On when a factor is a general factor

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Outline

1. Background
   - General factors in psychological research
   - Prior work
2. What is a general factor?
   - The basic problem
   - Alternative meanings, alternative graphics
3. Alternative estimation procedures
   - Several bad ways to estimate a general factor
   - Confirmatory Factor Analysis – Better, but not a panacea
   - Exploratory Factor Analysis – More powerful than commonly realized
   - Hierarchical Cluster Analysis – A useful alternative
   - Comparing four ways of estimating a general factor
4. Conclusion

The use of general and group factors in psychological research

1. Long history of general + group factors in the study of cognitive ability
   - Basic finding is that all cognitive tests share a positive manifold: i.e., they are positively correlated
   - Cattell-Horn-Carroll conceptualization of $g - G_c - G_f$ (Carroll, 1993; Horn & Cattell, 1966, 1982)
2. In personality domain, hierarchical models have also been common within separate sub-domains:
   - Cattell (1957, 1966), Eysenck & Himmelweit (1947), Eysenck (1967), and more recently by DeYoung, Peterson & Higgins (2002) and Digman (1997)
   - Models of anxiety and depression have been organized hierarchically (Zinbarg & Barlow, 1996; Zinbarg, Barlow & Brown, 1997)

Some claims for a general factor of all personality traits

1. Original meta-analysis by Musek (2007) of Big 5 data claimed a General Factor of Personality (GFP). This was followed by a torrent of research by Rushton and his associates (Rushton & Irwing, 2008; Rushton, Bons & Hur, 2008; Rushton & Irwing, 2009).
2. The basic claim can be argued for and against on substantive grounds (de Vries, 2011; Donnellan, Hopwood & Wright, 2012; Holden & Marjanovic, 2012; Hopwood, Wright & Brent Donnellan, 2011; Loehlin & Martin, 2011; Muncer, 2011; Pettersson, Turkheimer, Horn & Menatti, 2012; Weiss, Adams & Johnson, 2011; Zawadzki & Strelau, 2010).
3. Review articles in the Handbook of Individual Differences (Ferguson, Chamorro-Premuzic, Pickering & Weiss, 2011; Rushton & Irwing, 2011) and elsewhere (Just, 2011).
4. Time to consider what is a general factor and how to estimate it.

Why bother to consider general factors?

Although the issue of General Factor of Personality (GFP) has tended to dominate the recent literature, domain specific general factors are important to consider.

1. In developing scales to measure any psychological construct, it is useful to know what percentage of the scale is associated with a general factor for that scale.
   - This is essential to the problem of identifying what the scale is.
   - A classic example was the original Extraversion scale of Hans Eysenck. It was actually a measure of two slightly related constructs: impulsivity and sociability, each of which had important correlates in its own right (Rocklin & Revelle, 1981)
2. A basic concept is that at least 50% of the variance of any test should be general factor variance for that test. This partly reflects issues in factor indeterminacy.

Prior work

Some of what we are reporting has been discussed in earlier publications directed to the psychometric and methodologically interested. What follows is an attempt at getting these ideas across to the broader personality community because there seems to be some confusion about how to estimate the importance of a general factor.

1. Guttman (1945) reviewed multiple measures of internal consistency estimates of reliability. McDonald (1999) considered two forms of coefficient ω that are measures of a) the general factor saturation, and b) the total reliable variance of the test.
2. Cronbach (1951) (but see Cronbach & Shavelson, 2004) proposed that one of the Guttman measures of reliability ($\alpha = \lambda_3$) was particularly useful as a measure of reliability.

