

Fit is poor

```
> sem.sl <- sem(mod.om.sl,mat,400)
> summary(sem.sl)

 Model Chisquare =  280.96   Df =  25 Pr(>Chisq) = 0
 Chisquare (null model) =  3668.7   Df =  45
 Goodness-of-fit index =  0.8588
 Adjusted goodness-of-fit index =  0.68937
 RMSEA index =  0.16019   90% CI: (0.14362, 0.17732)
 Bentler-Bonnett NFI =  0.92342
 Tucker-Lewis NNFI =  0.87286
 Bentler CFI =  0.92937
 SRMR =  0.030791
 BIC =  131.17

 Normalized Residuals
    Min.  1st Qu.   Median     Mean  3rd Qu.     Max.
-1.17000 -0.28300  0.00591  0.06100  0.41400  1.34000
```

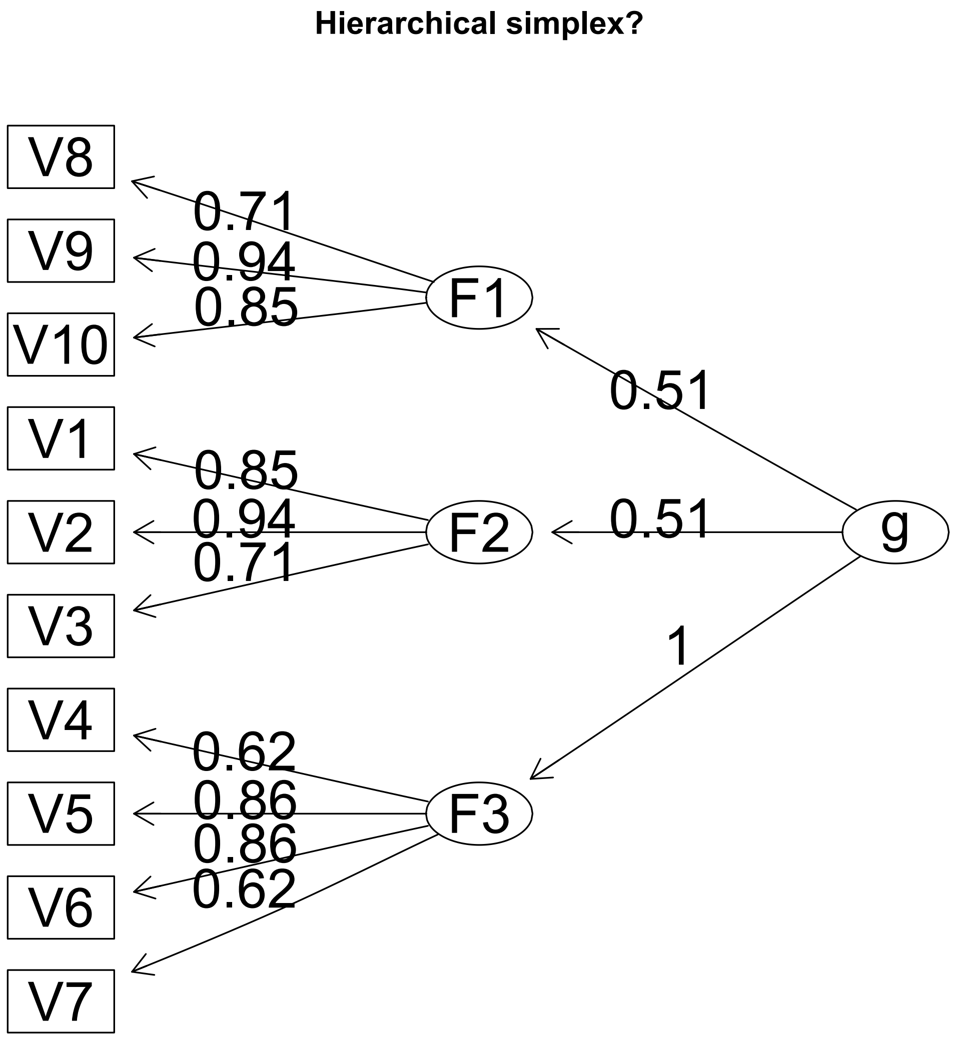
Parameters

```
Parameter Estimates
       Estimate Std Error z value Pr(>|z|)
V1      0.32270  0.053208   6.0649 1.3202e-09 V1 <--- g
V2      0.42395  0.052709   8.0431 8.8818e-16 V2 <--- g
V3      0.59272  0.051484  11.5125 0.0000e+00 V3 <--- g
V4      0.76129  0.048708  15.6297 0.0000e+00 V4 <--- g
V5      0.89089  0.043059  20.6902 0.0000e+00 V5 <--- g
V6      0.89089  0.043059  20.6902 0.0000e+00 V6 <--- g
V7      0.76129  0.048708  15.6297 0.0000e+00 V7 <--- g
V8      0.59272  0.051484  11.5125 0.0000e+00 V8 <--- g
V9      0.42395  0.052709   8.0431 8.8818e-16 V9 <--- g
V10     0.32270  0.053208   6.0649 1.3202e-09 V10 <--- g
F2*V1   0.75477  0.041595  18.1458 0.0000e+00 V1 <--- F2*
F2*V2   0.84396  0.037553  22.4738 0.0000e+00 V2 <--- F2*
F2*V3   0.65440  0.042739  15.3115 0.0000e+00 V3 <--- F2*
F2*V4   0.40657  0.045969   8.8444 0.0000e+00 V4 <--- F2*
F2*V5   0.17000  0.040276   4.2209 2.4330e-05 V5 <--- F2*
F1*V6   0.17000  0.040276   4.2209 2.4330e-05 V6 <--- F1*
F1*V7   0.40657  0.045969   8.8444 0.0000e+00 V7 <--- F1*
F1*V8   0.65440  0.042739  15.3114 0.0000e+00 V8 <--- F1*
F1*V9   0.84396  0.037553  22.4738 0.0000e+00 V9 <--- F1*
F1*V10  0.75477  0.041595  18.1458 0.0000e+00 V10 <--- F1*
e1      0.32619  0.028601  11.4048 0.0000e+00 V1 <--> V1
e2      0.10800  0.026355   4.0979 4.1696e-05 V2 <--> V2
e3      0.22044  0.021824  10.1009 0.0000e+00 V3 <--> V3
e4      0.25514  0.024627  10.3603 0.0000e+00 V4 <--> V4
```

