

# An introduction to R: a short course

Multivariate analysis

# The zelig website

## ZELIG: EVERYONE'S STATISTICAL SOFTWARE

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**Version:3.4-5** ([Download](#)) ([What's new](#))



Zelig is named after a Woody Allen movie about a man who had the strange ability to become the physical and psychological reflection of anyone he met and thus to fit perfectly in any situation.

Zelig is a single, easy-to-use program that can estimate, help interpret, and present the results of a large range of statistical methods. It literally *is* "everyone's statistical software" because Zelig uses [\(R\)](#) code from many researchers. We also hope it will *become* "everyone's statistical software" for applications, and we have designed it so that anyone can use it or add their methods to it. Zelig comes with detailed, self-contained documentation that minimizes startup costs for Zelig and R, automates graphics and summaries for all models, and, with only three simple commands required, generally makes the power of R accessible for all users. Zelig also works well for teaching, and is designed so that scholars can use the same program with students that they use for their research.

Zelig adds considerable infrastructure to improve the use of existing methods. It generalizes the program [Clarify](#) (for Stata), which translates hard-to-interpret coefficients into quantities of interest; combines multiply imputed data sets (such as output from [Amelia](#)) to deal with missing data; automates bootstrapping for all models; uses sophisticated nonparametric matching commands which improve parametric procedures (via [MatchIt](#)); allows one-line commands to run analyses in all designated strata; automates the creation of replication data files so that you (or, if you wish, anyone else) can replicate the results of your analyses (hence satisfying the [replication standard](#)); makes it easy to evaluate counterfactuals (via [WhatIf](#)); and allows conditional population and superpopulation inferences. Zelig includes many specific methods, based on likelihood, frequentist, Bayesian, robust Bayesian, and nonparametric theories of inference.

- [Documentation](#) and [Installation](#)
- [Installation](#), [Frequently Asked Questions](#)
- Please send **All** questions, bugs and requests: Zelig Mailing List, [\[Un\]Subscribe](#), or [Browse/Search Archives](#)
- A paper that describes the advances underlying Zelig software: Kosuke Imai, Gary King, and Olivia Lau. "**Toward A Common Framework for Statistical Analysis and Development**" *Journal of Computational and Graphical Statistics*, Vol. 17, No. 4 (December), pp. 892-913 ([Abstract: HTML](#) | [Paper: PDF](#))
- [Slides used to introduce Zelig](#)
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<http://gking.harvard.edu/zelig/>

# Multivariate analysis

- I. Dimension reduction through factor analysis, principal components analysis, cluster analysis, and multidimensional scaling
- II. Multiple measures of reliability
- III. Practical use of R for scoring inventories

# Dimension Reduction

- I. The problem: How best to summarize and think about many variables some of which are moderately correlated
- II. The solutions: rank reduction through FA, PCA, CA, MDS
- III.Examples will be tests and then items

# The Thurstone data set

```
> data(bifactor)
> colnames(Thurstone) <- 
c("Sentences", "Vocab", "S.comp", "F.letter", "4.letter", "Suffix",
  "Series", "Pedi", "letters")
>
> round(Thurstone, 2)
```

	Sentences	Vocab	S.comp	F.letter	4.letter	Suffix	Series	Pedi	letters
Sentences	1.00	0.83	0.78	0.44	0.43	0.45	0.45	0.54	0.38
Vocabulary	0.83	1.00	0.78	0.49	0.46	0.49	0.43	0.54	0.36
Sent.Completion	0.78	0.78	1.00	0.46	0.42	0.44	0.40	0.53	0.36
First.Letters	0.44	0.49	0.46	1.00	0.67	0.59	0.38	0.35	0.42
4.Letter.Words	0.43	0.46	0.42	0.67	1.00	0.54	0.40	0.37	0.45
Suffixes	0.45	0.49	0.44	0.59	0.54	1.00	0.29	0.32	0.32
Letter.Series	0.45	0.43	0.40	0.38	0.40	0.29	1.00	0.56	0.60
Pedigrees	0.54	0.54	0.53	0.35	0.37	0.32	0.56	1.00	0.45
Letter.Group	0.38	0.36	0.36	0.42	0.45	0.32	0.60	0.45	1.00

# How many dimensions

I. Chi Square test

II. Scree plot

III. Parallel analysis of random data

IV. Minimum Average Partial correlation

V. Very Simple Structure

VI. Do not use eigen value > 1 rule!

```
> factanal(covmat=Thurstone,factors=3,n.obs =213)
Call:
factanal(factors = 3, covmat = Thurstone, n.obs = 213)
Uniquenesses:
```

Sentences	Vocab	S.comp	F.letter	4.letter	Suffix	Series
Pedi	letters					
0.175	0.165	0.268	0.268	0.372	0.504	0.282
0.496	0.473					

Loadings:

	Factor1	Factor2	Factor3
Sentences	0.834	0.244	0.264
Vocabulary	0.827	0.318	0.223
Sent.Completion	0.775	0.284	0.227
First.Letters	0.228	0.792	0.230
4.Letter.Words	0.213	0.706	0.291
Suffixes	0.314	0.616	0.134
Letter.Series	0.232	0.179	0.795
Pedigrees	0.446	0.166	0.527
Letter.Group	0.154	0.311	0.638

	Factor1	Factor2	Factor3
SS loadings	2.454	1.902	1.642
Proportion Var	0.273	0.211	0.182
Cumulative Var	0.273	0.484	0.666

Test of the hypothesis that 3 factors are sufficient.

The chi square statistic is 2.82 on 12 degrees of freedom.

The p-value is 0.997

MLE  
factor  
analysis:  
factanal

Call:

```
factanal(factors = 2, covmat = Thurstone, n.obs = 213)
```

Uniquenesses:

Sentences	Vocab	S.comp	F.letter	4.letter	Suffix	Series
Pedi	letters					
0.168	0.178	0.269	0.322	0.344	0.537	0.680
0.612	0.677					

Loadings:

	Factor1	Factor2
Sentences	0.866	0.287
Vocabulary	0.839	0.343
Sent.Completion	0.795	0.314
First.Letters	0.255	0.783
4.Letter.Words	0.235	0.775
Suffixes	0.317	0.602
Letter.Series	0.372	0.426
Pedigrees	0.524	0.336
Letter.Group	0.269	0.501

	Factor1	Factor2
SS loadings	2.793	2.420
Proportion Var	0.310	0.269
Cumulative Var	0.310	0.579

Test of the hypothesis that 2 factors are sufficient.

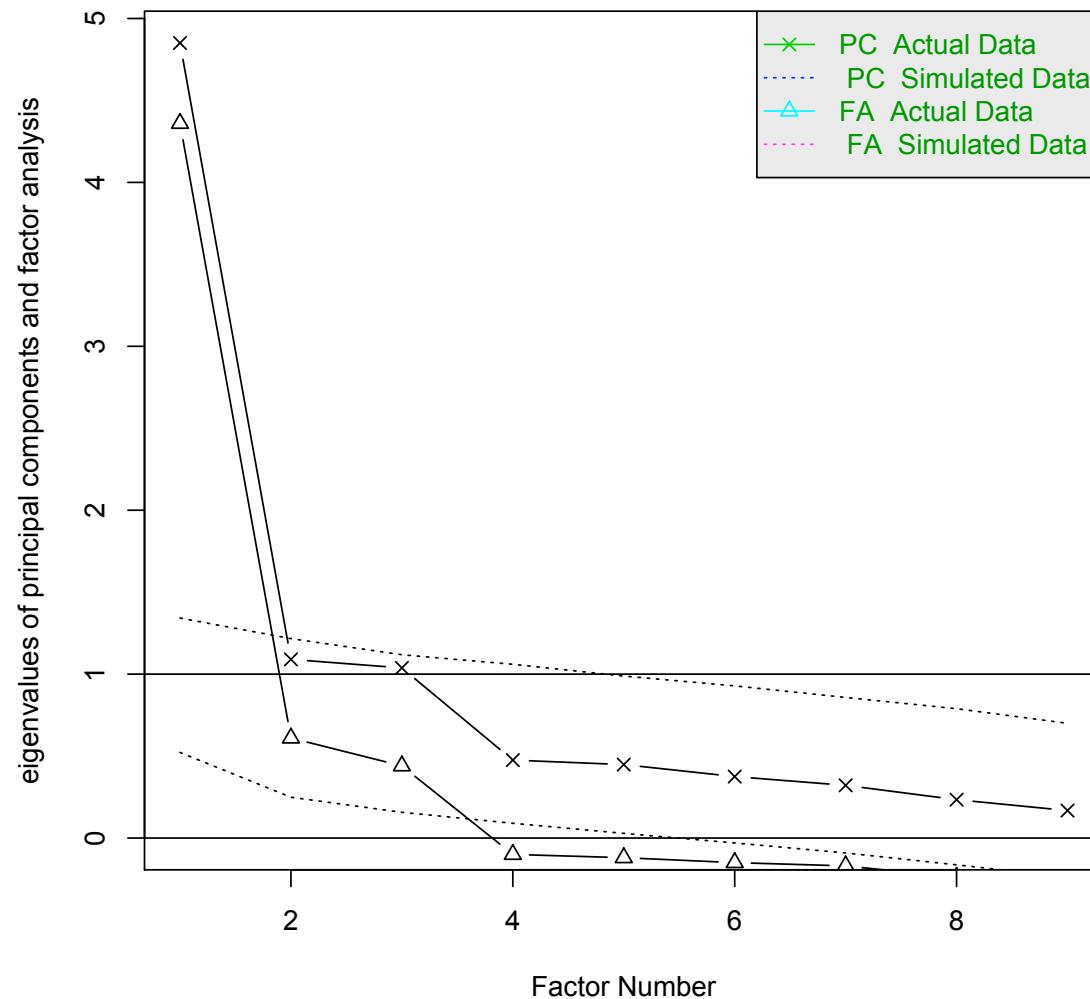
The chi square statistic is 82.84 on 19 degrees of freedom.

The p-value is 5.99e-10

chi square  
rejects a 2  
factor  
solution

# Parallel analysis

Parallel Analysis Scree Plots



# Very Simple Structure and MAP

```
> vss <- VSS(Thurstone, n.obs=213, SMC=FALSE)
> vss

Very Simple Structure
Call: VSS(x = Thurstone, n.obs = 213, SMC = FALSE)
VSS complexity 1 achieves a maximum of 0.88 with 1 factors
VSS complexity 2 achieves a maximum of 0.92 with 2 factors

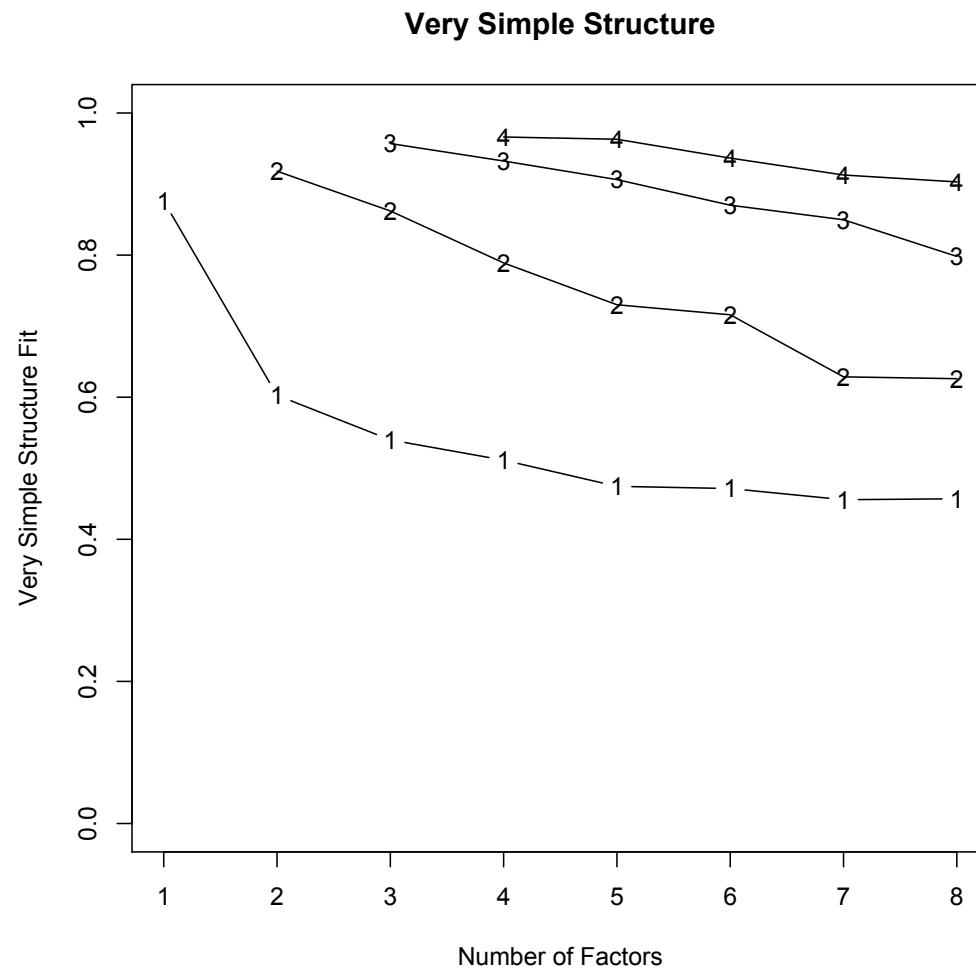
The Velicer MAP criterion achieves a minimum of 1 with 3 factors

Velicer MAP
[1] 0.07 0.07 0.07 0.11 0.20 0.31 0.59 1.00

Very Simple Structure Complexity 1
[1] 0.88 0.60 0.54 0.51 0.47 0.47 0.46 0.46

Very Simple Structure Complexity 2
[1] 0.00 0.92 0.86 0.79 0.73 0.72 0.63 0.63
```