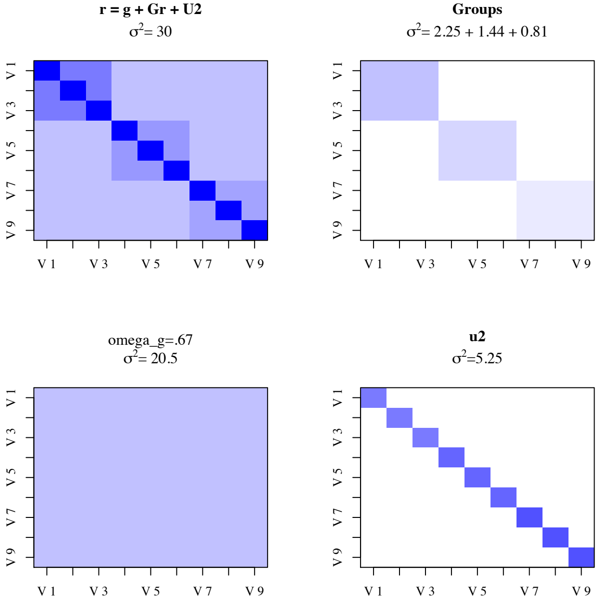
Prior work–continued

3. Zinbarg, Revelle, Yovel & Li (2005) distinguished between the two McDonald measures and labeled them as $\omega_{hierarchical}$ and ω_{total}. (To eliminate some of the confusion on the meaning of hierarchical versus higher order models, we will refer to $\omega_{general}$ rather than ω_h.)
4. Zinbarg, Yovel, Revelle & McDonald (2006) considered alternative ways to estimate ω_h and discussed some of the problems that we are now reporting.
5. Sijtsma (2008) discussed why α was inappropriate as a measure of internal consistency. See also Revelle & Zinbarg (2009).
6. Revelle & Wilt (2011, 2012) have reviewed how the use of inappropriate methods lead to problems in identifying a general factor of personality.

What is a general factor?

1. Conceptually analogous to the 3° background radiation in radio astronomy. A signal that is uniformly distributed across all measures.
2. In factor analytic terms: decomposition of a correlation matrix into a general factor and multiple group factors:
   - all items load on the general factor
   - only some items load on each group factor (so called cluster structure)
   - $R = FF' + U^2$ where $F = [g + G]$
3. The problem of a general factor is a basic issue of reliability in test theory where we decompose the total variance of a test into that which is common (general) to all items, that which is common to some items, that which is unique to one item, and that which is error variance.
4. We apply these ideas to the question of a general factor of a test battery.

A graphic representation of a general factor + 3 group factors



Factor analytic definition of a general factor

Let F = [g + G] be a column wise concatenation of a general factor and a set of group factors:

Variable	g	Group 1	Group 2	Group 3	...
	g	F1	F2	F3	
V1	g1	a1	0	0	
V2	g2	a2	0	0	
V3	g3	a3	0	0	
V4	g4	0	b4	0	
V5	g5	0	b5	0	
V6	g6	0	b6	0	
V7	g7	0	0	c7	
V8	g8	0	0	c8	
V9	g9	0	0	c9	

Variance decomposition of R

$R = FF' + U^2$ where $F = [g + G]$

For orthogonal F and G, the correlation matrix is a function of the general loadings as well as the group loadings:

$$R = gg' + GG' + U^2$$

The amount of variance attributable to the general factor is just ω_g (McDonald, 1999) where

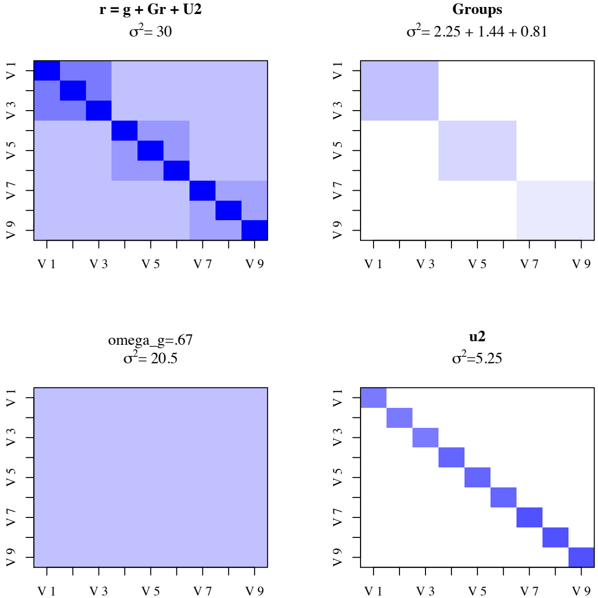
$$\omega_g = \frac{1'gg'1}{1'R1}$$

The total amount of reliable variance (that which is attributable to general + groups) is ω_t

