

Psychology 454: Latent Variable Modeling

Week 4: Latent models of real data

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Outline

- 1 Example data sets
- 2 Thurstone 9 variable problem
 - Factor extraction: how many and what algorithm
 - Various Rotations or Transformations
- 3 Confirmatory fits
 - Using sem
 - Bifactor models
 - Confirmatory Bifactor model
- 4 Holzinger 14 cognitive variables
- 5 Using lavaan
 - Traditional analyses of the Holzinger Swineford data set
 - SEM analysis of Holzinger Swineford data set

Real data rather than simulated

- Prior examples were all artificial data sets.
 - These have the advantage that we know truth.
 - They have the disadvantage that they don't give us experience with real data.
- Some classic data sets are available in *psych*, *lavaan* and *sem*.
- Using the `data` function to see what is available.
 - `data(package="psych")`

Some of the psych data sets

```
data (package="psych")
```

Bechtoldt	Seven data sets showing a bifactor solution.
Bechtoldt.1	Seven data sets showing a bifactor solution.
Bechtoldt.2	Seven data sets showing a bifactor solution.
Chen (Schmid)	12 variables created by Schmid and Leiman to show the Schmid–Leiman Transformation
Dwyer	8 cognitive variables used by Dwyer for an example .
Gorsuch	Example data set from Gorsuch (1997) for an example factor extension.
Harman.5	5 socio–economic variables from Harman (1967)
Harman.8	Correlations of eight physical variables (from Harman, 1967)
Harman.Burt (Harman)	Two data sets from Harman (1967). 9 cognitive variables from Burt
Harman.Holzinger (Harman)	Two data sets from Harman (1967). 9 cognitive variables from Holzinger and 8 emotional variables from Burt
Holzinger	Seven data sets showing a bifactor solution.
Holzinger.9	Seven data sets showing a bifactor solution.
Reise	Seven data sets showing a bifactor solution.
Schmid	12 variables created by Schmid and Leiman to show the Schmid–Leiman Transformation
Thurstone	Seven data sets showing a bifactor solution.
Thurstone.33	Seven data sets showing a bifactor solution.
Tucker	9 Cognitive variables discussed by Tucker and Lewis (1973)
West (Schmid)	12 variables created by Schmid and Leiman to show the Schmid–Leiman Transformation
all.income (income)	US family income from US census 2008
bfi	25 Personality items representing 5 factors
blot	Bonds Logical Operations Test – BLOT
bock.table (bock)	Bock and Liberman (1970) data set of 1000 observations of the LSAT

More of the psych data sets

burt	11 emotional variables from Burt (1915)
cities	Distances between 11 US cities
city.location (cities)	Distances between 11 US cities
cubits	Galtons example of the relationship between height and cubit or forearm length
cushny	A data set from Cushny and Peebles (1905) on the effect of three drugs on hours of sleep, used by Student (1908)
epi.bfi	13 personality scales from the Eysenck Personality Inventory and Big 5 inventory
flat (affect)	Two data sets of affect and arousal scores as a function of personality and movie conditions
galton	Galton Mid parent child height data
heights	A data.frame of the Galton (1888) height and cubit data set
income	US family income from US census 2008
iqitems	16 multiple choice IQ items
lsat6 (bock)	Bock and Liberman (1970) data set of 1000 observations of the LSAT
lsat7 (bock)	Bock and Liberman (1970) data set of 1000 observations of the LSAT
maps (affect)	Two data sets of affect and arousal scores as a function of personality and movie conditions
msq	75 mood items from the Motivational State Questionnaire for 3896 participants
neo	NEO correlation matrix from the NEO-PI-R manual
peas	Galtons Peas
sat.act	3 Measures of ability: SATV, SATQ, ACT
schmid.leiman (Schmid)	12 variables created by Schmid and Leiman to show the Schmid-Leiman Transformation
veg (vegetables)	Paired comparison of preferences for 9 vegetables
withinBetween	An example of the distinction between within group and between group correlations

Data sets in sem and lavaan

```
data(package="sem")
```

```
data(package="lavaan")
```

Data sets in package "sem":

Bollen Bollen's Data on Industrialization and Political Democracy

CNES Variables from the 1997 Canadian National Election Study

Klein Klein's Data on the U. S. Economy

Kmenta_1977 Partly Artificial Data on the U. S. Economy

Data sets in package "lavaan":

Demo.growth_1999 Demo dataset for a illustrating a linear growth model.

HolzingerSwineford1939_1939 Holzinger and Swineford Dataset (9 Variables)

PoliticalDemocracy_1999 Industrialization And Political Democracy Dataset

Also can read in from clipboard, web, from hard drive and import

- To read from clipboard: `read.clipboard()`
 - `read.clipboard(header = TRUE, ...)` #assumes headers and tab or space delimited
 - `read.clipboard.csv(header=TRUE,sep=',',...)` #assumes headers and comma delimited
 - `read.clipboard.tab(header=TRUE,sep='^',...)` #assumes headers and tab delimited
 - `read.clipboard.lower(diag=TRUE,names=FALSE,...)` #read in a matrix given the lower off diagonal
 - `read.clipboard.upper(diag=TRUE,names=FALSE,...)`
 - `read.clipboard.fwf(header=FALSE,widths=rep(1,10),...)` #read in data using a fixed format width (see `read.fwf` for instructions)
- To read from a file
 - `fn <- file.choose()` #this opens the system directory – navigate it to your file
 - `my.data <- read.table(fn)`

More on getting your data

```
#specify the name and address of the remote file
datafilename <- "http://personality-project.org/r/datasets/maps.mixx.epi.bfi.data"
#datafilename <- Desktop/epi.big5.txt read from local directory or
# datafilename <- file.choose() use the OS to find the file
#in all cases
person.data <- read.table(datafilename, header=TRUE) #read the data file

#Alternatively, to read in a comma delimited file:
#person.data <- read.table(datafilename, header=TRUE, sep=",")

names(person.data) #list the names of the variables

library(foreign) #allows you to read SPSS files e.g.,
datafilename <- "/Users/bill/Library/Favorites/R.tutorial/datasets/finkel.sav" #local
file
eli.data <- read.spss(datafilename, use.value.labels=TRUE, to.data.frame=TRUE)
```


Use the bifactor examples

The study of latent variable models in general and sem in particular is the combination of measurement models with structural models. The bifactor examples are useful to understand issues in reliability and estimating measurement models.

```
data(Thurstone)
data(Thurstone.33)
data(Holzinger)
data(Holzinger.9)
data(Bechtoldt)
data(Bechtoldt.1)
data(Bechtoldt.2)
data(Reise)
```

Two more **data** sets with similar structures are found in the Harman **data set**.

```
Bechtoldt.1: 17 x 17 correlation matrix of ability tests , N = 212.
Bechtoldt.2: 17 x 17 correlation matrix of ability tests , N = 213.
Holzinger: 14 x 14 correlation matrix of ability tests , N = 355
Holzinger.9: 9 x 9 correlation matrix of ability tests , N = 145
Reise: 16 x 16 correlation matrix of health satisfaction items. N = 35,000
Thurstone: 9 x 9 correlation matrix of ability tests , N = 213
Thurstone.33: Another 9 x 9 correlation matrix of ability items , N=4175
```

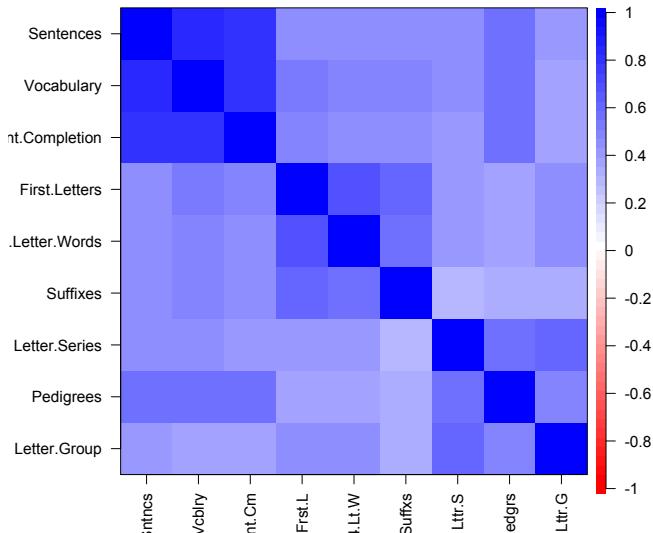
Thurstone correlation matrix

```
> colnames(Thurstone) <- abbreviate(rownames(Thurstone),6)
> Thurstone
```