# Very Simple Structure



# Principal Axis FA

```
> pa3 <- factor.pa(Thurstone,nfactors=3,n.obs=213)
> pa3
```

	V	PA1	PA2	PA3
Sentences	1	0.83		
Vocab	2	0.83	0.32	
S.comp	3	0.78		
F.letter	4		0.79	
4.letter	5		0.71	
Suffix	6	0.31	0.62	
Series	7			0.79
Pedi	8	0.45		0.53
letters	9		0.31	0.64

	PA1	PA2	PA3
SS loadings	2.46	1.91	1.64
Proportion Var	0.27	0.21	0.18
Cumulative Var	0.27	0.49	0.67

Test of the hypothesis that 3 factors are sufficient.

The degrees of freedom for the model is 12 and the fit was 0.01  
The number of observations was 213 with Chi Square = 2.97 with  
prob < 1

# Principal Components

```
> pc3
```

	V	PC1	PC2	PC3
Sentences	1	0.863		
Vocabulary	2	0.854	0.31	
Sent.Completion	3	0.849		
First.Letters	4		0.82	
4.Letter.Words	5		0.79	0.301
Suffixes	6	0.314	0.77	
Letter.Series	7			0.834
Pedigrees	8	0.534		0.613
Letter.Group	9		0.31	0.805

	PC1	PC2	PC3
SS loadings	2.73	2.25	1.99
Proportion Var	0.30	0.25	0.22
Cumulative Var	0.30	0.55	0.78

Test of the hypothesis that 3 factors are sufficient.

The degrees of freedom for the model is 12 and the fit was 0.62  
The number of observations was 213 with Chi Square = 127.9 with  
prob < 1.6e-21

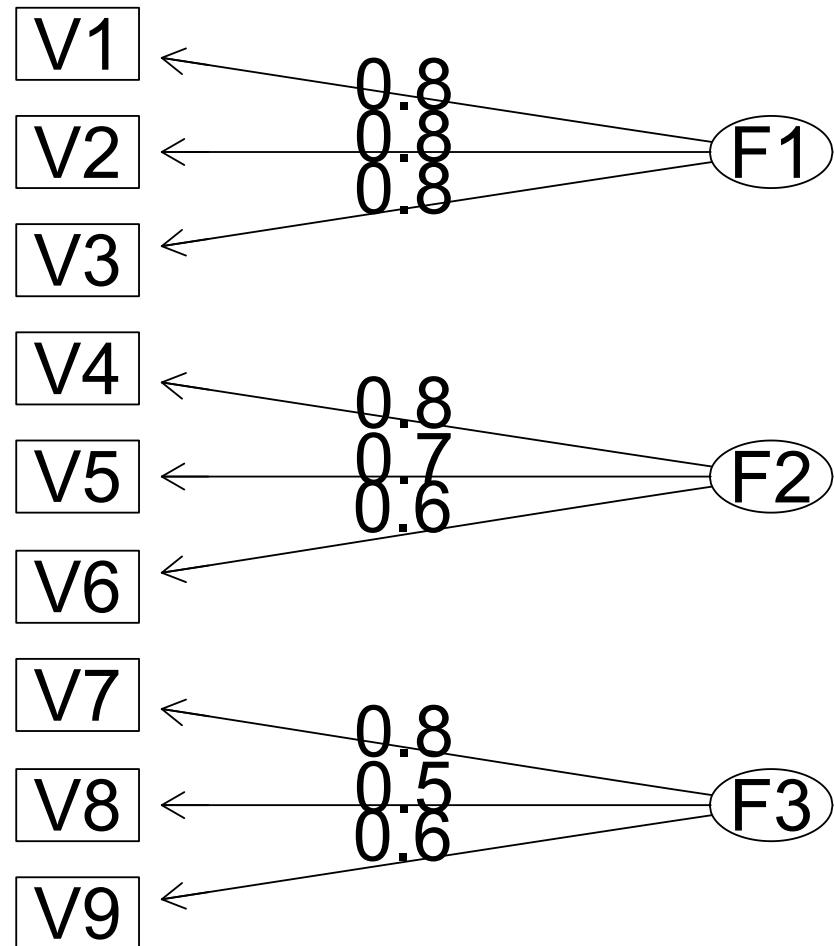
# Comparing solutions: factor congruence

```
> factor.congruence(list(f3,pa3,pc3))
```

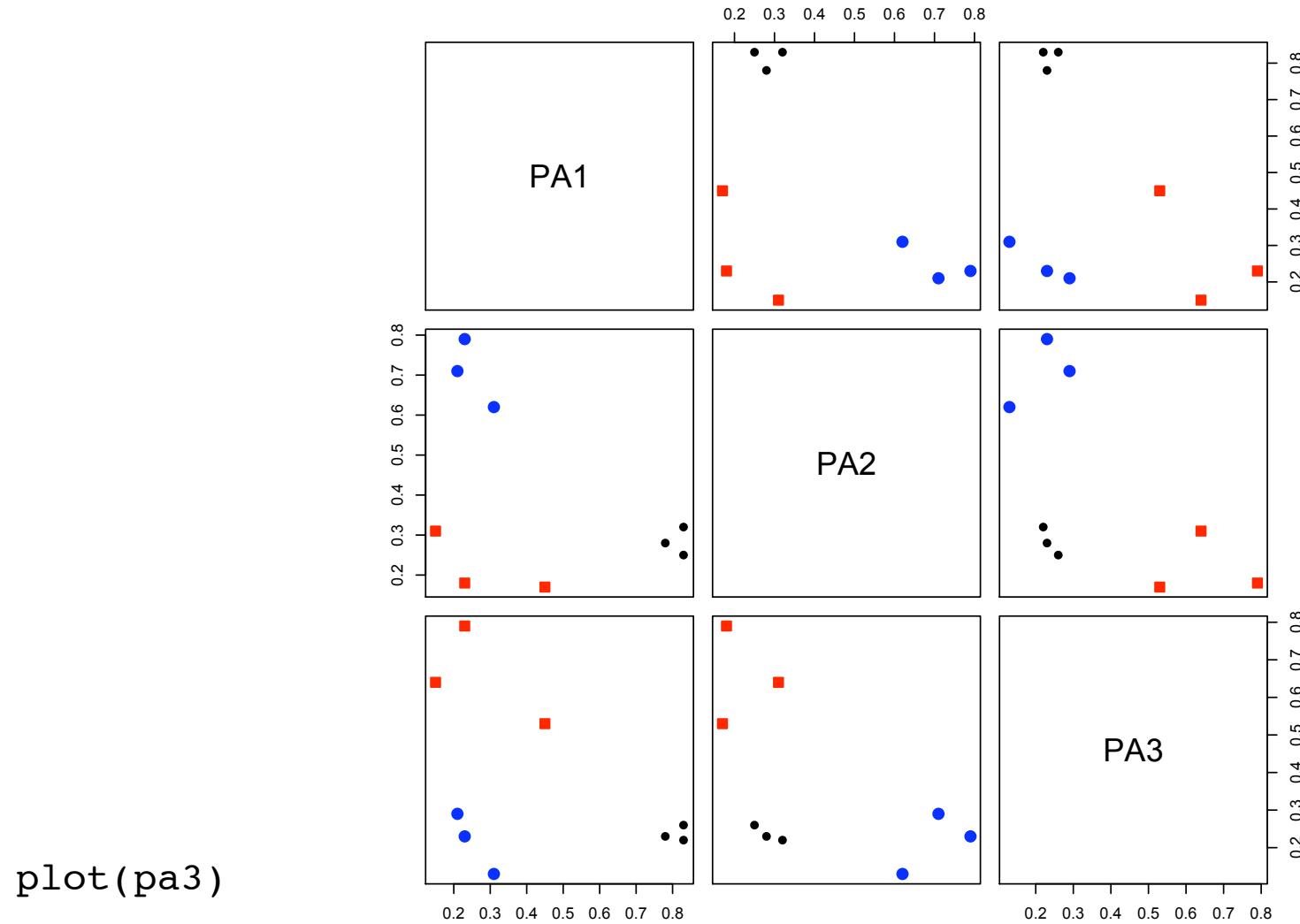
	Factor1	Factor2	Factor3	PA1	PA2	PA3	PC1	PC2	PC3
Factor1	1.00	0.64	0.62	1.00	0.64	0.62	1.00	0.59	0.55
Factor2	0.64	1.00	0.62	0.63	1.00	0.62	0.61	0.99	0.57
Factor3	0.62	0.62	1.00	0.62	0.62	1.00	0.61	0.56	0.99
PA1	1.00	0.63	0.62	1.00	0.64	0.62	1.00	0.59	0.55
PA2	0.64	1.00	0.62	0.64	1.00	0.62	0.61	0.99	0.57
PA3	0.62	0.62	1.00	0.62	0.62	1.00	0.61	0.56	0.99
PC1	1.00	0.61	0.61	1.00	0.61	0.61	1.00	0.56	0.54
PC2	0.59	0.99	0.56	0.59	0.99	0.56	0.56	1.00	0.50
PC3	0.55	0.57	0.99	0.55	0.57	0.99	0.54	0.50	1.00

# A misleading graph

Factor Analysis



# Plot the loadings: shows some cross loadings



# Rotations and transformations

I. Orthogonal rotations

A. Varimax, Quartimax

II. Oblique transformations

A. Promax, Quartimin, biquartimin, ...

```

> pa3o <- factor.pa(Thurstone,3,rotate="oblimin",n.obs=213)
Loading required package: GPArotation
> pa3o
      V   PA1   PA2   PA3
Sentences 1  0.90
Vocab      2  0.89
S.comp     3  0.84
F.letter   4          0.85
4.letter   5          0.75
Suffix     6          0.63
Series     7          0.83
Pedi       8  0.38          0.47
letters    9          0.64
              PA1   PA2   PA3
SS loadings 2.49  1.74  1.34
Proportion Var 0.28  0.19  0.15
Cumulative Var 0.28  0.47  0.62
With factor correlations of
      PA1   PA2   PA3
PA1  1.00  0.59  0.54
PA2  0.59  1.00  0.52
PA3  0.54  0.52  1.00
Test of the hypothesis that 3 factors are sufficient.
The degrees of freedom for the model is 12 and the fit was 0.01
The number of observations was 213 with Chi Square = 2.97 with
prob < 1