$$\omega_t = \frac{1'gg'1 + 1'GG'1}{1'R1}$$

The problem then is how to find ω_g.

A graphic representation of the problem



Several different procedures for estimating the general factor saturation have been used

1. Functions of the eigenvalues of first principal component or first factor
   - Size of eigen value / number of items
   - ω_g found from loadings on first factor
2. EFA with rotation to bifactor (Jennrich & Bentler, 2011) or biquartimin solutions
   - ω_g found from loadings on first factor
3. CFA/SEM with direct modeling of multi-layer solution
   - Model based upon theory (prior to observing data)
   - Model based upon data (fitting SEMs to data)
4. EFA with Schmid Leiman transformation to a hierarchical solution Schmid & Leiman (1957)
5. Hierarchical cluster analysis (ICLUST) and estimation of worst split half reliability (β) Revelle (1979)

An example factor matrix with general and 3 group factors

Table : All items load on the general factor, only some items load on any particular group factor.

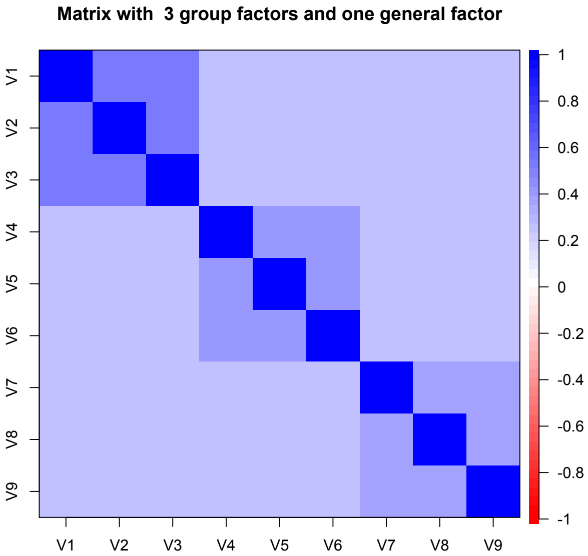
	g	F1	F2	F3
V1	0.5	0.5	0.0	0.0
V2	0.5	0.5	0.0	0.0
V3	0.5	0.5	0.0	0.0
V4	0.5	0.0	0.4	0.0
V5	0.5	0.0	0.4	0.0
V6	0.5	0.0	0.4	0.0
V7	0.5	0.0	0.0	0.3
V8	0.5	0.0	0.0	0.3
V9	0.5	0.0	0.0	0.3

Correlation matrix with general + three group factors

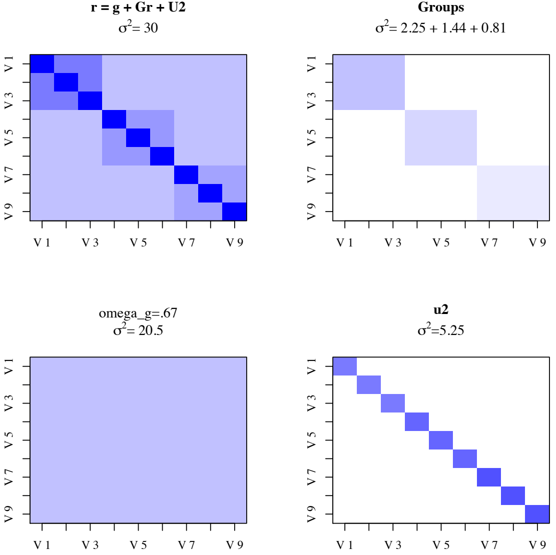
Table : Correlation matrix of 9 variables with a general factor and three group factors