Residuals are not bad

```
> round(residuals(sem.sl),2)
       V1    V2    V3    V4    V5    V6    V7    V8    V9   V10
V1   0.00  0.03 -0.05 -0.04 -0.01  0.04  0.02  0.02  0.03  0.03
V2   0.03  0.00  0.00 -0.03 -0.01  0.03  0.00  0.01  0.03  0.03
V3  -0.05  0.00  0.00  0.08  0.00 -0.02 -0.04 -0.02  0.01  0.02
V4  -0.04 -0.03  0.08  0.00  0.05 -0.04 -0.07 -0.04  0.00  0.02
V5  -0.01 -0.01  0.00  0.05  0.00  0.01 -0.04 -0.02  0.03  0.04
V6   0.04  0.03 -0.02 -0.04  0.01  0.00  0.05  0.00 -0.01 -0.01
V7   0.02  0.00 -0.04 -0.07 -0.04  0.05  0.00  0.08 -0.03 -0.04
V8   0.02  0.01 -0.02 -0.04 -0.02  0.00  0.08  0.00  0.00 -0.05
V9   0.03  0.03  0.01  0.00  0.03 -0.01 -0.03  0.00  0.00  0.03
V10  0.03  0.03  0.02  0.02  0.04 -0.01 -0.04 -0.05  0.03  0.00
```