	Sntncs	Vcblry	Snt.Cm	Frst.L	4.Lt.W	Suffxs	Lttr.S	Pedgrs	Lttr.G
Sentences	1.000	0.828	0.776	0.439	0.432	0.447	0.447	0.541	0.380
Vocabulary	0.828	1.000	0.779	0.493	0.464	0.489	0.432	0.537	0.358
Sent. Completion	0.776	0.779	1.000	0.460	0.425	0.443	0.401	0.534	0.359
First. Letters	0.439	0.493	0.460	1.000	0.674	0.590	0.381	0.350	0.424
4. Letter. Words	0.432	0.464	0.425	0.674	1.000	0.541	0.402	0.367	0.446
Suffixes	0.447	0.489	0.443	0.590	0.541	1.000	0.288	0.320	0.325
Letter. Series	0.447	0.432	0.401	0.381	0.402	0.288	1.000	0.555	0.598
Pedigrees	0.541	0.537	0.534	0.350	0.367	0.320	0.555	1.000	0.452
Letter. Group	0.380	0.358	0.359	0.424	0.446	0.325	0.598	0.452	1.000

The Thurstone 9 variable problem from Bechtoldt

Thurstone 9 variable problem



The number of factors problem

- “The number of factors problem is easy, I solve it everyday before breakfast. The problem is the right number” Kaiser.
 - Extract factors until χ^2 is not significant.
 - Extract factors until change in χ^2 is not significant.
 - Parallel analysis.
 - scree test
 - Very Simple Structure (VSS)
 - Minimum Absolute Partial (Velicer's MAP test)

Number of factors?

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

Parallel analysis suggests that the number of factors = 3 and
the number of components = 1

Very Simple Structure

Call: VSS(x = Thurstone, n.obs = 213, SMC = FALSE)

VSS complexity 1 achieves a maximum of 0.86 with 1 factors

VSS complexity 2 achieves a maximum of 0.91 with 2 factors

The Velicer MAP criterion achieves a minimum of 0.07 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

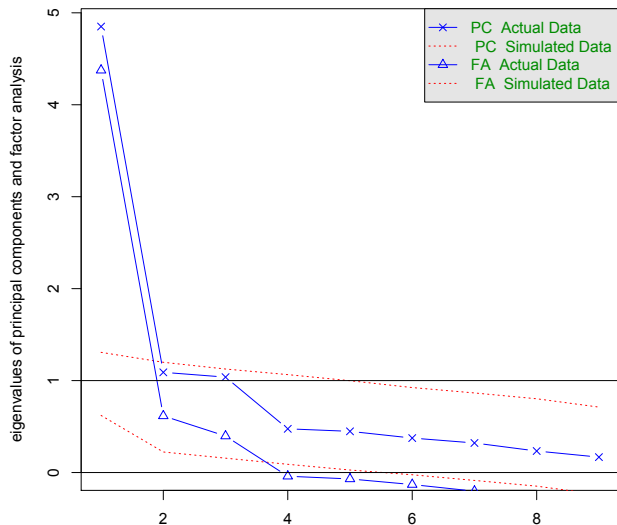
```
[1] 0.86 0.60 0.54 0.54 0.54 0.55 0.55 0.55
```

Very Simple Structure Complexity 2

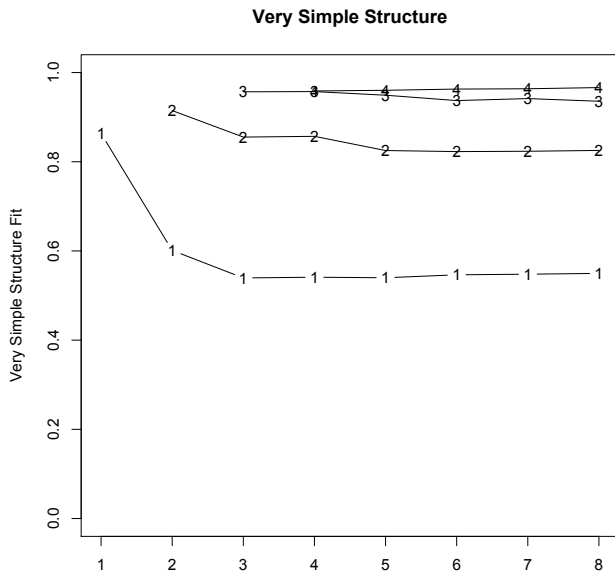
```
[1] 0.00 0.91 0.86 0.86 0.83 0.82 0.82 0.83
```

Parallel analysis of the Thurstone data set

Parallel Analysis Scree Plots



VSS fit function

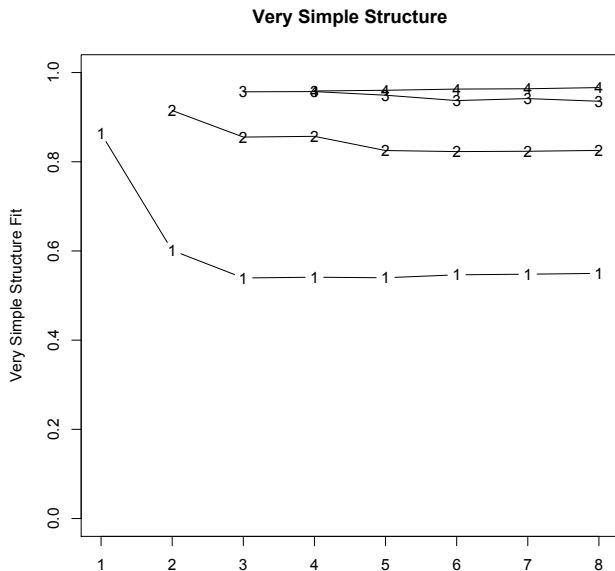


χ^2

```
> print(vss$vss.stats[,1:3], digits=3)
```

	dof	chisq	prob
1	27	2.32e+02	2.14e-34
2	19	8.30e+01	5.56e-10
3	12	2.82e+00	9.97e-01
4	6	1.49e+00	9.60e-01
5	1	2.44e-01	6.21e-01
6	-3	4.80e-07	NA
7	-6	4.16e-09	NA
8	-8	0.00e+00	NA

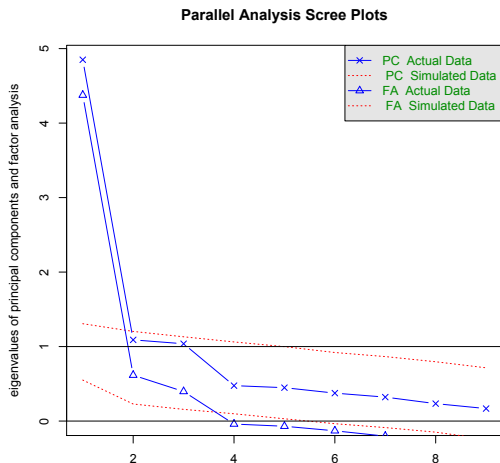
A Very Simple Structure Plot



Parallel analysis

```
> fa.parallel(Thurstone,n.obs=213)
```

Parallel analysis suggests that the number of factors = 3 and the number of components = 1



Minimal Residual FA

```
fa(Thurstone, n.obs=213)
```

```
> fa(Thurstone, n.obs=213)
```

```
Factor Analysis using method = minres
```

```
Call: fa(r = Thurstone, n.obs = 213)
```

```
Standardized loadings based upon correlation matrix
```

```
MR1 h2 u2
```

```
V1 0.87 0.75 0.25
```

```
V2 0.88 0.77 0.23
```

```
V3 0.83 0.70 0.30
```

```
V4 0.62 0.39 0.61
```

```
V5 0.61 0.37 0.63
```

```
V6 0.59 0.34 0.66
```

```
V7 0.57 0.32 0.68
```

```
V8 0.64 0.41 0.59
```

```
V9 0.52 0.27 0.73
```

```
MR1
```

```
SS loadings 4.32
```

```
Proportion Var 0.48
```

```
Test of the hypothesis that 1 factor is sufficient.
```

```
The degrees of freedom for the null model are 36 and the objective function was
```

```
5.2 with Chi Square of 1081.97
```

```
The degrees of freedom for the model are 27 and the objective function was 1.12
```

```
The root mean square of the residuals is 0.08
```

```
The df corrected root mean square of the residuals is 0.13
```

```
The number of observations was 213 with Chi Square = 231.55 with prob < 2.1e-34
```

```
Tucker Lewis Index of factoring reliability = 0.738
```

```
RMSEA index = 0.191 and the 90 % confidence intervals are 0.19 0.194
```

```
BIC = 86.70
```

Maximum likelihood

```
> fa(Thurstone, n.obs=213, fm="mle")
Factor Analysis using method = ml
Call: fa(r = Thurstone, n.obs = 213, fm = "mle")
Standardized loadings based upon correlation matrix
      ML1    h2    u2
V1 0.88 0.78 0.22
V2 0.90 0.80 0.20
V3 0.85 0.72 0.28
V4 0.59 0.35 0.65
V5 0.57 0.33 0.67
V6 0.57 0.32 0.68
V7 0.54 0.29 0.71
V8 0.63 0.40 0.60
V9 0.49 0.24 0.76
      ML1
SS loadings    4.22
Proportion Var 0.47
```

Test of the hypothesis that 1 **factor** is sufficient.