```

# Oblique solution Oblimin

```
> pa3p <- Promax(pa3)
> pa3p
```

	V	PA1	PA2	PA3
Sentences	1	0.911		
Vocab	2	0.904		
S.comp	3	0.848		
F.letter	4		0.869	
4.letter	5		0.759	
Suffix	6		0.650	
Series	7			0.8865
Pedi	8	0.350		0.4969
letters	9			0.6800

	PA1	PA2	PA3
SS loadings	2.54	1.80	1.52
Proportion Var	0.28	0.20	0.17
Cumulative Var	0.28	0.48	0.65

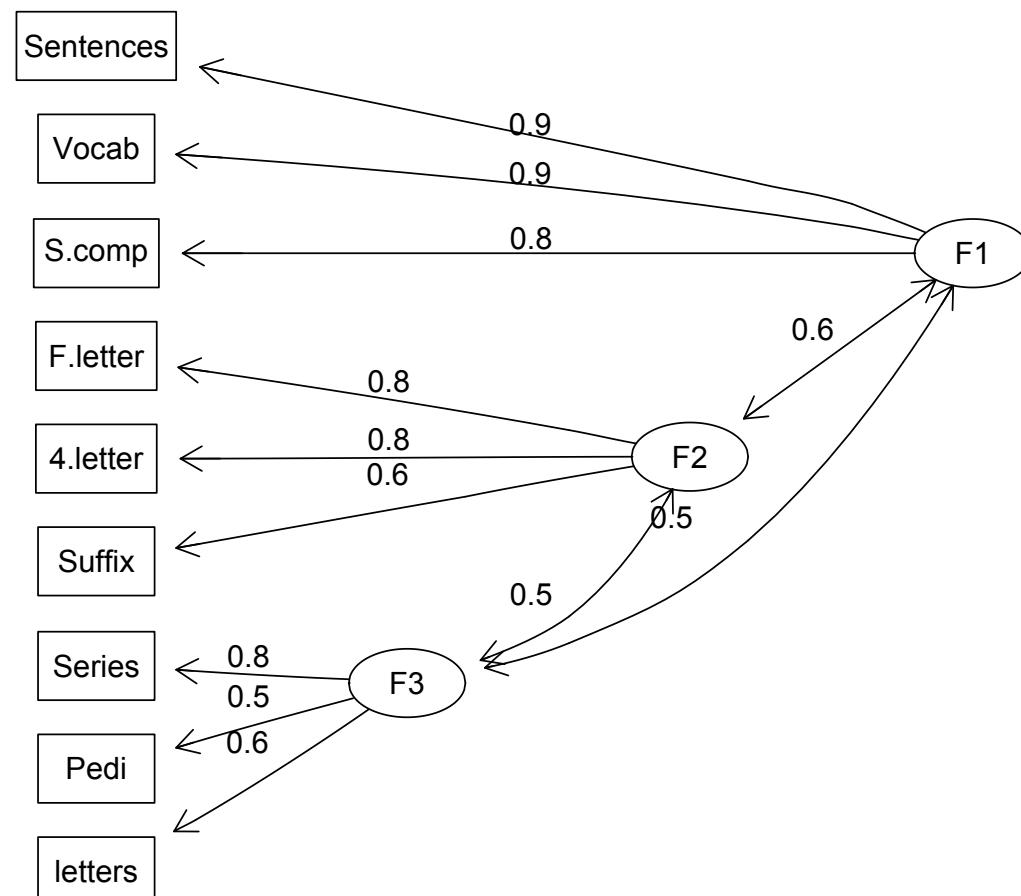
With factor correlations of

	PA1	PA2	PA3
PA1	1.00	0.61	0.61
PA2	0.61	1.00	0.58
PA3	0.61	0.58	1.00

# Oblique: Promax

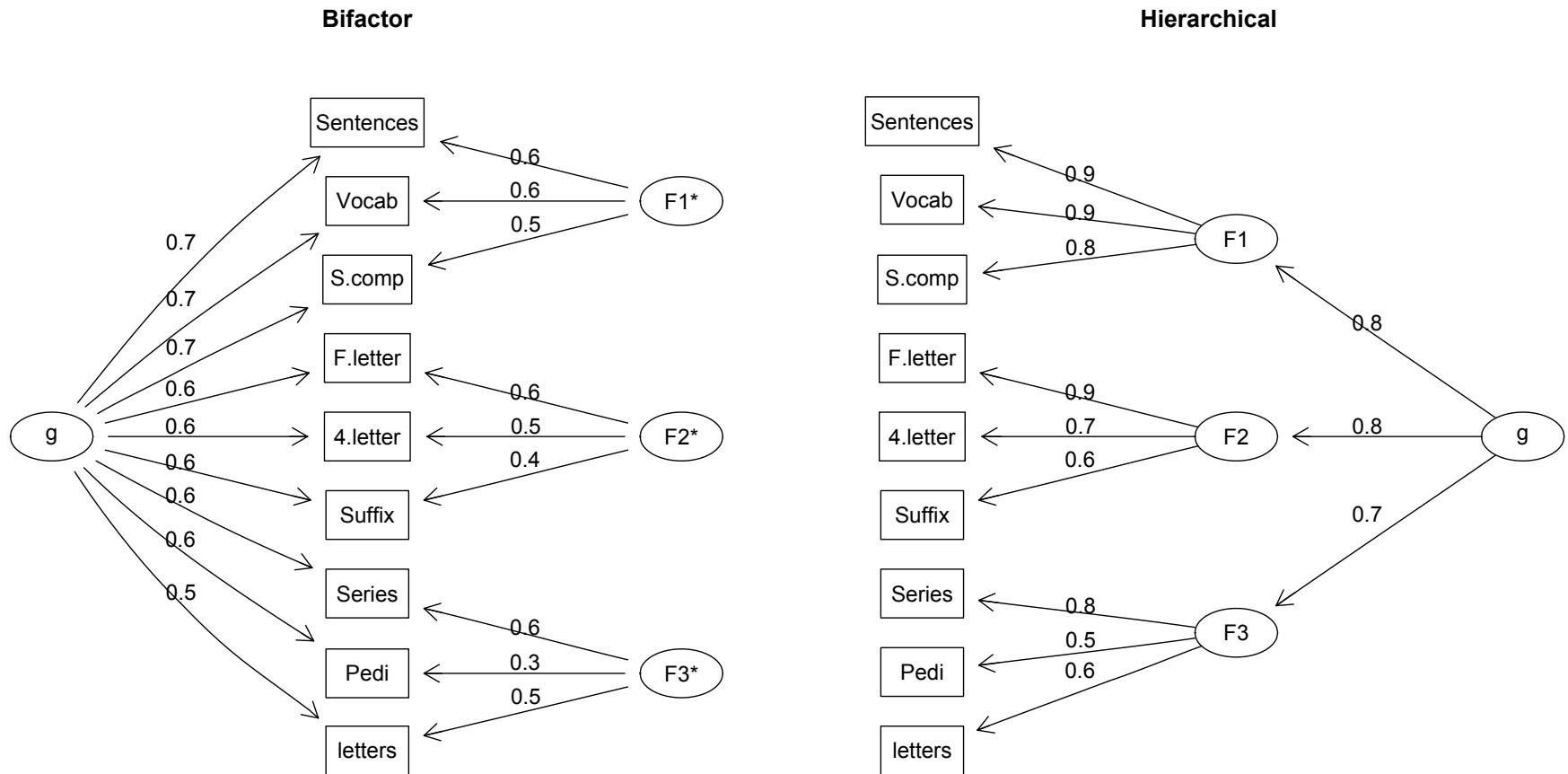
# A more accurate graphic

Factor Analysis



```
> fa.graph(pa3o,labels=colnames(Thurstone))
```

# Hierarchical solutions



```

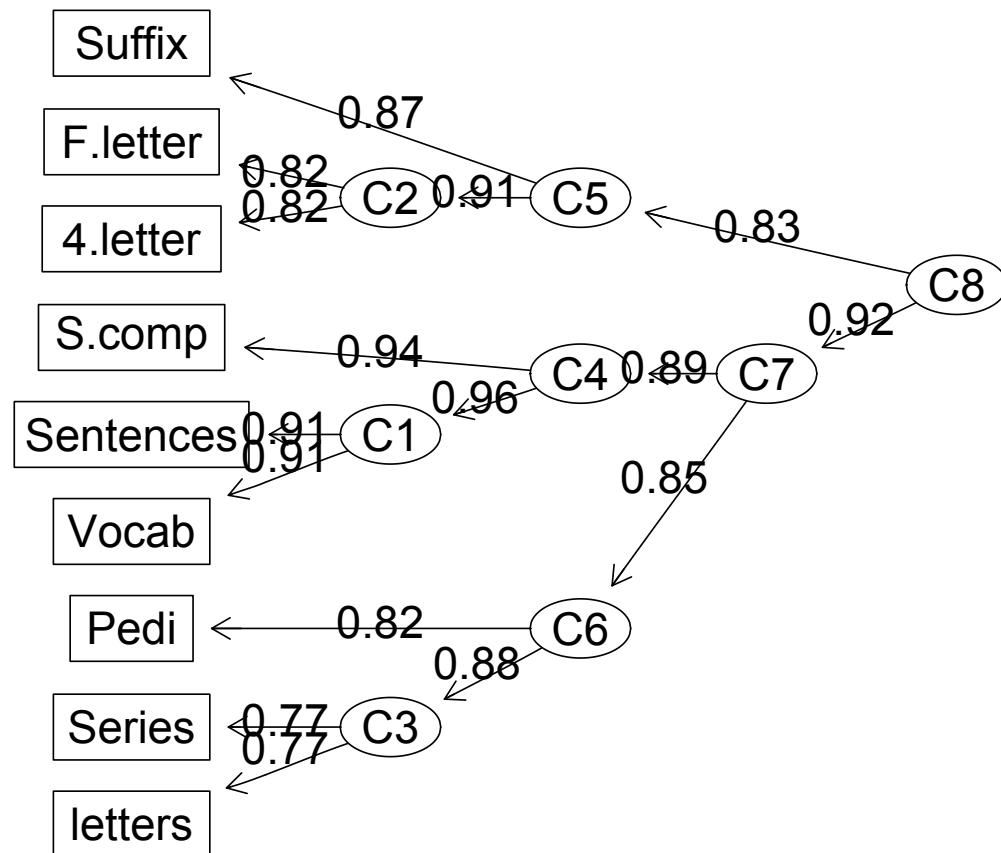
> omsl <-omega(Thurstone,title="Bifactor")
> omsl <-omega(Thurstone,sl=FALSE,title="Hierarchical")
  
```

# Hierarchical Clustering

- I. Find the similarity matrix (correlations)
- II. Find the most similar pair of items/tests
- III. Combine them and repeat II and III until some criterion (alpha, beta) fails to increase