Hierarchical model



Can be fit with a great deal of work

I. Initial model does not work

II. Fix some paths to 1

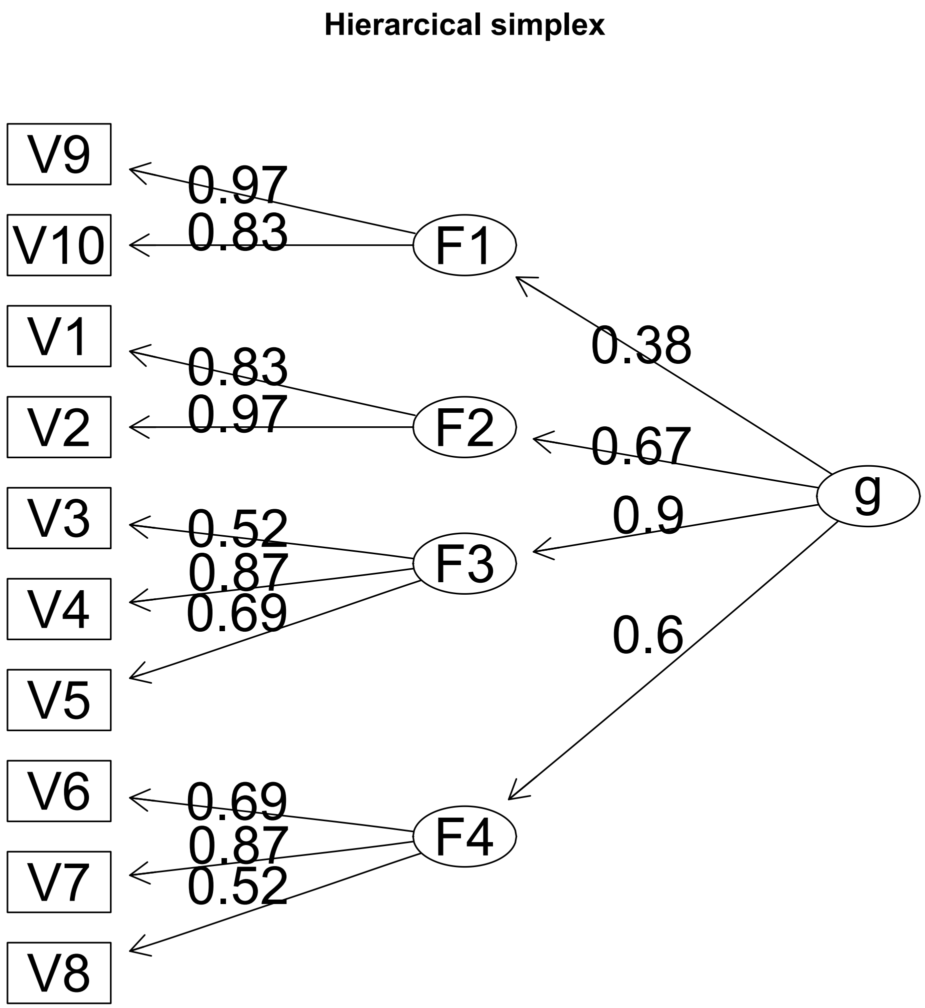
III. Give start values based upon EFA

IV. Start values from EFA, fix some to 1

```
> mod.sem.om2
   Path       Parameter StartValue
1  g->F1      gF1       0.51
2  g->F2      gF2       0.51
3  g->F3      <fixed>   1
4  F2->V1     F2V1      0.85
5  F2->V2     F2V2      0.94
6  F2->V3     F2V3      0.71
7  F3->V4     F3V4      0.62
8  F3->V5     F3V5      0.86
9  F3->V6     F3V6      0.86
10 F3->V7     F3V7      0.62
11 F1->V8     F1V8      0.71
12 F1->V9     <fixed>   1
13 F1->V10    F1V10     0.85
14 V1<->V1    e1
15 V2<->V2    e2
16 V3<->V3    e3
17 V4<->V4    e4
18 V5<->V5    e5
19 V6<->V6    e6
20 V7<->V7    e7
21 V8<->V8    e8
22 V9<->V9    e9
23 V10<->V10 e10
24 F1<->F1    <fixed>   1
25 F2<->F2    <fixed>   1
26 F3<->F3    <fixed>   1
27 g<->g      <fixed>   1
```

Very tweaked values

```
> summary(sem.om.2)

 Model Chisquare =  773.58   Df =  34 Pr(>Chisq) = 0
 Chisquare (null model) =  3668.7   Df =  45
 Goodness-of-fit index =  0.7509
 Adjusted goodness-of-fit index =  0.59704
 RMSEA index =  0.23349   90% CI: (NA, NA)
 Bentler-Bonnett NFI =  0.78914
 Tucker-Lewis NNFI =  0.72988
 Bentler CFI =  0.79591
 SRMR =  0.18282
 BIC =  569.87

 Normalized Residuals
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
 -2.240  -0.373   0.719   1.720   3.500  11.900
```