The degrees of freedom **for the null model** are 36 and the objective **function** was 5.2 with Chi Square of 1081.97

The degrees of freedom **for the model** are 27 and the objective **function** was 1.1

The root **mean square** of the **residuals** is 0.08

The **df** corrected root **mean square** of the **residuals** is 0.14

The number of observations was 213 with Chi Square = 228.59 with prob < 8e-34

Tucker Lewis Index of factoring reliability = 0.742

RMSEA **index** = 0.19 and the 90 % confidence intervals are 0.189 0.192

BIC = 83.83

Fit based upon **off** diagonal values = 0.94

Measures of **factor** score adequacy

Comparing min res and mle

Standardized loadings based upon correlation **matrix**

	MR1	h2	u2
V1	0.87	0.75	0.25
V2	0.88	0.77	0.23
V3	0.83	0.70	0.30
V4	0.62	0.39	0.61
V5	0.61	0.37	0.63
V6	0.59	0.34	0.66
V7	0.57	0.32	0.68
V8	0.64	0.41	0.59
V9	0.52	0.27	0.73

	ML1	h2	u2
V1	0.88	0.78	0.22
V2	0.90	0.80	0.20
V3	0.85	0.72	0.28
V4	0.59	0.35	0.65
V5	0.57	0.33	0.67
V6	0.57	0.32	0.68
V7	0.54	0.29	0.71
V8	0.63	0.40	0.60
V9	0.49	0.24	0.76

	MR1
SS loadings	4.32
Proportion Var	0.48
Chi Square =	231.55
with prob <	2.1e-34

	ML1
SS loadings	4.22
Proportion Var	0.47
Chi Square =	228.59
with prob <	8e-34

2 maximum likelihood factors

```
> f2 <- fa(Thurstone, 2, n.obs=213, fm="mle")
> f2
```

Factor Analysis using method = ml

Call: fa(r = Thurstone, nfactors = 2, n.obs = 213, fm = "mle")

Standardized loadings based upon correlation **matrix**

	ML1	ML2	h2	u2
V1	0.94	-0.05	0.83	0.17
V2	0.89	0.03	0.82	0.18
V3	0.85	0.02	0.73	0.27
V4	-0.02	0.84	0.68	0.32
V5	-0.04	0.84	0.66	0.34
V6	0.13	0.59	0.46	0.54
V7	0.28	0.35	0.32	0.68
V8	0.50	0.17	0.39	0.61
V9	0.12	0.49	0.32	0.68

	ML1	ML2
SS loadings	2.92	2.29
Proportion Var	0.32	0.25
Cumulative Var	0.32	0.58

With **factor** correlations of

	ML1	ML2
ML1	1.00	0.64
ML2	0.64	1.00

2 factor goodness of fits

Test of the hypothesis that 2 factors are sufficient.

The degrees of freedom **for the null model** are 36 and the objecti
 was 5.2 with Chi Square of 1081.97

The degrees of freedom **for the model** are 19 and the
 objective **function** was 0.4

The root **mean** square of the **residuals** is 0.05

The **df** corrected root **mean** square of the **residuals** is 0.1

The number of observations was 213 with Chi Square = 82.84
 with prob < 6e-10

Tucker Lewis Index of factoring reliability = 0.884

RMSEA **index** = 0.128 and the 90 % confidence intervals are
 0.127 0.131

BIC = -19.02

Fit based upon **off** diagonal values = 0.98

Measures of **factor** score adequacy

	ML1	ML2
Correlation of scores with factors	0.97	0.93
Multiple R square of scores with factors	0.93	0.86
Minimum correlation of possible factor scores	0.86	0.72

3 MLE factors of Thurstone data

```
> f3 <- fa(Thurstone, 3, n.obs=213, fm="mle")
> f3
```

```
Call: fa(r = Thurstone, nfactors = 3, n.obs = 213, fm = "mle")
```

Standardized loadings based upon correlation matrix

	ML1	ML2	ML3	h2	u2
V1	0.91	-0.04	0.04	0.83	0.17
V2	0.89	0.06	-0.03	0.84	0.16
V3	0.83	0.04	0.00	0.73	0.27
V4	0.00	0.86	0.01	0.73	0.27
V5	-0.01	0.74	0.10	0.63	0.37
V6	0.18	0.63	-0.08	0.50	0.50
V7	0.03	-0.01	0.84	0.72	0.28
V8	0.37	-0.05	0.47	0.50	0.50
V9	-0.06	0.21	0.64	0.53	0.47

	ML1	ML2	ML3
SS loadings	2.64	1.86	1.49
Proportion Var	0.29	0.21	0.17
Cumulative Var	0.29	0.50	0.67

With factor correlations of

	ML1	ML2	ML3
ML1	1.00	0.59	0.54
ML2	0.59	1.00	0.52
ML3	0.54	0.52	1.00

with fit statistics

Test of the hypothesis that 3 factors are sufficient.

The degrees of freedom **for** the **null model** are 36 and the
objective **function** was 5.2 with Chi Square of 1081.97

The degrees of freedom **for** the **model** are 12 and the
objective **function** was 0.01

The root **mean** square of the **residuals** is 0

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

The number of observations was 213 with
Chi Square = 2.82 with prob < 1

Tucker Lewis Index of factoring reliability = 1.027

RMSEA **index** = 0 and the 90 % confidence intervals are 0 0.023

BIC = -61.51

Fit based upon **off** diagonal values = 1

Measures of **factor** score adequacy

	ML1	ML2	ML3
Correlation of scores with factors	0.96	0.92	0.90
Multiple R square of scores with factors	0.93	0.85	0.81
Minimum correlation of possible factor scores	0.86	0.71	0.63

Orthogonal Rotations and oblique Transformations

- Should the latent variables be allowed to correlate?
 - Factors as extracted are orthogonal.
 - Factors as interpreted typically are allowed to be oblique
- Consider five cases
 - unrotated: factors as extracted (rotate="none")
 - rotated using VARIMAX (or Quartimax)
 - transformed using PROCRUSTES
 - transformed using oblimin
 - transformed using geominQ

Unrotated versus Varimax Rotation

```
> fa(Thurstone, 3, n.obs=213, rotate="none")
> fa(Thurstone, 3, n.obs=213, rotate="Varimax")
```

Factor Analysis using method =
minres

Call: fa(r = Thurstone, nfactors = 3, n.obs = 213, rotate = "none")

Standardized loadings based upon correlation **matrix**

	MR1	MR2	MR3	h2	u2		MR1	MR2	MR3	h2	u2
V1	0.87	-0.27	0.02	0.82	0.18	V1	0.86	0.20	0.22	0.82	0.18
V2	0.88	-0.24	-0.06	0.84	0.16	V2	0.85	0.27	0.18	0.84	0.16
V3	0.83	-0.22	-0.03	0.73	0.27	V3	0.80	0.24	0.19	0.73	0.27
V4	0.66	0.45	-0.32	0.73	0.27	V4	0.29	0.78	0.20	0.73	0.27
V5	0.63	0.43	-0.21	0.63	0.37	V5	0.27	0.70	0.26	0.63	0.37
V6	0.60	0.24	-0.29	0.50	0.50	V6	0.36	0.60	0.10	0.50	0.50
V7	0.60	0.32	0.50	0.72	0.28	V7	0.28	0.18	0.78	0.72	0.28
V8	0.65	0.05	0.29	0.50	0.50	V8	0.48	0.15	0.50	0.50	0.50
V9	0.54	0.38	0.30	0.53	0.47	V9	0.20	0.32	0.62	0.53	0.47