# ICLUST of Thurstone

ICLUST



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

# Multidimensional scaling

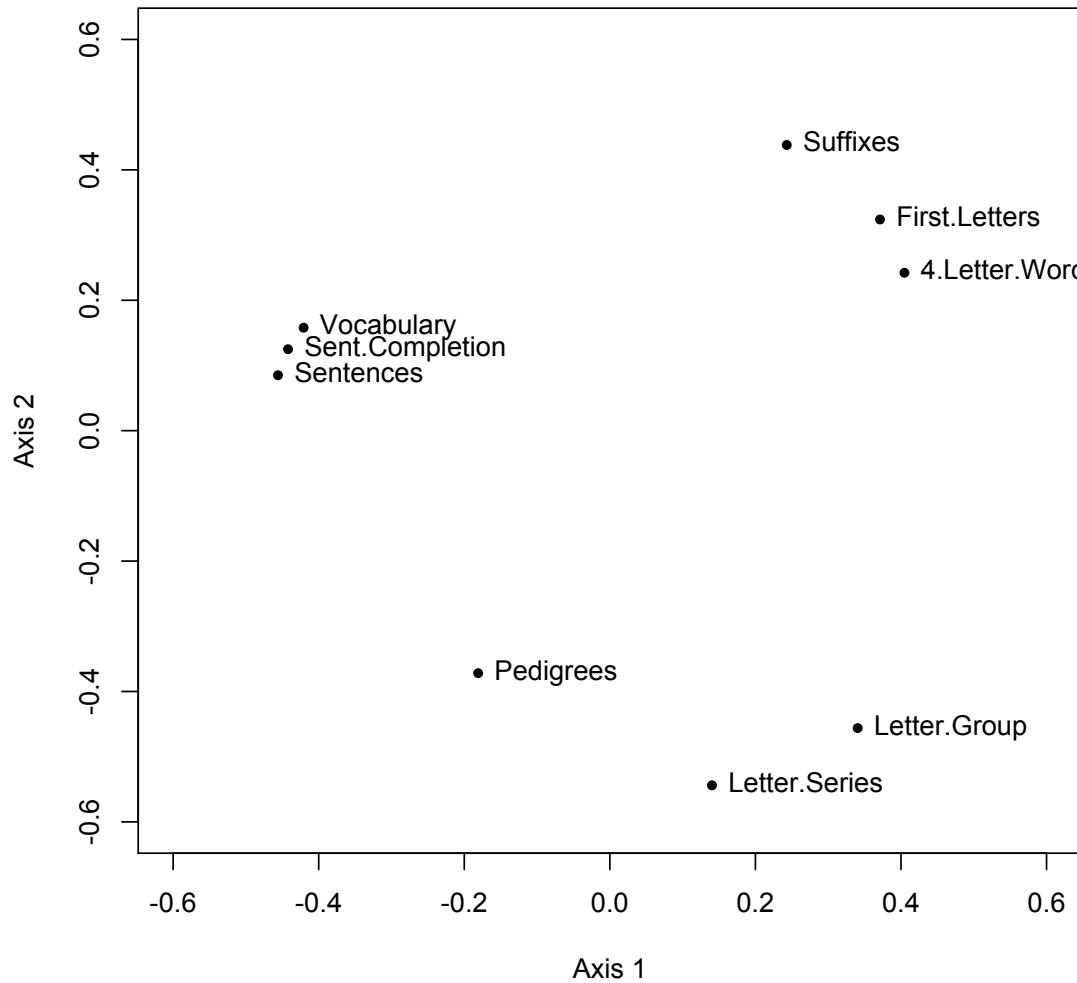
- I. Convert correlations to distances
- II. Multidimensional scaling will remove a general factor since it considers relative ranking of distances

# MDS

```
> Thurs.dist <- sqrt(2*(1-Thurstone))  
> mdsT <- cmdscale(Thurs.dist,2)  
> round(mdsT,2)
```

	[ ,1 ]	[ ,2 ]
Sentences	-0.46	0.08
Vocabulary	-0.42	0.16
Sent.Completion	-0.44	0.12
First.Letters	0.37	0.32
4.Letter.Words	0.40	0.24
Suffixes	0.24	0.44
Letter.Series	0.14	-0.54
Pedigrees	-0.18	-0.37
Letter.Group	0.34	-0.46

# MDS plot



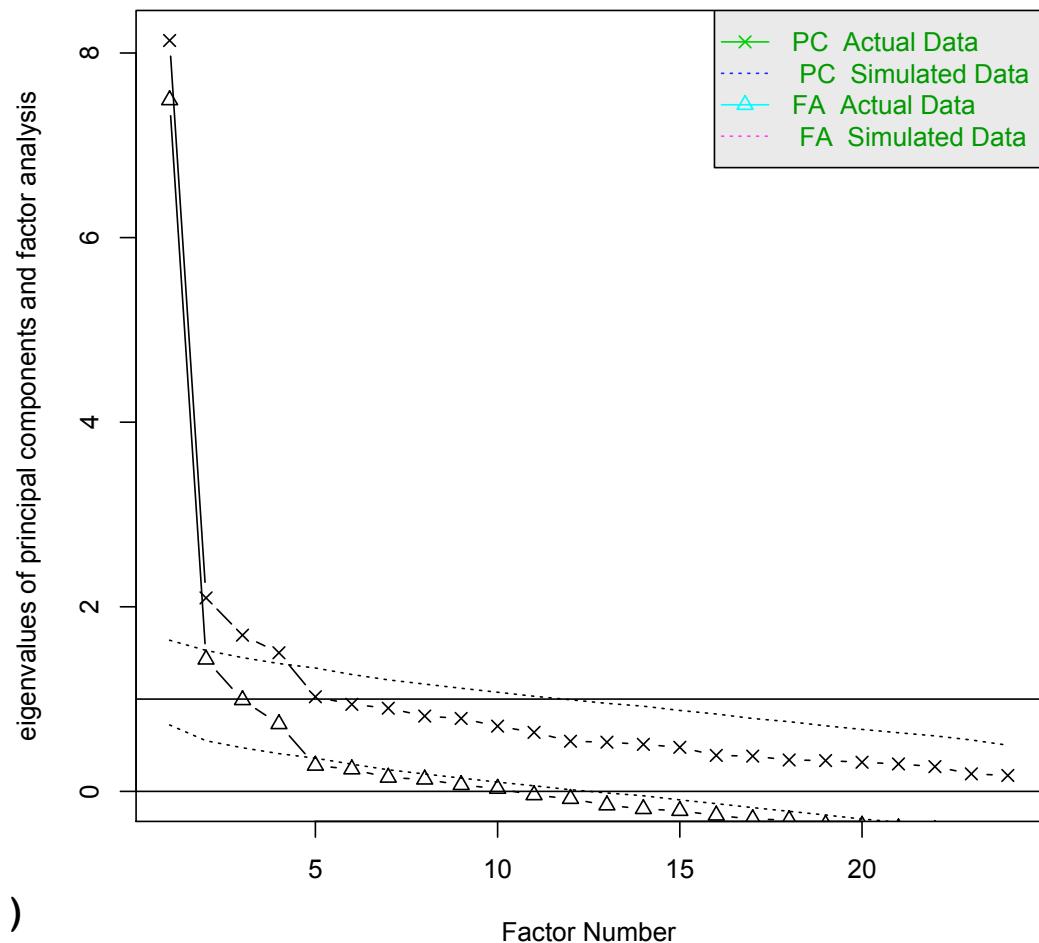
```
position <- rep(4,9)
plot(mdst,xlim=c(-.6,.6),ylim=c(-.6,.6),ylab="Axis 2",xlab="Axis 1")
text(mdst,rownames(mdst),pos=position)
```

# A more complex example

- I. Holzinger-Harman 24 mental ability tests
- II. Compare FA, CA, MDS

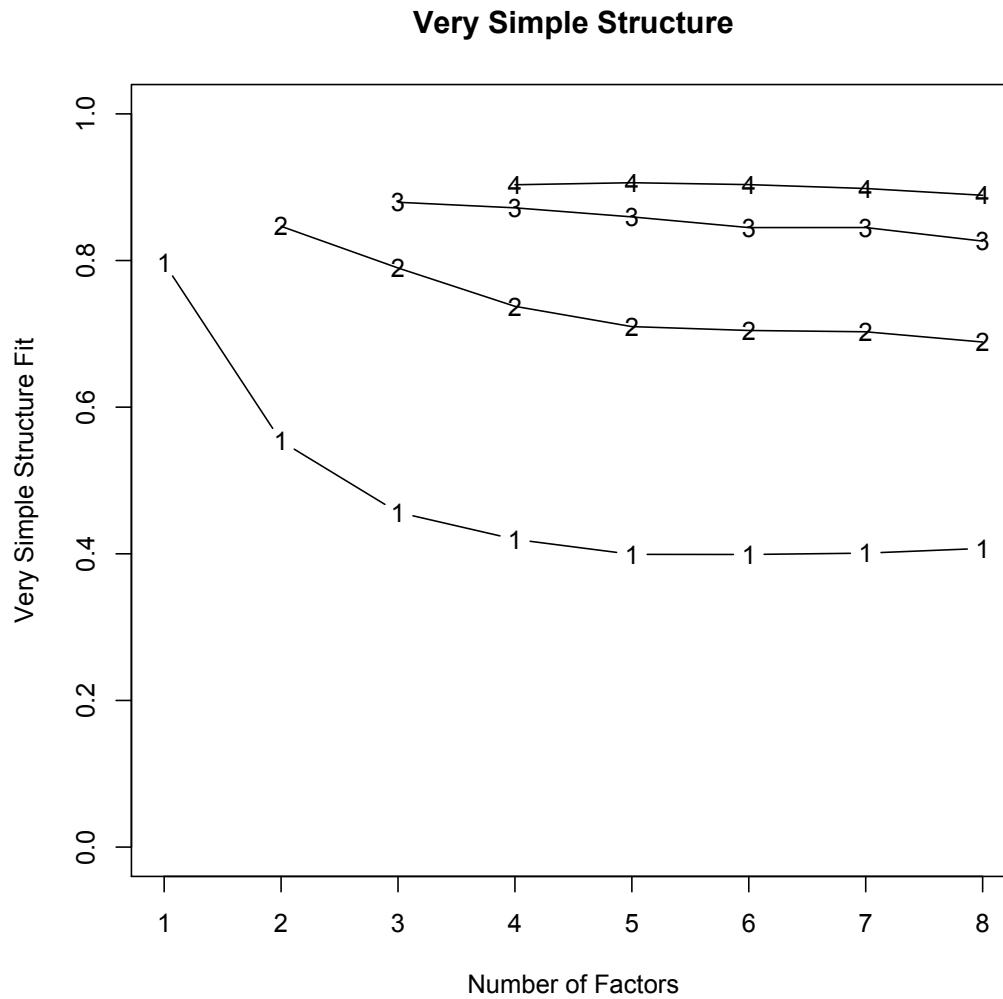
# Parallel analysis

Parallel Analysis Scree Plots



```
> hh <- Harman74.cor$cov  
> fa.parallel(hh,n.obs=228)
```

# VSS says 1 big factor



```
> vss <- VSS(hh, n.obs=228)
```

```
> vss
```

# MAP suggests 4

Very Simple Structure

Call: VSS(x = hh, n.obs = 228)

VSS complexity 1 achieves a maximum of 0.8 with 1 factors

VSS complexity 2 achieves a maximum of 0.85 with 2 factors

The Velicer MAP criterion achieves a minimum of 0.03 with 4 factors

Velicer MAP

```
[1] 0.02 0.02 0.02 0.02 0.02 0.02 0.03 0.03
```

Very Simple Structure Complexity 1

```
[1] 0.80 0.55 0.46 0.42 0.40 0.40 0.40 0.41
```

Very Simple Structure Complexity 2

```
[1] 0.00 0.85 0.79 0.74 0.71 0.70 0.70 0.69
```

# Chi square says > 8

```
> vss$vss.stats[,1:3]
  dof      chisq      prob
1 252 1012.9000 9.259262e-92
2 229  693.9911 2.649458e-48
3 207  485.1213 2.232607e-24
4 186  370.8825 2.174718e-14
5 166  307.7273 1.479600e-10
6 147  266.8324 5.628353e-09
7 129  226.6602 2.396296e-07
8 112  182.6407 2.832707e-05
>
```

```

<- fa4o <- factor.pain(4, n.obs=220, rotate= "oblique", 
> fa4o