	V1	V2	V3	V4	V5	V6	V7	V8	V9
V1	1.00	0.50	0.50	0.25	0.25	0.25	0.25	0.25	0.25
V2	0.50	1.00	0.50	0.25	0.25	0.25	0.25	0.25	0.25
V3	0.50	0.50	1.00	0.25	0.25	0.25	0.25	0.25	0.25
V4	0.25	0.25	0.25	1.00	0.41	0.41	0.25	0.25	0.25
V5	0.25	0.25	0.25	0.41	1.00	0.41	0.25	0.25	0.25
V6	0.25	0.25	0.25	0.41	0.41	1.00	0.25	0.25	0.25
V7	0.25	0.25	0.25	0.25	0.25	0.25	1.00	0.34	0.34
V8	0.25	0.25	0.25	0.25	0.25	0.25	0.34	1.00	0.34
V9	0.25	0.25	0.25	0.25	0.25	0.25	0.34	0.34	1.00

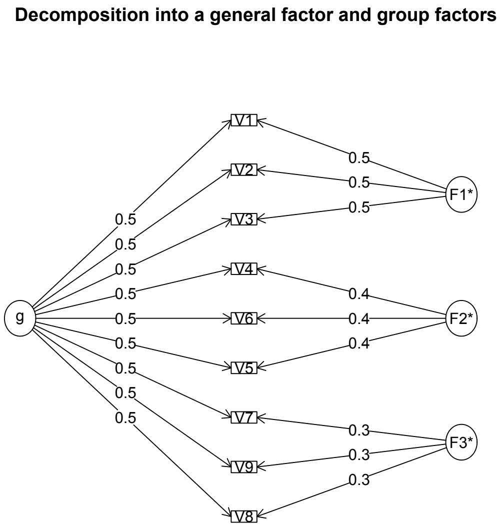
9 variables with one general and 3 group factors



A graphic representation of the problem and solution: $\omega_g = 20.5/30 = .67$

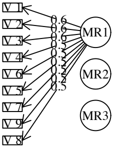


Decompose the variance into general plus group factors

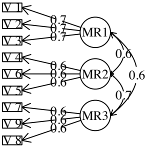


Four alternative rotations to represent a general factor

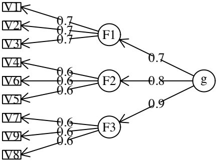
Unrotated factors



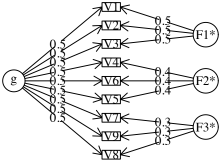
Oblique Factor Solution



Hierarchical Solution



Higher Order Model



How not to estimate a general factor

1. Similar examples of these problems were given in Zinbarg et al. (2006).
2. The magnitude of the first factor
   - The size of the eigen value of the first compared to the number of variables.
     - For positively correlated items, this just reflects the average correlation of the matrix, not a general factor.
   - Finding ω_g from the loadings on the first (unrotated) factor. $\omega_g = .77$
3. The correlation of lower level factors.