	MR1	MR2	MR3
SS loadings	4.47	0.86	0.67
Proportion Var	0.50	0.10	0.07
Cumulative Var	0.50	0.59	0.67

	MR1	MR2	MR3
SS loadings	2.73	1.78	1.48
Proportion Var	0.30	0.20	0.16
Cumulative Var	0.30	0.50	0.67

Varimax versus Quartimax

```
> fa(Thurstone, 3, n.obs=213, rotate="varimax")
> fa(Thurstone, 3, n.obs=213, rotate="quartimax")
```

	MR1	MR2	MR3	h2	u2
V1	0.86	0.20	0.22	0.82	0.18
V2	0.85	0.27	0.18	0.84	0.16
V3	0.80	0.24	0.19	0.73	0.27
V4	0.29	0.78	0.20	0.73	0.27
V5	0.27	0.70	0.26	0.63	0.37
V6	0.36	0.60	0.10	0.50	0.50
V7	0.28	0.18	0.78	0.72	0.28
V8	0.48	0.15	0.50	0.50	0.50
V9	0.20	0.32	0.62	0.53	0.47

	MR1	MR2	MR3
SS loadings	2.73	1.78	1.48
Proportion Var	0.30	0.20	0.16
Cumulative Var	0.30	0.50	0.67

	MR1	MR2	MR3	h2	u2
V1	0.91	0.02	0.05	0.82	0.18
V2	0.91	0.09	0.01	0.84	0.16
V3	0.85	0.07	0.03	0.73	0.27
V4	0.47	0.71	0.11	0.73	0.27
V5	0.45	0.63	0.18	0.63	0.37
V6	0.48	0.51	0.01	0.50	0.50
V7	0.45	0.12	0.71	0.72	0.28
V8	0.58	0.05	0.40	0.50	0.50
V9	0.37	0.27	0.56	0.53	0.47

	MR1	MR2	MR3
SS loadings	3.70	1.27	1.03
Proportion Var	0.41	0.14	0.11
Cumulative Var	0.41	0.55	0.67

Varimax versus Quartimin

```
> fa(Thurstone, 3, n.obs=213,
      rotate="Varimax")
```

	MR1	MR2	MR3	h2	u2
V1	0.86	0.20	0.22	0.82	0.18
V2	0.85	0.27	0.18	0.84	0.16
V3	0.80	0.24	0.19	0.73	0.27
V4	0.29	0.78	0.20	0.73	0.27
V5	0.27	0.70	0.26	0.63	0.37
V6	0.36	0.60	0.10	0.50	0.50
V7	0.28	0.18	0.78	0.72	0.28
V8	0.48	0.15	0.50	0.50	0.50
V9	0.20	0.32	0.62	0.53	0.47

	MR1	MR2	MR3
SS loadings	2.73	1.78	1.48
Proportion Var	0.30	0.20	0.16
Cumulative Var	0.30	0.50	0.67

```
> fa(Thurstone, 3, n.obs=213, rotate="quartimin")
```

	MR1	MR2	MR3	h2	u2
V1	0.91	-0.04	0.04	0.82	0.18
V2	0.89	0.06	-0.03	0.84	0.16
V3	0.83	0.04	0.00	0.73	0.27
V4	0.00	0.86	0.00	0.73	0.27
V5	-0.01	0.74	0.10	0.63	0.37
V6	0.18	0.63	-0.08	0.50	0.50
V7	0.03	-0.01	0.84	0.72	0.28
V8	0.37	-0.05	0.47	0.50	0.50
V9	-0.06	0.21	0.64	0.53	0.47

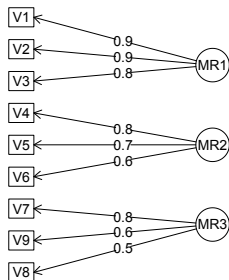
	MR1	MR2	MR3
SS loadings	2.64	1.86	1.50
Proportion Var	0.29	0.21	0.17
Cumulative Var	0.29	0.50	0.67

With **factor** correlations of

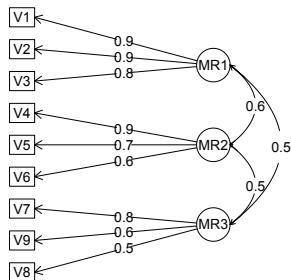
	MR1	MR2	MR3
MR1	1.00	0.59	0.54
MR2	0.59	1.00	0.52
MR3	0.54	0.52	1.00

Visualizing the difference: Varimax versus quartimin

Orthogonal Rotation



Oblique Transformation



Specifying the parameters in sem using the RAM notation

- Need to specify each path
- Need to specify the error variance paths as well
 - A short cut can be done by using *psych*
 - See the vignette ‘psych for sem’ for more details
- Apply this to the Thurstone problem

create the sem commands by using psych

```
f3 <- fa(Thurstone, 3, fm='mle')
mod3 <- structure.diagram(f3, cut=.45, errors=TRUE)
mod3
```

	Path	Parameter	Value
[1,]	"ML1->V1"	"F1V1"	NA
[2,]	"ML1->V2"	"F1V2"	NA
[3,]	"ML1->V3"	"F1V3"	NA
[4,]	"ML2->V4"	"F2V4"	NA
[5,]	"ML2->V5"	"F2V5"	NA
[6,]	"ML2->V6"	"F2V6"	NA
[7,]	"ML3->V7"	"F3V7"	NA
[8,]	"ML3->V8"	"F3V8"	NA
[9,]	"ML3->V9"	"F3V9"	NA
[10,]	"V1<->V1"	"x1e"	NA
[11,]	"V2<->V2"	"x2e"	NA
...			
[18,]	"V9<->V9"	"x9e"	NA
[19,]	"ML2<->ML1"	"rF2F1"	NA
[20,]	"ML3<->ML1"	"rF3F1"	NA
[21,]	"ML3<->ML2"	"rF3F2"	NA
[22,]	"ML1<->ML1"	NA	"1"
[23,]	"ML2<->ML2"	NA	"1"
[24,]	"ML3<->ML3"	NA	"1"

Running sem

```
> rownames(Thurstone) <- colnames(Thurstone) #to get the names to
match the modle
> sem3 <- sem(mod3, Thurstone, N=213)
> summary(sem3, digits=2)
```

```
Model Chisquare = 38    Df = 24 Pr(>Chisq) = 0.033
Chisquare (null model) = 1102    Df = 36
Goodness-of-fit index = 0.96
Adjusted goodness-of-fit index = 0.92
RMSEA index = 0.053    90% CI: (0.015, 0.083)
Bentler-Bonnett NFI = 0.97
Tucker-Lewis NNFI = 0.98
Bentler CFI = 0.99
SRMR = 0.044
BIC = -90
```

Normalized Residuals

Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
-0.97	-0.42	0.00	0.04	0.09	1.63

With parameter estimates

Parameter Estimates

	Estimate	Std Error	z value	Pr(> z)	
F1V1	0.90	0.054	16.7	0.0e+00	V1 <— ML1
F1V2	0.91	0.054	17.0	0.0e+00	V2 <— ML1
F1V3	0.86	0.056	15.3	0.0e+00	V3 <— ML1
F2V4	0.84	0.061	13.8	0.0e+00	V4 <— ML2
F2V5	0.80	0.062	12.9	0.0e+00	V5 <— ML2
F2V6	0.70	0.064	10.9	0.0e+00	V6 <— ML2
F3V7	0.78	0.065	12.0	0.0e+00	V7 <— ML3
F3V8	0.72	0.067	10.7	0.0e+00	V8 <— ML3
F3V9	0.70	0.067	10.5	0.0e+00	V9 <— ML3
x1e	0.18	0.028	6.4	1.7e-10	V1 <—> V1
x2e	0.16	0.028	5.9	3.0e-09	V2 <—> V2
x3e	0.27	0.033	8.0	1.6e-15	V3 <—> V3
x4e	0.30	0.051	5.9	2.7e-09	V4 <—> V4
x5e	0.36	0.052	7.0	3.4e-12	V5 <—> V5
x6e	0.51	0.060	8.4	0.0e+00	V6 <—> V6
x7e	0.39	0.062	6.3	2.3e-10	V7 <—> V7
x8e	0.48	0.065	7.4	1.8e-13	V8 <—> V8
x9e	0.51	0.065	7.7	9.5e-15	V9 <—> V9
rF2F1	0.64	0.051	12.6	0.0e+00	ML1 <—> ML2
rF3F1	0.67	0.054	12.5	0.0e+00	ML1 <—> ML3
rF3F2	0.64	0.059	10.7	0.0e+00	ML2 <—> ML3