```

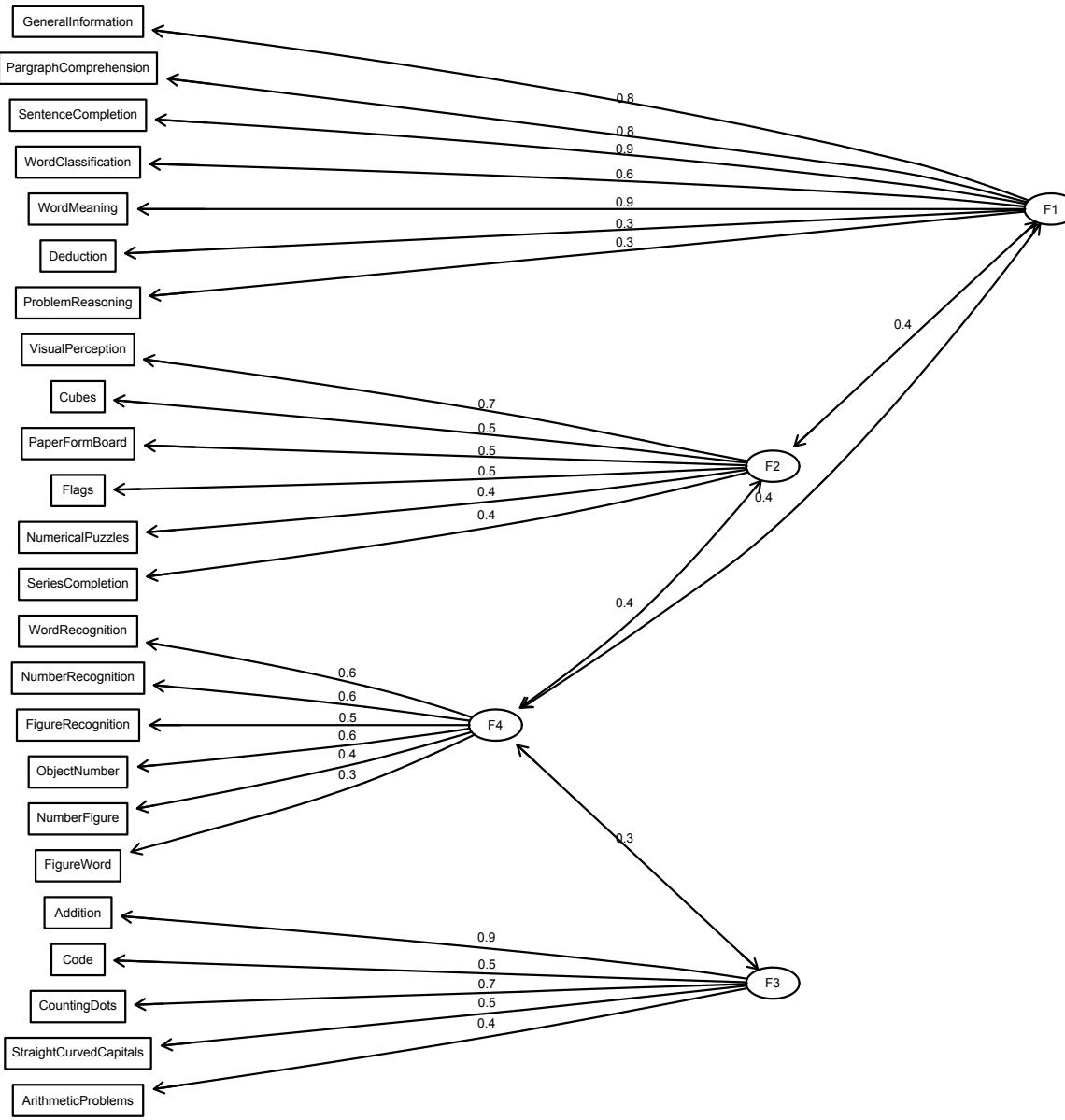
	V	PA1	PA3	PA2	PA4
VisualPerception	1		0.69		
Cubes	2		0.46		
PaperFormBoard	3		0.54		
Flags	4		0.52		
GeneralInformation	5	0.76			
ParagraphComprehension	6	0.80			
SentenceCompletion	7	0.87			
WordClassification	8	0.56			
WordMeaning	9	0.86			
Addition	10			0.86	
Code	11			0.49	0.30
CountingDots	12			0.70	
StraightCurvedCapitals	13		0.42	0.47	
WordRecognition	14				0.58
NumberRecognition	15				0.55
FigureRecognition	16		0.33		0.52
ObjectNumber	17				0.59
NumberFigure	18				0.43
FigureWord	19				0.32
Deduction	20	0.33	0.31		With factor correlations
NumericalPuzzles	21		0.37	0.33	PA1 PA3 PA2 PA4
ProblemReasoning	22	0.31	0.30		PA1 1.00 0.41 0.30 0.40
SeriesCompletion	23	0.30	0.44		PA3 0.41 1.00 0.27 0.38
ArithmeticProblems	24			0.41	PA2 0.30 0.27 1.00 0.32