4 factor model

Doing the Four Step

a sem debate

SEM 2000, Volume 7, issue 1 (open access)

Doing the Four Step

I. Les Hayduk

II. Stan Mulaik

III. Peter Bentler

Four step nested sequence

I. Step 1: The unrestricted model

II. Step 2: The measurement model

III. Step 3: The structural equation model

IV. Step 4: Tests of pre-specified hypotheses

Step 1: The unrestricted model

I. A common factors model using exploratory analysis

II. This is open to rotation, unless some parameters are fixed.

III. If this fit is poor, examine the data, extract more factors,

Step 2: The measurement model

I. A confirmatory factor analysis with some (many) loadings set to zero.

II. (not really "measurement" in the sense of Michell or others)

Step 3: The structural equation model

I. Regression model of the latent variables.

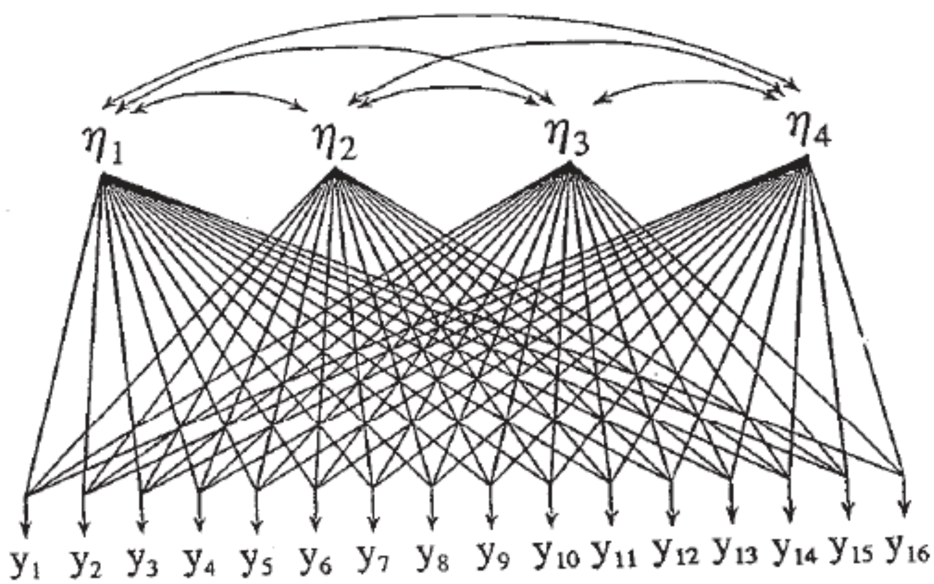
II. Are some latents unrelated?