Exploratory bifactor model

```
omt <- omega(Thurstone)
omega.diagram(omt, sl=FALSE)
```

Omega

Call: omega(m = Thurstone)

Alpha: 0.89

G.6: 0.91

Omega Hierarchical: 0.74

Omega H asymptotic: 0.79

Omega Total 0.93

Schmid Leiman Factor loadings greater than 0.2

	g	F1*	F2*	F3*	h2	u2	p2
V1	0.71	0.57			0.82	0.18	0.61
V2	0.73	0.55			0.84	0.16	0.63
V3	0.68	0.52			0.73	0.27	0.63
V4	0.65		0.56		0.73	0.27	0.57
V5	0.62		0.49		0.63	0.37	0.61
V6	0.56		0.41		0.50	0.50	0.63
V7	0.59			0.61	0.72	0.28	0.48
V8	0.58	0.23		0.34	0.50	0.50	0.66
V9	0.54			0.46	0.53	0.47	0.56

With : 1 2 3 4 5 6 7 8 9

With fit statistics

With eigenvalues of:

	g	F1*	F2*	F3*
	3.58	0.96	0.74	0.71

general/max 3.71 max/min = 1.35

mean percent general = 0.6 with sd = 0.05 and cv of 0.09

The degrees of freedom are 12 and the fit is 0.01

The number of observations was 213 with Chi Square = 2.82

with prob < 1

The root mean square of the residuals is 0

The df corrected root mean square of the residuals is 0.01

RMSEA index = 0 and the 90 % confidence intervals are 0 0.023

BIC = -61.51

Compare this with the adequacy of just a general factor and no gro

The degrees of freedom for just the general factor are 27 and the

1.48

The number of observations was 213 with Chi Square = 307.1

with prob < 2.8e-49

The root mean square of the residuals is 0.1

The df corrected root mean square of the residuals is 0.16

RMSEA index = 0.224 and the 90 % confidence intervals are

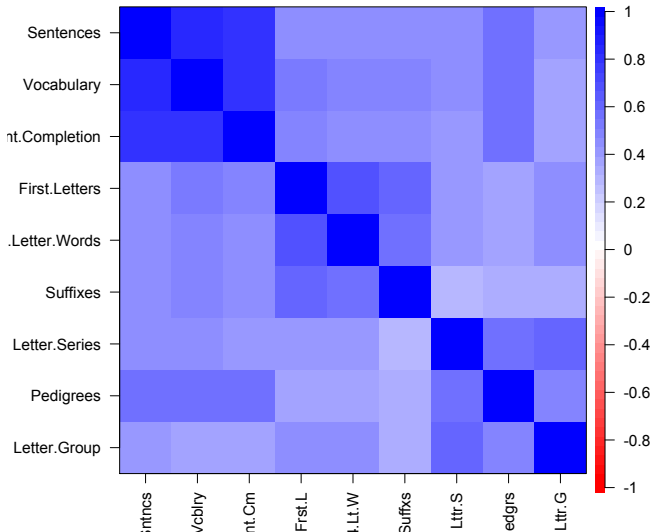
0.223 0.226

BIC = 162.35

Measures of factor score adequacy

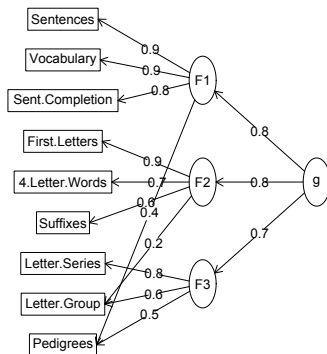
A correlation plot to show a general factor

Thurstone 9 variable problem

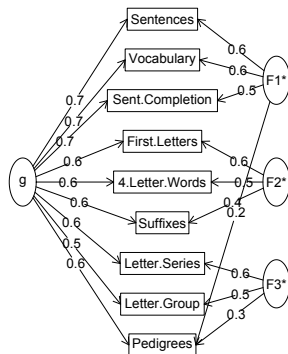


Two ways of showing a hierarchical structure

Hierarchical (multilevel) Structure



Omega



Exploratory versus confirmatory bifactor model

- omega will do exploratory bifactoring
- omegaSem will do exploratory and then confirmatory based upon that solution.
 - This is not true “confirmatory” in that the solution was decided on in an exploratory fashion.
 - True confirmatory tests a prior hypothesis
- omegaSem reports both exploratory and confirmatory results.
- The sem model is hidden as part of the structure but may be found from the `str` command

omegaSem

Alpha: 0.89
 G.6: 0.91
 Omega Hierarchical: 0.74
 Omega H asymptotic: 0.79
 Omega Total: 0.93

Schmid Leiman Factor loadings greater than 0.2

	g	F1*	F2*
F3* h2 u2 p2			
Sentences	0.71	0.57	
0.82 0.18 0.61			
Vocabulary	0.73	0.55	
0.84 0.16 0.63			
Sent. Completion	0.68	0.52	
0.73 0.27 0.63			
First. Letters	0.65		0.56
0.73 0.27 0.57			
4. Letter. Words	0.62		0.49
0.63 0.37 0.61			
Suffixes	0.56		0.41
0.50 0.50 0.63			
Letter. Series	0.59		
0.61 0.72 0.28	0.48		
Pedigrees	0.58	0.23	
0.34 0.50 0.50	0.66		
Letter. Group	0.54		
0.46 0.53 0.47	0.56		

With eigenvalues of:

Omega Hierarchical from a confirmatory model
 using sem = 0.79
 Omega Total from a confirmatory model
 using sem = 0.93

With loadings of

	g	F1*	F2*	F3*
h2 u2				
Sentences	0.77	0.49		
0.83 0.17				
Vocabulary	0.79	0.45		
0.83 0.17				
Sent. Completion	0.75	0.40		
0.73 0.27				
First. Letters	0.61		0.61	
0.75 0.25				
4. Letter. Words	0.60		0.51	
0.61 0.39				
Suffixes	0.57		0.39	
0.48 0.52				
Letter. Series	0.57			
0.73 0.85 0.15				
Pedigrees	0.66			
0.25 0.50 0.50				
Letter. Group	0.53			
0.41 0.45 0.55				

With eigenvalues of:

g F1* F2* F3*

The sem model is an object in omegaSem output

```
omts <- omegaSem(Thurstone, n.obs=213)
omts$omegaSem$model
```

Path	Parameter	Initial Value
[1,] "g->Sentences"	"Sentences"	NA
[2,] "g->Vocabulary"	"Vocabulary"	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
[...]		
[27,] "Letter.Group<->Letter.Group"	"e9"	NA
[28,] "F1<->F1*"	NA	"1"
[29,] "F2<->F2*"	NA	"1"
[30,] "F3<->F3*"	NA	"1"
[31,] "g<->g"	NA	"1"

Using the sem model from omeaSem

```
> sem.t.om <- sem(omts$omegaSem$model, Thurstone, N=213)
> summary(sem.t.om)
```

```
Model Chisquare = 24.216    Df = 18 Pr(>Chisq) = 0.14807
Chisquare (null model) = 1101.9    Df = 36
Goodness-of-fit index = 0.97578
Adjusted goodness-of-fit index = 0.93944
RMSEA index = 0.040361    90% CI: (NA, 0.077994)
Bentler-Bonnett NFI = 0.97802
Tucker-Lewis NNFI = 0.98834
Bentler CFI = 0.99417
SRMR = 0.034895
BIC = -72.287
```