# 4 oblique factors

## Factor Analysis

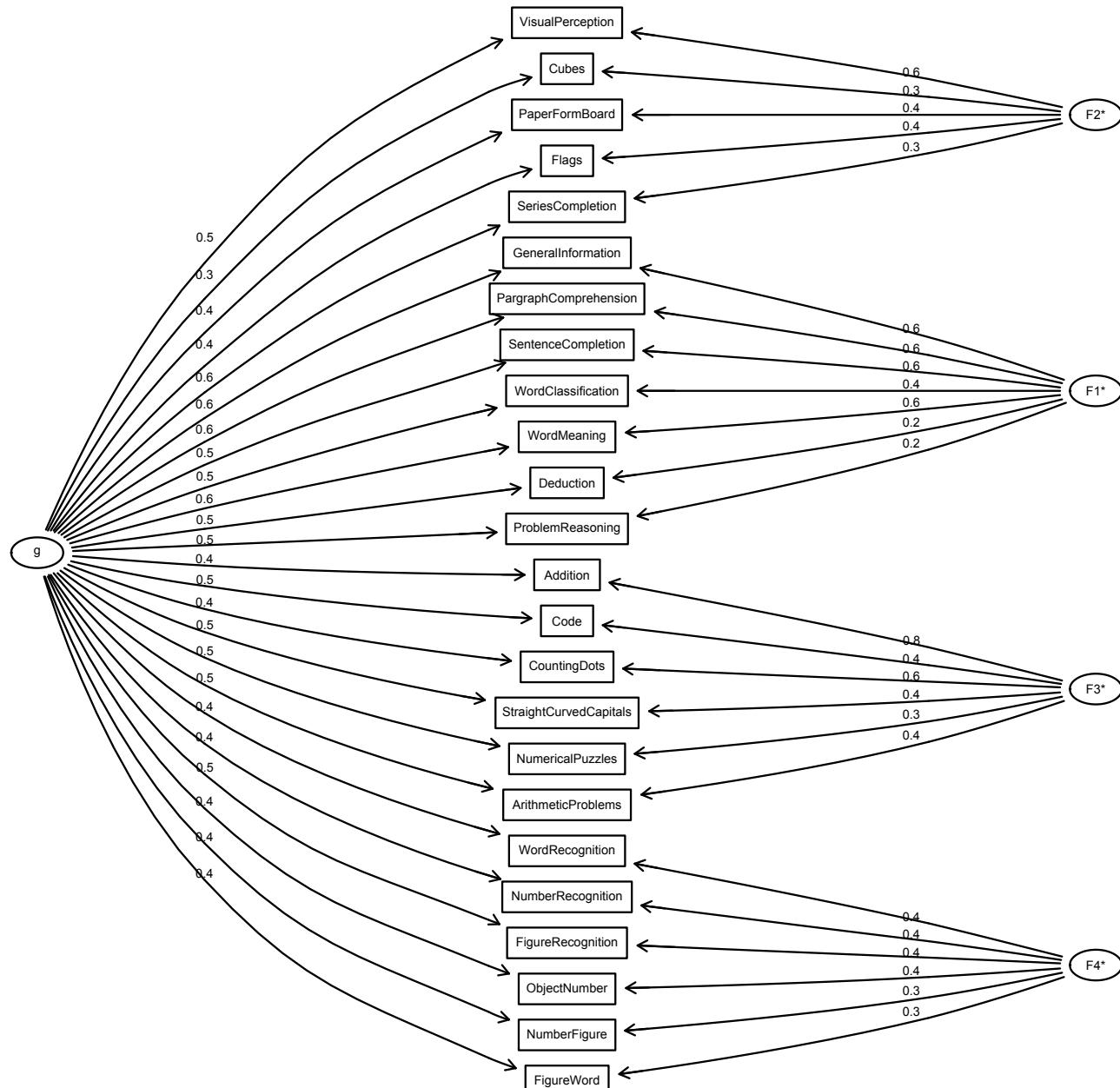
4

correlated  
factors

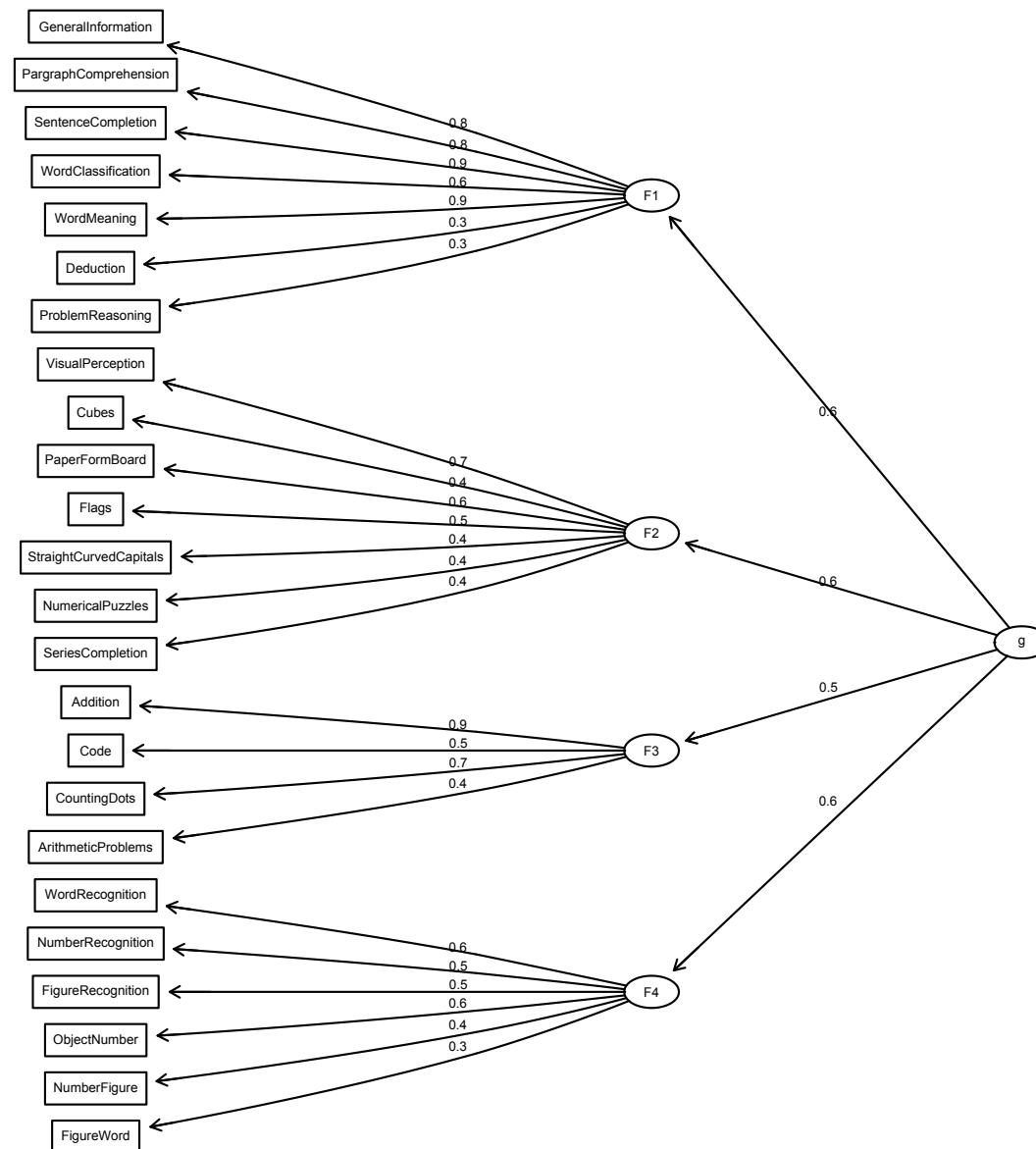


## Holzinger Harman problem -- Bifactor

```
om4 <-omega(hh,4,title="Holzinger Harman problem -- Bifactor")
```

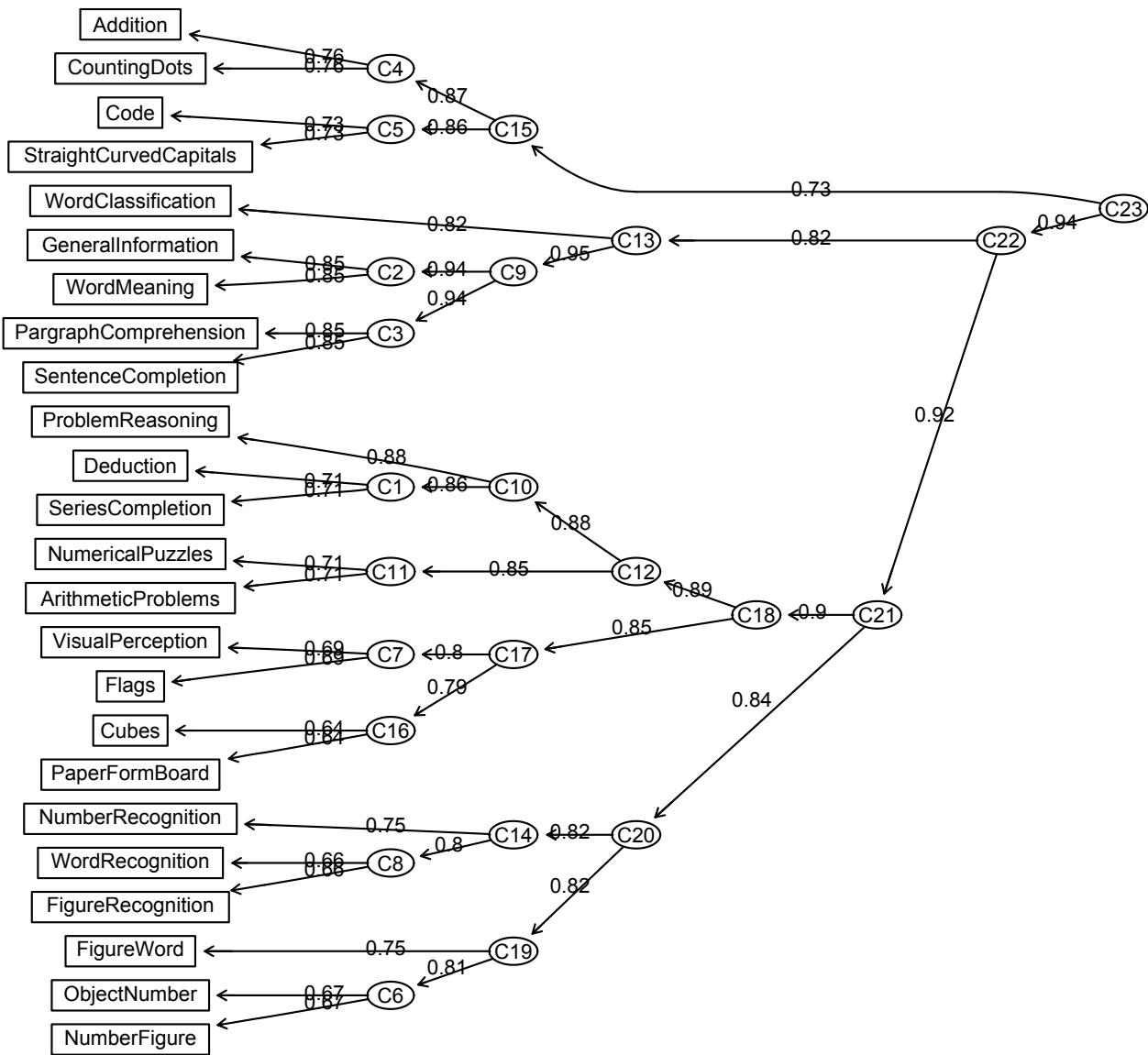


## Holzinger Harman problem -- Hierarchical



```
> om4 <-omega(hh,4,title="Holzinger Harman problem -- Hierarchical",sl=FALSE)
```

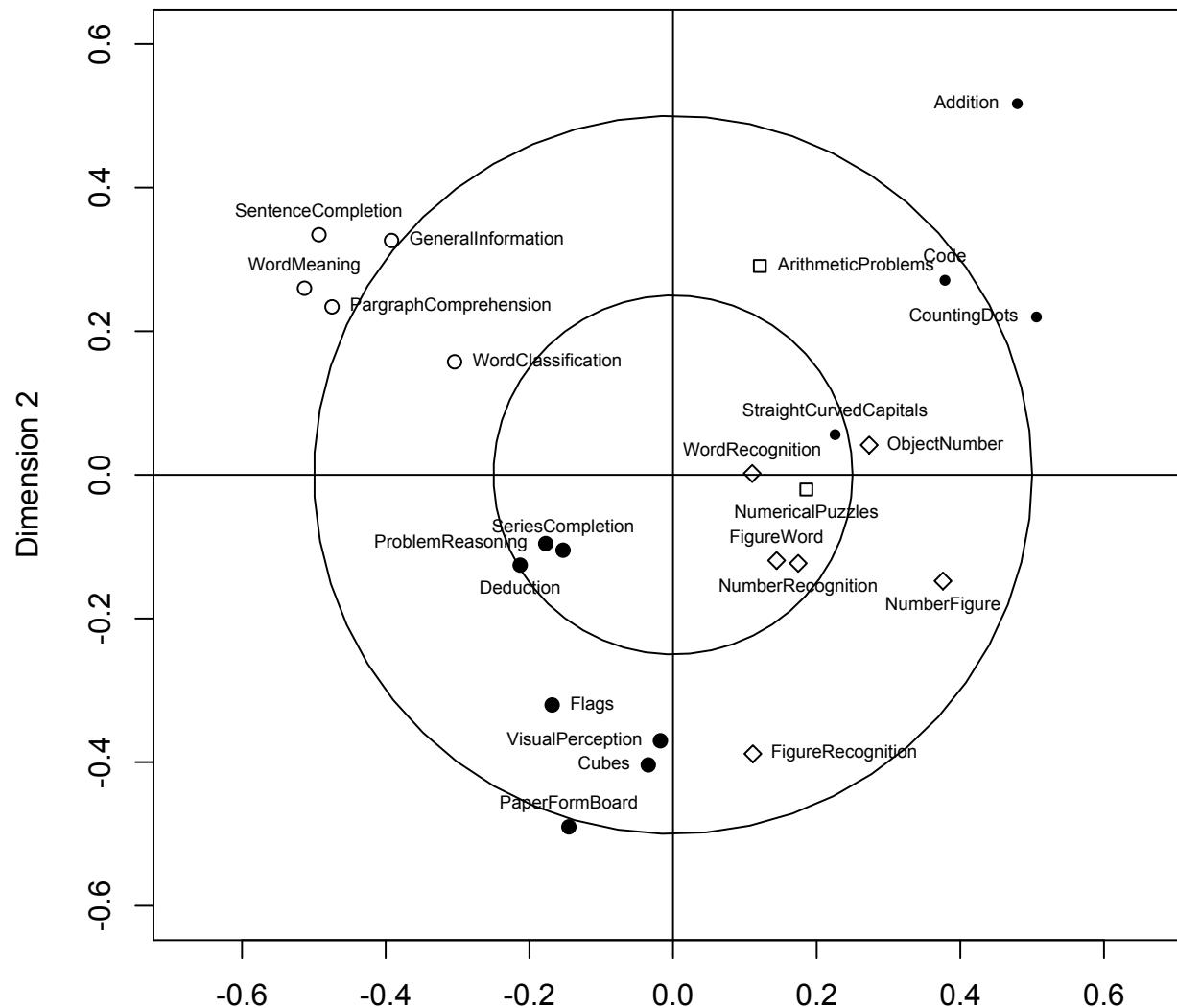
## ICLUST of Holzinger Harman 24 mental measurements



```
ic4 <- ICLUST(hh, title="ICLUST of Holzinger Harman 24 mental measurements")
```

# MDS of HH problem

Multidimensional Scaling of 24 ability tests



# code for MDS plot

```
> dis24 <- sqrt(2*(1-Harman74.cor$cov))
> mds24 <- cmdscale(dis24,2)
> plot.char <- c( 19, 19, 19, 19,    21, 21,    21, 21,    21,
20, 20, 20,
+      20, 23, 23, 23,    23, 23, 23, 19,    22, 19, 19, 22 )
> plot(mds24,xlim=c(-.6,.6),ylim=c(-.6,.6),xlab="Dimension
1",ylab="Dimension 2",asp=1,pch=plot.char)
> position <- c(2,2,3,4,   4,4,3,4,   3,2,3,2,   3,3,1,4,
4,1,3,1,   1,2,3,4)
> text(mds24,rownames(mds24),cex=.6,pos=position)
> abline(v=0,h=0)
> title("Multidimensional Scaling of 24 ability tests")
> #draw circles at .25 and .50 units away from the center
> segments = 51
> angles <- (0:segments) * 2 * pi/segments
>           unit.circle <- cbind(cos(angles), sin(angles))
>           lines(unit.circle*.25)
>           lines(unit.circle*.5)
```

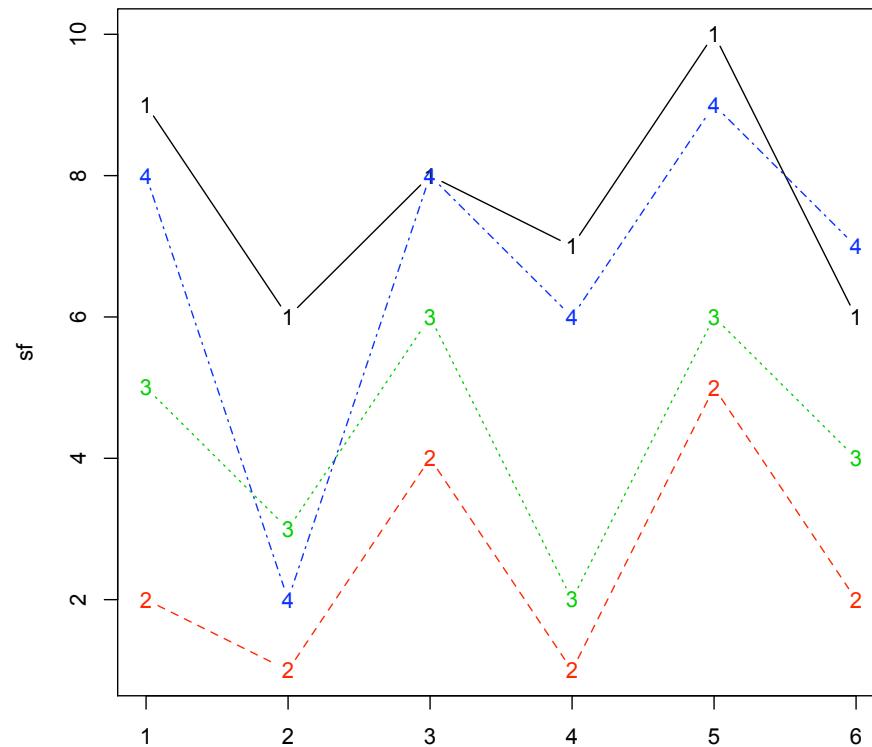
# Reliability of scales and raters

- I. First consider the reliability of raters using the IntraClass Correlation (see Shrout and Fleiss for the definitive discussion)
- II. Types of reliability of ratings (1 or n per target)
  - A. each target rated by a different judge, judges are random
  - B. random sample of k judges rate targets
  - C. Fixed set of k judges give ratings