Step 4: Tests of prespecified hypotheses

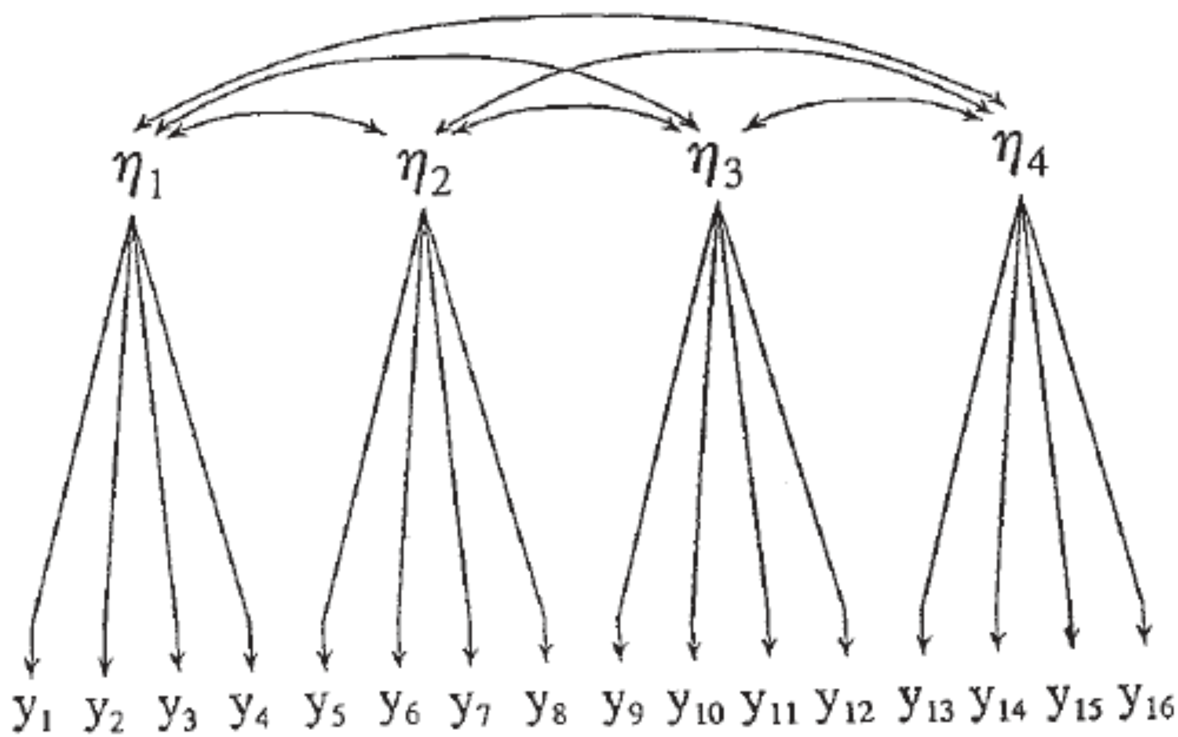
I. Can be done sequentially with more and more parameters fixed

Hayduk’s critique

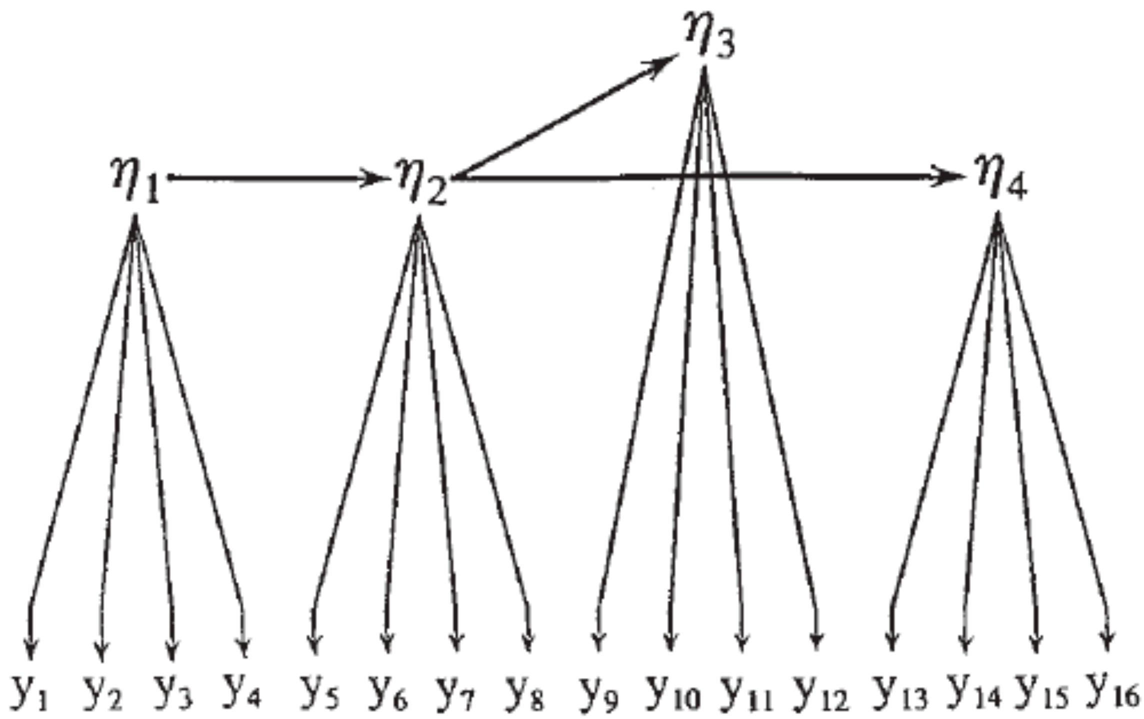
Step 1: EFA


η_1
η_2
η_3
η_4
y_1 y_2 y_3 y_4 y_5 y_6 y_7 y_8 y_9 y_{10} y_{11} y_{12} y_{13} y_{14} y_{15} y_{16}