Normalized Residuals

Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
-0.8210	-0.3340	0.0000	0.0282	0.1560	1.8000

sem parameter estimates

Parameter Estimates

	Estimate	Std. Error	z value	Pr(> z)	
Sentences	0.76787	0.072626	10.57291	0.0000e+00	Sentences $\leftarrow$ g
Vocabulary	0.79092	0.072418	10.92170	0.0000e+00	Vocabulary $\leftarrow$ g
Sent. Completion	0.75362	0.073402	10.26709	0.0000e+00	Sent. Completion $\leftarrow$ g
First. Letters	0.60838	0.072201	8.42617	0.0000e+00	First. Letters $\leftarrow$ g
4. Letter. Words	0.59733	0.073851	8.08843	6.6613e-16	4. Letter. Words $\leftarrow$ g
Suffixes	0.57179	0.071492	7.99792	1.3323e-15	Suffixes $\leftarrow$ g
Letter. Series	0.56689	0.074271	7.63282	2.2871e-14	Letter. Series $\leftarrow$ g
Pedigrees	0.66233	0.069321	9.55455	0.0000e+00	Pedigrees $\leftarrow$ g
Letter. Group	0.52995	0.078985	6.70955	1.9522e-11	Letter. Group $\leftarrow$ g
F1*Sentences	0.48787	0.085457	5.70898	1.1366e-08	Sentences $\leftarrow$ F1*
F1*Vocabulary	0.45232	0.090422	5.00233	5.6640e-07	Vocabulary $\leftarrow$ F1*
F1*Sent. Completion	0.40445	0.093402	4.33024	1.4895e-05	Sent. Completion $\leftarrow$ F1*
F2*First. Letters	0.61405	0.085794	7.15733	8.2268e-13	First. Letters $\leftarrow$ F2*
F2*4. Letter. Words	0.50581	0.084848	5.96130	2.5024e-09	4. Letter. Words $\leftarrow$ F2*
F2*Suffixes	0.39432	0.078289	5.03671	4.7359e-07	Suffixes $\leftarrow$ F2*
F3*Letter. Series	0.72730	0.159499	4.55988	5.1184e-06	Letter. Series $\leftarrow$ F3*
F3*Pedigrees	0.24684	0.089011	2.77317	5.5513e-03	Pedigrees $\leftarrow$ F3*
F3*Letter. Group	0.40915	0.122180	3.34875	8.1177e-04	Letter. Group $\leftarrow$ F3*
e1	0.17236	0.034113	5.05265	4.3571e-07	Sentences $\longleftrightarrow$ Sentences
e2	0.16984	0.030037	5.65438	1.5641e-08	Vocabulary $\longleftrightarrow$ Vocabulary
e3	0.26847	0.033188	8.08958	6.6613e-16	Sent. Completion $\longleftrightarrow$ Sent. Completion
e4	0.25281	0.079472	3.18115	1.4669e-03	First. Letters $\longleftrightarrow$ First. Letters
e5	0.38735	0.063194	6.12960	8.8103e-10	4. Letter. Words $\longleftrightarrow$ 4. Letter. Words
e6	0.51757	0.059639	8.67838	0.0000e+00	Suffixes $\longleftrightarrow$ Suffixes
e7	0.14967	0.223242	0.67044	5.0257e-01	Letter. Series $\longleftrightarrow$ Letter. Series
e8	0.50039	0.059655	8.38800	0.0000e+00	Pedigrees $\longleftrightarrow$ Pedigrees
e9	0.55175	0.084725	6.51223	7.4044e-11	Letter. Group $\longleftrightarrow$ Letter. Group

14 cognitive variables from Holzinger

```
> lowerCor(Holzinger)
```

	T1	T2	T3.4	T6	T28	T29	T32	T34	T35	T36a	T13	T18	T25b
T77													
T1	1.00												
T2	0.52	1.00											
T3.4	0.49	0.79	1.00										
T6	0.42	0.42	0.28	1.00									
T28	0.47	0.28	0.17	0.48	1.00								
T29	0.33	0.41	0.29	0.62	0.50	1.00							
T32	-0.44	-0.42	-0.31	-0.57	-0.52	-0.59	1.00						
T34	-0.11	-0.31	-0.40	0.11	-0.07	-0.13	0.13	1.00					
T35	-0.23	-0.56	-0.42	-0.15	-0.16	-0.39	0.14	0.41	1.00				
T36a	-0.03	0.02	-0.22	0.20	-0.01	0.13	-0.15	0.40	0.01	1.00			
T13	0.04	0.59	0.47	0.07	-0.09	0.19	-0.29	-0.45	-0.71	0.02	1.00		
T18	-0.02	0.54	0.34	0.08	-0.15	0.22	-0.33	-0.46	-0.70	0.08	0.87	1.00	
T25b	-0.03	0.47	0.42	0.01	-0.19	0.07	-0.26	-0.59	-0.68	-0.14	0.81	0.81	1.00
T77	-0.01	0.44	0.35	-0.03	-0.15	0.10	-0.26	-0.61	-0.70	-0.13	0.79	0.82	0.79
1.00													

```
>
```

How many factors

```
> vss.h <- vss(Holzinger, n.obs=355)
> vss.h
```

Very Simple Structure

```
Call: VSS(x = x, n = n, rotate = rotate, diagonal = diagonal, fm = fm,
  n.obs = n.obs, plot = plot, title = title)
```

VSS complexity 1 achieves a maximum of 0.75 with 1 factors

VSS complexity 2 achieves a maximum of 0.83 with 2 factors

The Velicer MAP criterion achieves a minimum of 0.03 with 2 factors

Velicer MAP

```
[1] 0.03 0.03 0.03 0.04 0.06 0.07 0.10 0.14
```

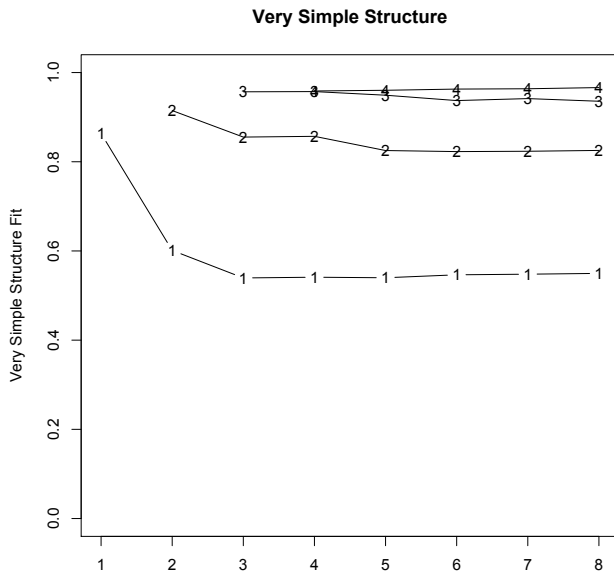
Very Simple Structure Complexity 1

```
[1] 0.75 0.59 0.56 0.51 0.49 0.48 0.44 0.44
```

Very Simple Structure Complexity 2

```
[1] 0.00 0.83 0.82 0.77 0.73 0.70 0.62 0.61
```

Holzinger 14 variable problem



Chi square test

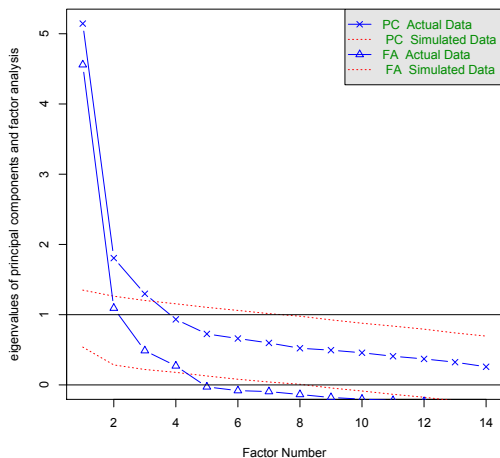
```
> print(vss.h$vss.stats[,1:4], digits=3)
```

	dof	chisq	prob	sqresid
1	77	543.38	2.64e-71	8.84
2	64	231.86	7.26e-21	5.85
3	52	118.10	4.74e-07	4.51
4	41	41.66	4.42e-01	3.65
5	31	27.16	6.64e-01	3.45
6	22	13.58	9.16e-01	3.01
7	14	5.79	9.71e-01	2.87
8	7	2.65	9.15e-01	2.77

Parallel analysis of Holzinger 14 variables

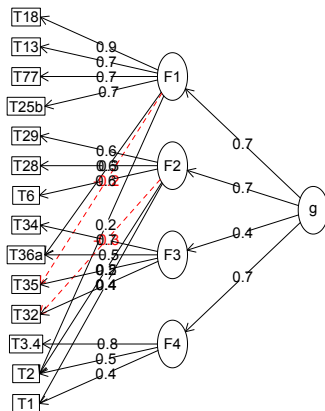
> fa.parallel(Holzinger,n.obs=355) Parallel analysis suggests that the number of factors = 4 and the number of components = 3