	MR1	MR2	MR3
MR1	1.00	0.55	0.61
MR2	0.55	1.00	0.67
MR3	0.61	0.67	1.00

Estimating a general factor from the loadings on the first factor

```
Factor Analysis using method =  minres
Call: fa(r = r, nfactors = 4, rotate = "bifactor")
Standardized loadings (pattern matrix)
based upon correlation matrix
     MR1   MR2   MR3   MR4   h2   u2
V1  0.57  0.41  0.00  0.00 0.50 0.50
V2  0.57  0.41  0.00  0.00 0.50 0.50
V3  0.57  0.41  0.00  0.00 0.50 0.50
V4  0.60 -0.23 -0.02 -0.08 0.42 0.58
V5  0.60 -0.23 -0.01  0.03 0.41 0.59
V6  0.60 -0.23 -0.01  0.05 0.41 0.59
V7  0.43  0.01  0.40  0.00 0.34 0.66
V8  0.43  0.01  0.40  0.00 0.34 0.66
V9  0.43  0.01  0.40  0.00 0.34 0.66

                       MR1  MR2  MR3  MR4
SS loadings           2.62 0.67 0.47 0.01
Proportion Var        0.29 0.07 0.05 0.00
Cumulative Var        0.29 0.36 0.42 0.42
Proportion Explained  0.70 0.18 0.13 0.00
Cumulative Proportion 0.70 0.87 1.00 1.00
```

Finding ω_g from the first factor. $\omega_g = .77$

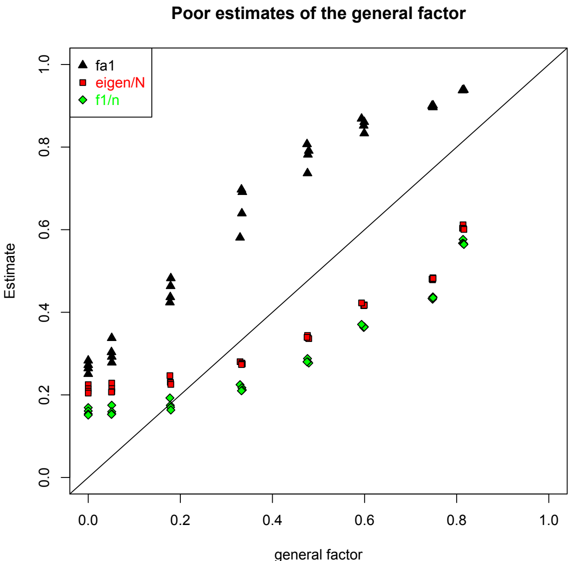
The correlations of lower level factors

```
   MR1  MR2  MR3   h2   u2
1 0.71 0.00 0.00 0.50 0.50
2 0.71 0.00 0.00 0.50 0.50
3 0.71 0.00 0.00 0.50 0.50
4 0.00 0.64 0.00 0.41 0.59
5 0.00 0.64 0.00 0.41 0.59
6 0.00 0.64 0.00 0.41 0.59
7 0.00 0.00 0.58 0.34 0.66
8 0.00 0.00 0.58 0.34 0.66
9 0.00 0.00 0.58 0.34 0.66

                       MR1  MR2  MR3
SS loadings           1.50 1.23 1.02
 Proportion Var        0.17 0.14 0.11
 Cumulative Var        0.17 0.30 0.42
 Proportion Explained  0.40 0.33 0.27
 Cumulative Proportion 0.40 0.73 1.00

 With factor correlations of
     MR1  MR2  MR3
MR1 1.00 0.55 0.61
MR2 0.55 1.00 0.67
MR3 0.61 0.67 1.00
```

Simulations show this is uniformly a bad procedure

1. Design variables
   - Sample sizes 100, 200, 400, 800.
   - g factor loadings of 0, .1, .2, .3, .4, .5, .6.
   - 50 replications of each condition.
   - Number variables were 6, 12, 24, 36.
   - except for the 6 variable case, 3 group factors (loadings of .6 and .7) and many minor (loadings of $\pm .2$).
   - Also replicated this result with 3 group factors (loadings of .6 and .7) and no minor factors.
2. Estimates found
   - Variance accounted for by loadings on first factor
   - Size of first eigen value from principal components
   - Size of first eigen value from factor analysis
3. First procedure severely over estimates, the latter two overestimate for small values of ω_g, underestimate for large values