# 4 judges rate 6 subjects

```
> sf
```

	J1	J2	J3	J4
S1	9	2	5	8
S2	6	1	3	2
S3	8	4	6	8
S4	7	1	2	6
S5	10	5	6	9
S6	6	2	4	7



# Simple correlations (these will remove means for raters)

```
> round(cor(sf),2)
      J1    J2    J3    J4
J1  1.00  0.75  0.73  0.75
J2  0.75  1.00  0.89  0.73
J3  0.73  0.89  1.00  0.72
J4  0.75  0.73  0.72  1.00
```

# ICC

```
> ICC(sf)
```

	type	ICC	F	df1	df2	p	lower bound	upper bound
Single_raters_absolute	ICC1	0.17	1.79	5	18	0.16	-0.13	0.72
Single_random_raters	ICC2	0.29	11.03	5	15	0.00	0.02	0.76
Single_fixed_raters	ICC3	0.71	11.03	5	15	0.00	0.34	0.95
Average_raters_absolute	ICC1k	0.44	1.79	5	18	0.16	-0.88	0.91
Average_random_raters	ICC2k	0.62	11.03	5	15	0.00	0.07	0.93
Average_fixed_raters	ICC3k	0.91	11.03	5	15	0.00	0.68	0.99

```
> alpha(sf)
```

## Alpha of raters

Reliability analysis

Call: alpha(x = sf)

raw_alpha	std.alpha	G6(smc)	average_r	mean	sd
0.91	0.93	0.92	0.76	21	6.7

Reliability if an item is dropped:

	raw_alpha	std.alpha	G6(smc)	average_r
J1	0.88	0.91	0.89	0.78
J2	0.87	0.89	0.85	0.73
J3	0.87	0.90	0.85	0.74
J4	0.92	0.92	0.90	0.79

## Item statistics

	n	r	r.cor	mean	sd
J1	6	0.89	0.83	7.7	1.6
J2	6	0.93	0.92	2.5	1.6
J3	6	0.92	0.91	4.3	1.6
J4	6	0.88	0.82	6.7	2.5

# Reliability of a single scale

```
> round(cor(bfi[,1:10],use="pairwise"),2)
```

	A1	A2	A3	A4	A5	C1	C2	C3	C4	C5
A1	1.00	-0.30	-0.23	-0.12	-0.19	-0.03	-0.06	0.01	0.19	0.08
A2	-0.30	1.00	0.39	0.24	0.41	0.06	0.06	0.22	-0.15	-0.12
A3	-0.23	0.39	1.00	0.27	0.45	0.07	0.12	0.16	-0.14	-0.12
A4	-0.12	0.24	0.27	1.00	0.22	0.07	0.17	0.08	-0.15	-0.17
A5	-0.19	0.41	0.45	0.22	1.00	0.10	0.06	0.20	-0.14	-0.10
C1	-0.03	0.06	0.07	0.07	0.10	1.00	0.44	0.41	-0.39	-0.23
C2	-0.06	0.06	0.12	0.17	0.06	0.44	1.00	0.35	-0.36	-0.24
C3	0.01	0.22	0.16	0.08	0.20	0.41	0.35	1.00	-0.37	-0.36
C4	0.19	-0.15	-0.14	-0.15	-0.14	-0.39	-0.36	-0.37	1.00	0.53
C5	0.08	-0.12	-0.12	-0.17	-0.10	-0.23	-0.24	-0.36	0.53	1.00

# Mindless reliability

```
> alpha(bfi[1:10])
```

Reliability analysis

```
Call: alpha(x = bfi[1:10])
```

raw_alpha	std.alpha	G6(smc)	average_r	mean	sd
0.19	0.25	0.44	0.032	40	4.7

Reliability if an item is dropped:

Item statistics

	raw_alpha	std.alpha	G6(smc)	average_r	n	r	r.cor	mean	sd
A1	0.290	0.354	0.51	0.057	A1	1000	0.099	-0.21	2.3
A2	0.082	0.133	0.35	0.017	A2	994	0.508	0.47	4.8
A3	0.045	0.101	0.33	0.012	A3	989	0.552	0.54	4.6
A4	0.108	0.173	0.40	0.023	A4	993	0.448	0.31	4.8
A5	0.042	0.093	0.32	0.011	A5	988	0.563	0.55	4.6
C1	0.133	0.190	0.38	0.025	C1	997	0.421	0.34	4.4
C2	0.123	0.182	0.38	0.024	C2	997	0.434	0.35	4.2
C3	0.105	0.154	0.36	0.020	C3	995	0.478	0.44	4.3
C4	0.336	0.392	0.50	0.067	C4	986	0.005	-0.24	2.6
C5	0.329	0.364	0.49	0.060	C5	997	0.077	-0.17	3.5

# somewhat better reliability

```
> keys <- make.keys(10, list(all=c(-1, 2:8, -9, -10)))
> alpha(bfi[1:10], keys)
```

```
Reliability analysis
Call: alpha(x = bfi[1:10], keys = keys)
```

raw_alpha	std.alpha	G6(smc)	average_r	mean	sd
0.72	0.72	0.75	0.21	40	4.7

Reliability if an item is dropped:

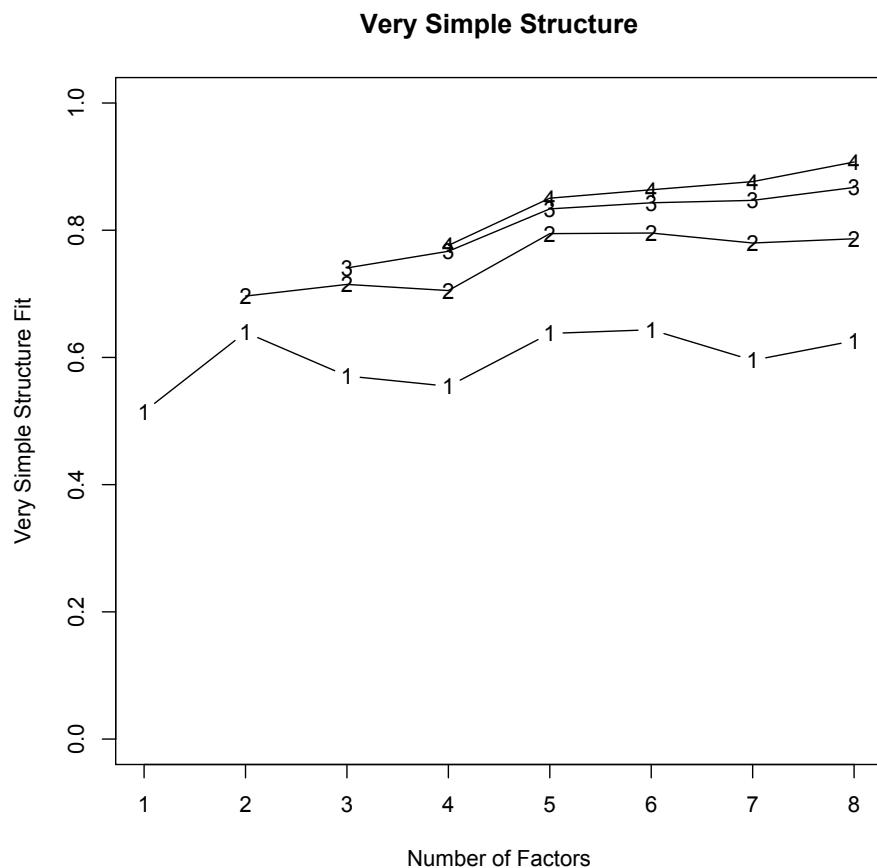
	raw_alpha	std.alpha	G6(smc)	average_r		n	r	r.cor	mean	sd
A1	0.72	0.72	0.74	0.23	A1	1000	0.41	0.29	2.3	1.3
A2	0.70	0.70	0.72	0.20	A2	994	0.55	0.49	4.8	1.1
A3	0.70	0.70	0.72	0.20	A3	989	0.55	0.49	4.6	1.2
A4	0.71	0.71	0.74	0.22	A4	993	0.46	0.35	4.8	1.4
A5	0.70	0.70	0.72	0.21	A5	988	0.53	0.46	4.6	1.2
C1	0.70	0.70	0.72	0.21	C1	997	0.52	0.46	4.4	1.2
C2	0.70	0.70	0.72	0.21	C2	997	0.54	0.47	4.2	1.3
C3	0.69	0.69	0.71	0.20	C3	995	0.59	0.54	4.3	1.3
C4	0.67	0.68	0.70	0.19	C4	986	0.64	0.61	2.6	1.4
C5	0.70	0.70	0.72	0.20	C5	997	0.55	0.49	3.5	1.5

# Examine the items

VSS suggests 2 factors!

## The items

- A1 Am indifferent to the feelings of others.
- A2 Inquire about others' well-being.
- A3 Know how to comfort others.
- A4 Love children.
- A5 Make people feel at ease.
- C1 Am exacting in my work.
- C2 Continue until everything is perfect.
- C3 Do things according to a plan.
- C4 Do things in a half-way manner.
- C5 Waste my time.



# Omega reliability

```
> om2 <- omega(bfi[1:10],2)
Warning messages:
1: In schmid(m, nfactors, pc, digits, rotate = rotate, n.obs =
n.obs, :
  Three factors are required for identification -- general factor
  loadings set to be equal. Proceed with caution.
2: In schmid(m, nfactors, pc, digits = digits, n.obs = n.obs, ...):
  Three factors are required for identification -- general factor
  loadings set to be equal. Proceed with caution.
```

```
> om2
Omega
Call: omega(m = bfi[1:10], nfactors = 2)
Alpha: 0.72
G.6: 0.75
Omega Hierarchical: 0.36
Omega Total 0.77
```

Schmid Leiman Factor loadings greater than 0.2

	g	F1*	F2*	h2	u2
A1-	0.21		0.30		0.87
A2	0.36		0.53	0.41	0.59
A3	0.36		0.55	0.43	0.57
A4	0.24		0.28		0.86
A5	0.36		0.54	0.42	0.58
C1	0.30	0.51		0.36	0.64
C2	0.30	0.48		0.32	0.68
C3	0.37	0.48		0.37	0.63
C4-	0.40	0.58		0.50	0.50
C5-	0.33	0.48		0.33	0.67

With eigenvalues of:

g F1\* F2\*

1.1	1.3	1.1
-----	-----	-----

Omega h is  
low

```
> keys <-  
make.keys(10, list(all=c(-1,2:8,-9,-10), agree=c(-1,2:5), con=c(6:8,-9,-  
0)))  
> score.items(keys, bfi[1:10])  
Call: score.items(keys = keys, items = bfi[1:10])
```