Parallel Analysis Scree Plots

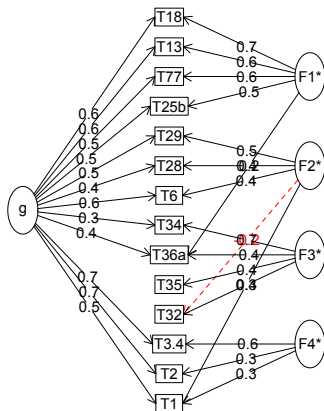


Exploratory Omega solution for Holzinger 14 variable problem

Holzinger 14 cognitive variables



Holzinger 14 cognitive variables



Omega for Holzinger – exploratory and confirmatory

```
Call: omegaSem(m = Holzinger, nfactors = 4, n.obs = 355)
```

```
Omega
```

```
Alpha:           0.85
G.6:             0.88
Omega Hierarchical: 0.64
Omega H asymptotic: 0.71
Omega Total       0.9
```

```
Schmid Leiman Factor loadings greater than
0.2
```

	g	F1*	F2*	F3*	F4*
h2	u2	p2			
T1	0.52		0.27		
0.27	0.42	0.58	0.64		
T2	0.69				
0.34	0.66	0.34	0.72		
T3.4	0.65				
0.57	0.75	0.25	0.56		
T6	0.57		0.42		
0.54	0.46	0.59			
T28	0.44		0.44		
0.40	0.60	0.49			
T29	0.51		0.47		
0.50	0.50	0.54			
T32			-0.25	0.38	
0.26	0.74	0.13			
T34	0.32			0.66	
0.54	0.46	0.19			
T35				0.44	

```
Omega Hierarchical from a confirmatory model
0.75
```

```
Omega Total
from a confirmatory model using sem =
0.9
```

```
With loadings of
```

	g	F1*	F2*	F3*	F4*	h2	u2
T1	0.59					0.37	0.63
T2	0.80				0.26	0.71	0.29
T3.4	0.64				0.57	0.74	0.26
T6	0.65		0.36			0.55	0.45
T28	0.50		0.34			0.36	0.64
T29	0.57		0.45			0.53	0.47
T32				0.32		0.13	0.87
T34	0.36			0.65		0.55	0.45
T35				0.44		0.22	0.78
T36a	0.51			0.38		0.41	0.59
T13	0.64	0.51				0.67	0.33
T18	0.60	0.57				0.68	0.32
T25b	0.40	0.55				0.55	0.45

lavaan

- Mimics input of LISREL and MPlus
 - Easier to set up than sem
 - Clearly targets MPlus
 - Further help available at <http://lavaan.ugent.be/>
 - Example data sets from MPlus

An example from lavaan

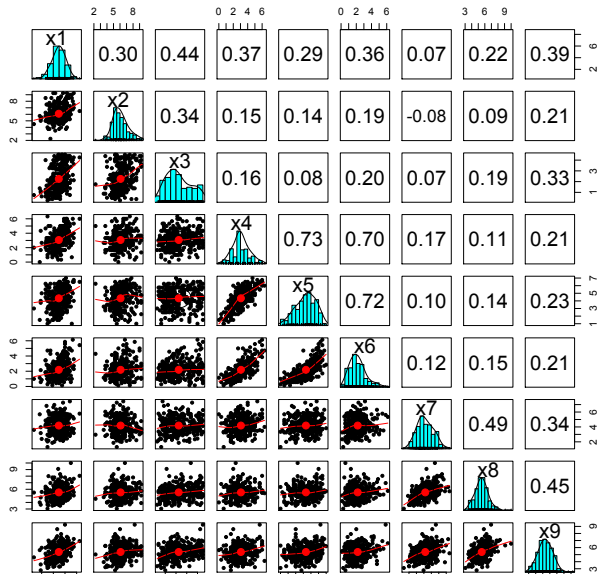
- ① Holzinger Swineford data set from three schools
 - First describe the data
 - descriptive stats and graphics
- ② Then consider the structure of the 9 variables
 - Using fa
 - Using sem/lavaan

Holzing descriptive statistics

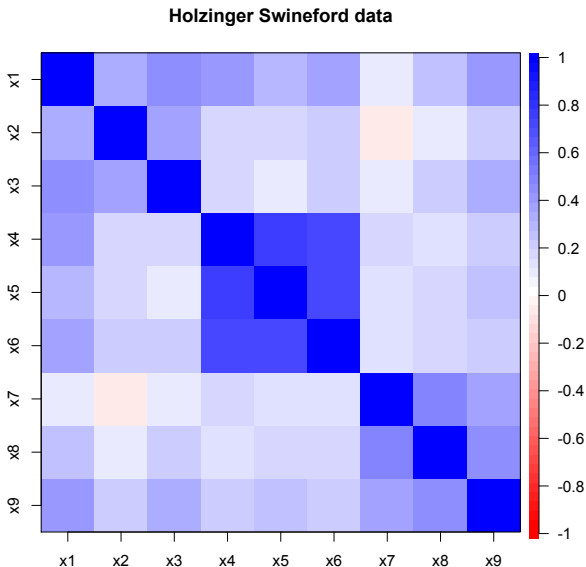
> describe(HolzingerSwineford1939)

	var	n	mean	sd	median	trimmed	mad	min	max	range	skew	kurtosis
se												
id	1	301	176.55	105.94	163.00	176.78	140.85	1.00	351.00	350.00	-0.01	
-1.36	6.11											
sex	2	301	1.51	0.50	2.00	1.52	0.00	1.00	2.00	1.00	-0.06	
-2.00	0.03											
ageyr	3	301	13.00	1.05	13.00	12.89	1.48	11.00	16.00	5.00	0.69	
0.20	0.06											
agemo	4	301	5.38	3.45	5.00	5.32	4.45	0.00	11.00	11.00	0.09	
-1.22	0.20											
school*	5	301	1.52	0.50	2.00	1.52	0.00	1.00	2.00	1.00	-0.07	
-2.00	0.03											
grade	6	300	7.48	0.50	7.00	7.47	0.00	7.00	8.00	1.00	0.09	
-2.00	0.03											
x1	7	301	4.94	1.17	5.00	4.96	1.24	0.67	8.50	7.83	-0.25	
0.31	0.07											
x2	8	301	6.09	1.18	6.00	6.02	1.11	2.25	9.25	7.00	0.47	
0.33	0.07											
x3	9	301	2.25	1.13	2.12	2.20	1.30	0.25	4.50	4.25	0.38	
-0.91	0.07											
x4	10	301	3.06	1.16	3.00	3.02	0.99	0.00	6.33	6.33	0.27	
0.08	0.07											
x5	11	301	4.34	1.29	4.50	4.40	1.48	1.00	7.00	6.00	-0.35	
-0.55	0.07											
x6	12	301	2.19	1.10	2.00	2.09	1.06	0.14	6.14	6.00	0.86	
0.82	0.06											
x7	13	301	4.19	1.09	4.09	4.16	1.10	1.30	7.43	6.13	0.25	
-0.31	0.06											
x8	14	301	5.53	1.01	5.50	5.40	0.06	2.05	10.00	6.05	0.53	

Pairs panels of HolzingerSwineford1939

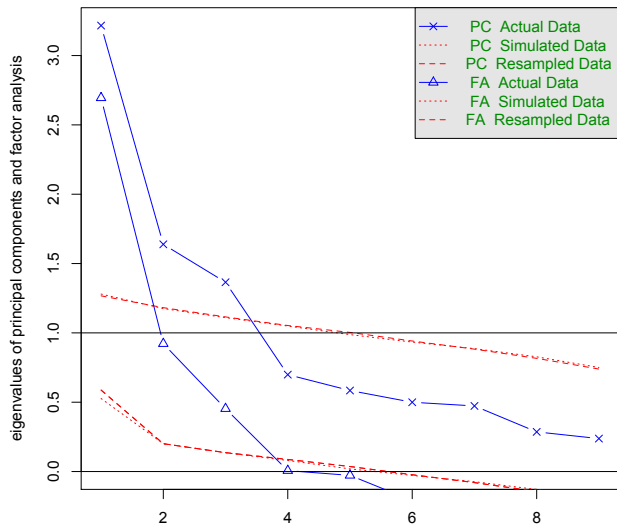


Weaker correlations than the Thurstone data set



Parallel Analysis of the Holzinger Swineford data set

Parallel Analysis Scree Plots



Extract 3 factors from Holzinger Swineford data set

```
> hs.fa <- fa(HolzingerSwineford1939[,7:15],3)
> hs.fa
```

Factor Analysis using method = minres

Call: fa(r = HolzingerSwineford1939[, 7:15], nfactors = 3)

Standardized loadings (pattern **matrix**) based upon correlation **matrix**

	MR1	MR3	MR2	h2	u2
x1	0.19	0.60	0.03	0.49	0.51
x2	0.04	0.51	-0.12	0.25	0.75
x3	-0.07	0.69	0.02	0.46	0.54
x4	0.84	0.02	0.01	0.72	0.28
x5	0.89	-0.07	0.01	0.76	0.24
x6	0.81	0.08	-0.01	0.69	0.31
x7	0.04	-0.15	0.72	0.50	0.50
x8	-0.03	0.10	0.70	0.53	0.47
x9	0.03	0.37	0.46	0.46	0.54

	MR1	MR3	MR2
SS loadings	2.24	1.34	1.28
Proportion Var	0.25	0.15	0.14
Cumulative Var	0.25	0.40	0.54
Proportion Explained	0.46	0.28	0.26
Cumulative Proportion	0.46	0.74	1.00

With **factor** correlations of

	MR1	MR3	MR2
MR1	1.00	0.33	0.22
MR3	0.33	1.00	0.27
MR2	0.22	0.27	1.00

With goodness of fit stats

Test of the hypothesis that 3 factors are sufficient.