Step 2: Measurement



Step 3: Base model



The importance of Chi square (to Hayduk)

If the base (Step-3) model has sufficient integrity to represent a specific perspective or theoretical stance, then it is newsworthy whether it fits or fails. A failing model should be published by highlighting the style of failure, and the evidence resulting in failure, and not excused as close enough to overlook the failings (Hayduk, 1996, p. 4; Hayduk & Avakame, 1990). A discipline preferring to accept close-fit models, as opposed to highlighting the remaining failings of models, is degenerating as a discipline because it is unable to encourage its practitioners to build models with sufficient integrity and clarity that either fit or failure is informative.

Throwing in a handful of free concept covariances (Step-2 model) followed by a bucket of free loadings (Step 1) directly attacks whatever precision the researcher might have imbedded in the real Step-3 model. Combining this with a plea that chi-square should be overlooked in favor of anything close seems sufficient to guarantee that whatever precision was included in the Step 3 is lost under the onslaught of the progressive loosenings.

The aforementioned difficulties arise no matter which particular test of close fit the four-stepper adopts. Additional problems may accompany the specific test of close fit one uses, such as the RMSEA suggested by Stan.[49]

Number of Indicators

I. Mulaik and Millsap

   A. 3 are just identified, not testable

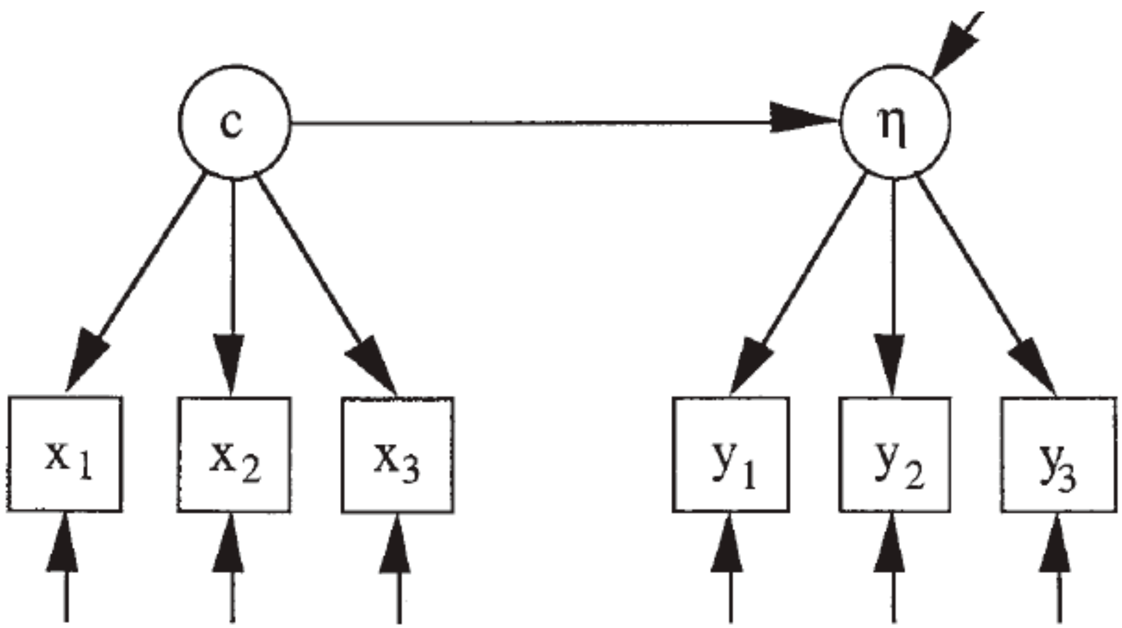
   B. at least 4 to allow for testing

   C. Marsh simulation study shows more are better

II. Hayduk

   A. 1 or 2 is enough, otherwise becomes unwieldy

Three indicators seemingly correlated factors



Confounding method four indicators allow test