(Unstandardized) Alpha:

	all	agree	con
alpha	0.72	0.65	0.74

Average item correlation:

	all	agree	con
average.r	0.2	0.27	0.36

Guttman 6\* reliability:

	all	agree	con
Lambda.6	0.74	0.62	0.72

Scale intercorrelations corrected for attenuation

raw correlations below the diagonal, alpha on the diagonal

corrected correlations above the diagonal:

	all	agree	con
all	0.72	1.10	1.13
agree	0.75	0.65	0.36
con	0.83	0.25	0.74

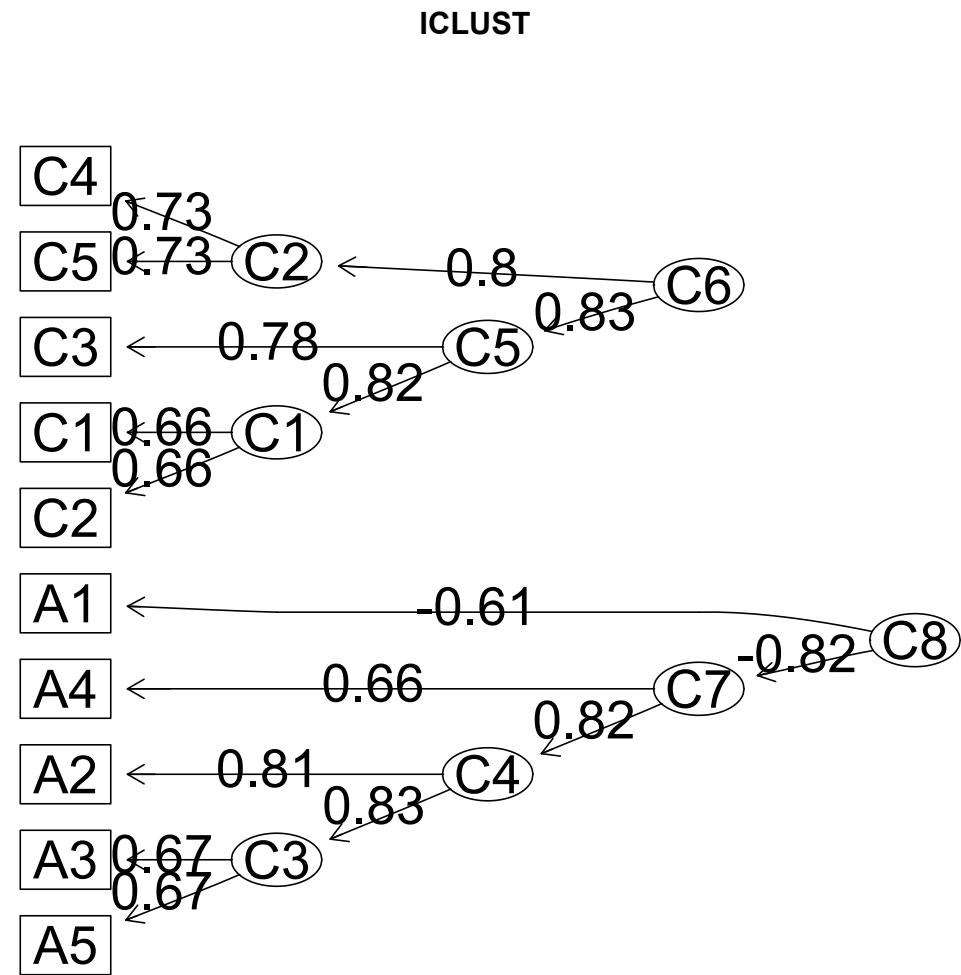
# Score 3 scales

# Item scale correlations

Item by scale correlations:  
corrected for item overlap and scale reliability

	all	agree	con
A1	-0.28	-0.37	-0.12
A2	0.47	0.63	0.21
A3	0.47	0.63	0.21
A4	0.34	0.37	0.22
A5	0.44	0.58	0.20
C1	0.46	0.13	0.59
C2	0.47	0.19	0.55
C3	0.54	0.25	0.60
C4	-0.62	-0.30	-0.69
C5	-0.50	-0.23	-0.56
>			

# ICLUST shows 2 scales



# Structural Equation modeling in R

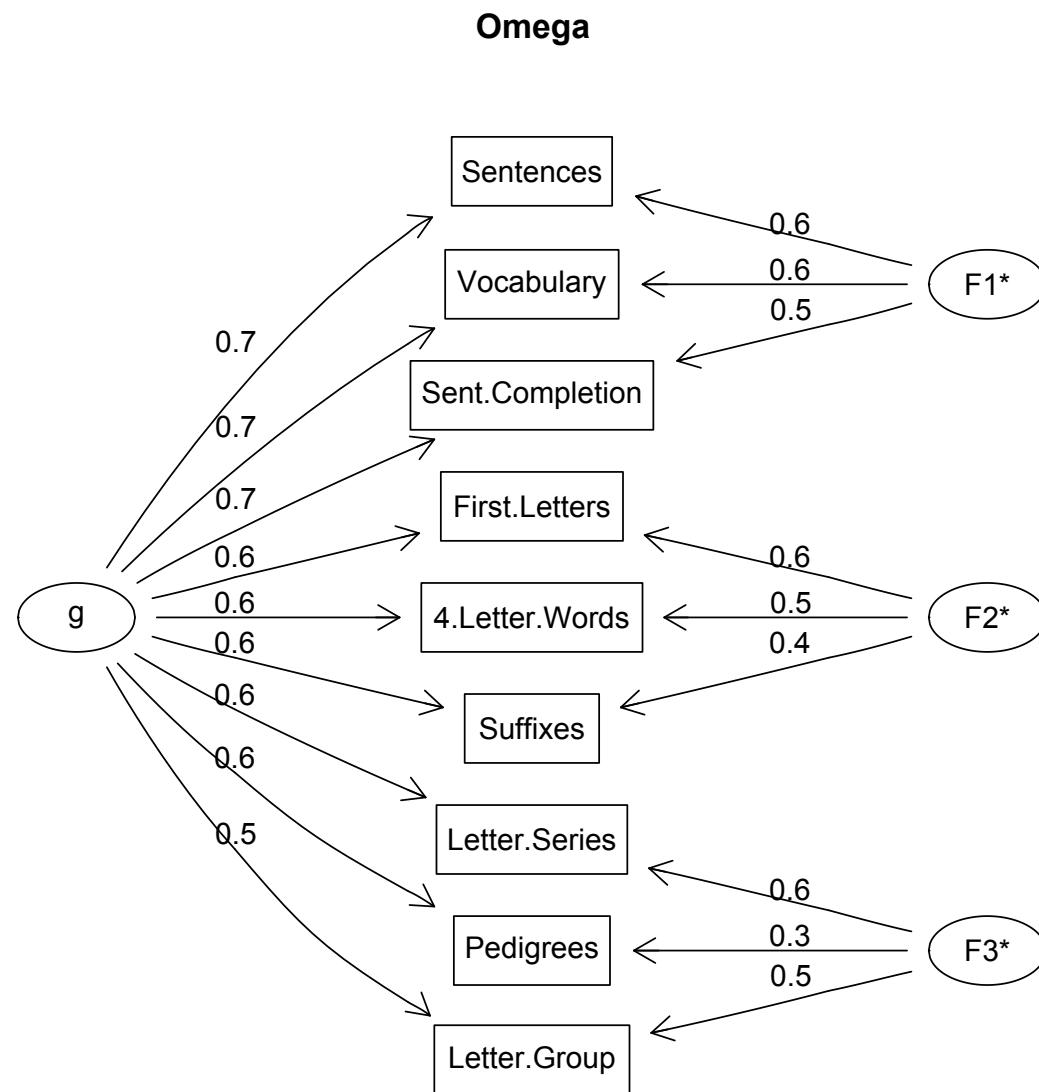
- I. sem by John Fox
- II. does not do multiple group analyses
- III.Mx in R is a coming attraction
- IV.Using psych as a front end to sem to generate the model commands

```
> om <- omega(Thurstone) #creates the path model and the model commands
> om$model
```

Path	Parameter	Initial
Value		
[1,] "g->Sentences"	"Sentences"	NA
[2,] "g->Vocabulary"	"Vocabulary"	NA
[3,] "g->Sent.Completion"	"Sent.Completion"	NA
[4,] "g->First.Letters"	"First.Letters"	NA
[5,] "g->4.Letter.Words"	"4.Letter.Words"	NA
[6,] "g->Suffixes"	"Suffixes"	NA
[7,] "g->Letter.Series"	"Letter.Series"	NA
[8,] "g->Pedigrees"	"Pedigrees"	NA
[9,] "g->Letter.Group"	"Letter.Group"	NA
[10,] "F1*->Sentences"	"F1*Sentences"	NA
[11,] "F1*->Vocabulary"	"F1*Vocabulary"	NA
[12,] "F1*->Sent.Completion"	"F1*Sent.Completion"	NA
[13,] "F2*->First.Letters"	"F2*First.Letters"	NA
[14,] "F2*->4.Letter.Words"	"F2*4.Letter.Words"	NA
[15,] "F2*->Suffixes"	"F2*Suffixes"	NA
[16,] "F3*->Letter.Series"	"F3*Letter.Series"	NA
[17,] "F3*->Pedigrees"	"F3*Pedigrees"	NA
[18,] "F3*->Letter.Group"	"F3*Letter.Group"	NA
[19,] "Sentences<->Sentences"	"e1"	NA
[20,] "Vocabulary<->Vocabulary"	"e2"	NA
[21,] "Sent.Completion<->Sent.Completion"	"e3"	NA
[22,] "First.Letters<->First.Letters"	"e4"	NA
[23,] "4.Letter.Words<->4.Letter.Words"	"e5"	NA
[24,] "Suffixes<->Suffixes"	"e6"	NA
[25,] "Letter.Series<->Letter.Series"	"e7"	NA
[26,] "Pedigrees<->Pedigrees"	"e8"	NA
[27,] "Letter.Group<->Letter.Group"	"e9"	NA

# The model

# The model



# Do the sem

```
> library(sem)
> sem.bf <- sem(om$model,Thurstone,213)
> summary(sem.bf,digits=2)

Model Chisquare = 24    Df = 18 Pr(>Chisq) = 0.15
Chisquare (null model) = 1102    Df = 36
Goodness-of-fit index = 0.98
Adjusted goodness-of-fit index = 0.94
RMSEA index = 0.04    90% CI: (NA, 0.078)
Bentler-Bonnett NFI = 0.98
Tucker-Lewis NNFI = 0.99
Bentler CFI = 1
SRMR = 0.035
BIC = -72

Normalized Residuals
  Min. 1st Qu. Median      Mean 3rd Qu.      Max.
-8.2e-01 -3.3e-01 -8.9e-07  2.8e-02  1.6e-01  1.8e+00
```

# Parameter values

Parameter Estimates

	Estimate	Std Error	z value	Pr(> z )	
Sentences	0.77	0.073	10.57	0.0e+00	Sentences <--- g
Vocabulary	0.79	0.072	10.92	0.0e+00	Vocabulary <--- g
Sent.Completion	0.75	0.073	10.27	0.0e+00	Sent.Completion <--- g
First.Letters	0.61	0.072	8.43	0.0e+00	First.Letters <--- g
4.Letter.Words	0.60	0.074	8.09	6.7e-16	4.Letter.Words <--- g
Suffixes	0.57	0.071	8.00	1.3e-15	Suffixes <--- g
Letter.Series	0.57	0.074	7.63	2.3e-14	Letter.Series <--- g
Pedigrees	0.66	0.069	9.55	0.0e+00	Pedigrees <--- g
Letter.Group	0.53	0.079	6.71	2.0e-11	Letter.Group <--- g
F1*Sentences	0.49	0.085	5.71	1.1e-08	Sentences <--- F1*
F1*Vocabulary	0.45	0.090	5.00	5.7e-07	Vocabulary <--- F1*
F1*Sent.Completion	0.40	0.093	4.33	1.5e-05	Sent.Completion <--- F1*
F2*First.Letters	0.61	0.086	7.16	8.2e-13	First.Letters <--- F2*
F2*4.Letter.Words	0.51	0.085	5.96	2.5e-09	4.Letter.Words <--- F2*
F2*Suffixes	0.39	0.078	5.04	4.7e-07	Suffixes <--- F2*
F3*Letter.Series	0.73	0.159	4.56	5.1e-06	Letter.Series <--- F3*
F3*Pedigrees	0.25	0.089	2.77	5.6e-03	Pedigrees <--- F3*
F3*Letter.Group	0.41	0.122	3.35	8.1e-04	Letter.Group <--- F3*
e1	0.17	0.034	5.05	4.4e-07	Sentences <--> Sentences
e2	0.17	0.030	5.65	1.6e-08	Vocabulary <--> Vocabulary
e3	0.27	0.033	8.09	6.7e-16	Sent.Completion <--> Sent.Com
e4	0.25	0.079	3.18	1.5e-03	First.Letters <-First.Letters
e5	0.39	0.063	6.13	8.8e-10	4.Letter.Words <--> 4.Letter.W
e6	0.52	0.060	8.68	0.0e+00	Suffixes <--> Suffixes
e7	0.15	0.223	0.67	5.0e-01	Letter.Series <--> Letter.Ser
e8	0.50	0.060	8.39	0.0e+00	Pedigrees <--> Pedigrees