The degrees of freedom **for** the **null model** are 36 and the objective **function** was 3.05 with Chi Square of 904.1

The degrees of freedom **for** the **model** are 12 and the objective **function** was 0.08

The root **mean** square of the **residuals** (RMSR) is 0.01

The **df** corrected root **mean** square of the **residuals** is 0.03

The number of observations was 301 with Chi Square = 22.38 with prob < 0.034

Tucker Lewis Index of factoring reliability = 0.964

RMSEA **index** = 0.055 and the 90 % confidence intervals are 0.015 0.088

BIC = -46.11

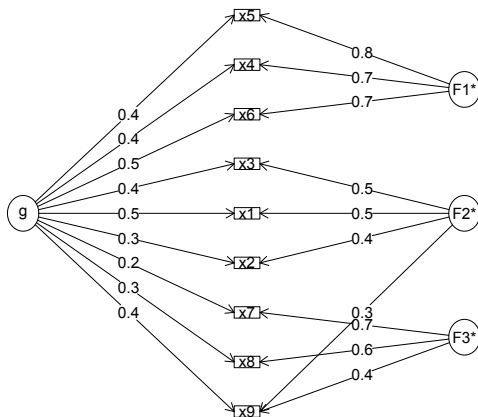
Fit based upon **off** diagonal values = 1

Measures of **factor** score adequacy

	MR1	MR3	MR2
Correlation of scores with factors	0.94	0.84	0.85
Multiple R square of scores with factors	0.89	0.71	0.72
Minimum correlation of possible factor scores	0.78	0.42	0.45

Weak evidence for hierarchical structure

Omega



Omega analysis of Holzinger Swineford data

```
> om<- omega(HolzingerSwineford1939[,7:15])
> om
Omega
Call: omega(m = HolzingerSwineford1939[, 7:15])
Alpha: 0.76
G.6: 0.81
Omega Hierarchical: 0.45
Omega H asymptotic: 0.53
Omega Total 0.85
```

```
Schmid Leiman Factor loadings greater than 0.2
      g  F1*  F2*  F3*  h2  u2  p2
x1 0.49      0.46      0.49 0.51 0.50
x2 0.30      0.39      0.25 0.75 0.35
x3 0.41      0.53      0.46 0.54 0.38
x4 0.45 0.72      0.72 0.28 0.28
x5 0.41 0.76      0.76 0.24 0.23
x6 0.46 0.69      0.69 0.31 0.30
x7 0.23      0.66 0.50 0.50 0.11
x8 0.35      0.64 0.53 0.47 0.23
x9 0.45      0.28 0.42 0.46 0.54 0.44
```

```
With eigenvalues of:
      g  F1*  F2*  F3*
1.46 1.62 0.75 1.02
```

Omega fit statistics for Holzinger Swineford

general/max 0.9 max/min = 2.15
 mean percent general = 0.31 with sd = 0.12 and cv of 0.38

The degrees of freedom are 12 and the fit is 0.08
 The number of observations was 301 with Chi Square = 22.38 with prob < 0.034
 The root mean square of the residuals is 0.01
 The df corrected root mean square of the residuals is 0.03
 RMSEA index = 0.055 and the 90 % confidence intervals are 0.015 0.088
 BIC = -46.11

Compare this with the adequacy of just a general factor and no group factors
 The degrees of freedom for just the general factor are 27 and the fit is 1.75
 The number of observations was 301 with Chi Square = 517.18 with prob < 4.4e-92
 The root mean square of the residuals is 0.14
 The df corrected root mean square of the residuals is 0.23

RMSEA index = 0.248 and the 90 % confidence intervals are 0.227 0.264
 BIC = 363.09

Measures of factor score adequacy

	g	F1*	F2*	F3*
Correlation of scores with factors	0.68	0.84	0.67	0.78
Multiple R square of scores with factors	0.46	0.71	0.44	0.61
Minimum correlation of factor score estimates	-0.07	0.43	-0.11	0.22

The lavaan commands

```
# The Holzinger and Swineford (1939) example
HS.model <- '
  visual_1 =~ x1_1 + x2_1 + x3_1
  textual_1 =~ x4_1 + x5_1 + x6_1
  speed_1 =~ x7_1 + x8_1 + x9_1

fit <- lavaan(HS.model, data=HolzingerSwineford1939,
              auto.var=TRUE, auto.fix.first=TRUE,
              auto.cov.lv.x=TRUE)
summary(fit, fit.measures=TRUE)
```

lavaan output

lavaan (0.4–14) converged normally after 41 iterations

Number of observations	301
Estimator	ML
Minimum Function Chi-square	85.306
Degrees of freedom	24
P-value	0.000
Chi-square test baseline model :	
Minimum Function Chi-square	918.852
Degrees of freedom	36
P-value	0.000
Full model versus baseline model :	
Comparative Fit Index (CFI)	0.931
Tucker-Lewis Index (TLI)	0.896
Loglikelihood and Information Criteria:	
Loglikelihood user model (H0)	-3737.745
Loglikelihood unrestricted model (H1)	-3695.092
Number of free parameters	21
Akaike (AIC)	7517.490
Bayesian (BIC)	7595.339
Sample-size adjusted Bayesian (BIC)	7528.739
Root Mean Square Error of Approximation:	
RMSEA	0.092
90 Percent Confidence Interval	0.071 0.114
P-value RMSEA ≤ 0.05	0.001

and the parameter estimates

Parameter estimates:

Information	Expected			
Standard Errors	Standard			
	Estimate	Std. err	Z-value	P(> z)
Latent variables:				
visual =~				
x1	1.000			
x2	0.553	0.100	5.554	0.000
x3	0.729	0.109	6.685	0.000
textual =~				
x4	1.000			
x5	1.113	0.065	17.014	0.000
x6	0.926	0.055	16.703	0.000
speed =~				
x7	1.000			
x8	1.180	0.165	7.152	0.000
x9	1.082	0.151	7.155	0.000
Covariances:				
visual ~~				
textual	0.408	0.074	5.552	0.000
speed	0.262	0.056	4.660	0.000
textual ~~				
speed	0.173	0.049	3.518	0.000
Variances:				
x1	0.549	0.114		
x2	1.134	0.102		
x3	0.844	0.091		
x4	0.371	0.048		
x5	0.446	0.058		
x6	0.356	0.043		
x7	0.799	0.081		
x8	0.488	0.074		

Do this again, but fix the latent variable variance to 1

	Estimate	Std. err	Z-value	P(> z)
Latent variables:				
visual =~				
x1	0.900	0.081	11.127	0.000
x2	0.498	0.077	6.429	0.000
x3	0.656	0.074	8.817	0.000
textual =~				
x4	0.990	0.057	17.474	0.000
x5	1.102	0.063	17.576	0.000
x6	0.917	0.054	17.082	0.000
speed =~				
x7	0.619	0.070	8.903	0.000
x8	0.731	0.066	11.090	0.000
x9	0.670	0.065	10.305	0.000
Covariances:				
visual ~~				
textual	0.459	0.064	7.189	0.000
speed	0.471	0.073	6.461	0.000
textual ~~				
speed	0.283	0.069	4.117	0.000
Variances:				
x1	0.549	0.114		
x2	1.134	0.102		
x3	0.844	0.091		
x4	0.371	0.048		
x5	0.446	0.058		
x6	0.356	0.043		
x7	0.799	0.081		
x8	0.488	0.074		
x9	0.566	0.071		
visual	1.000			