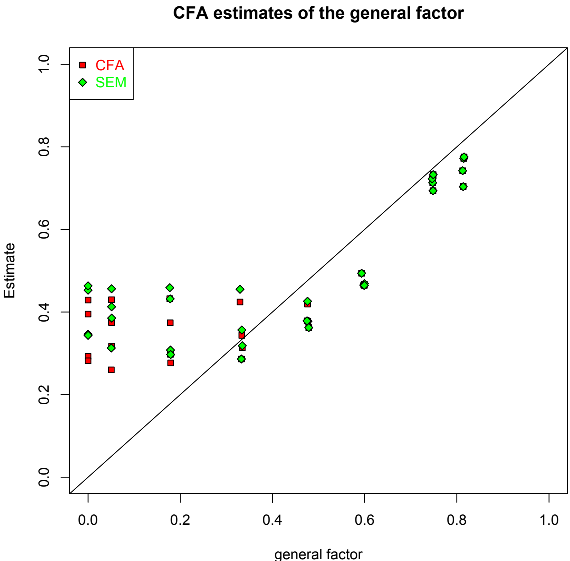
Three ways not to estimate a general factor



What about CFA or SEM approaches

1. Confirmatory Factor Analysis (done using the *sem* package in R)
    - Model based upon ideal model.
    - Model based pattern of loadings from EFA rotated to simple structure + a general factor.
2. Simulation method the same as before.
3. Both approaches are good for high levels of g loadings, but overestimate in case of $\omega_g < .4$
4. Intriguingly, the biased estimates for values of $\omega_g < .4$ are roughly what proponents of the GFP report (Revelle & Wilt, 2012).

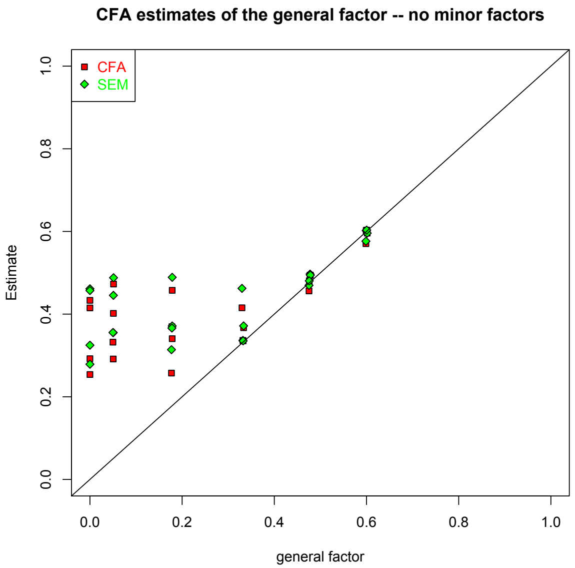
Confirmatory approaches to estimate a general factor



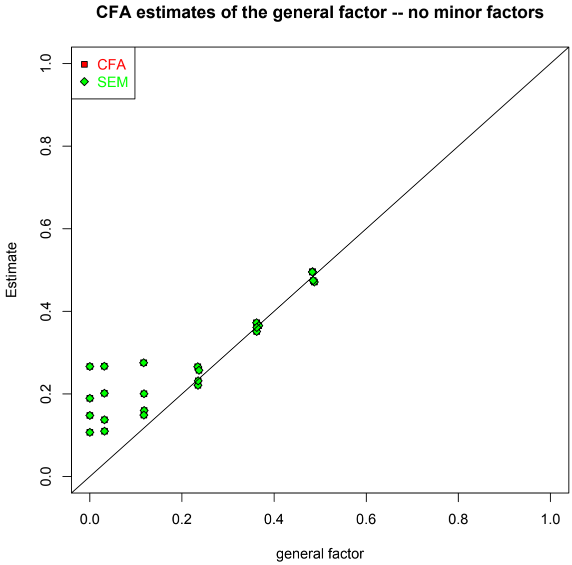
Large overestimates for the no general factor case – due to "correlated residuals"?

1. The simulations were done with 3 large factors and many minor factors. This follows the suggestions of MacCallum, Browne & Cai (2007) that real data are messy.
   - Maximum Likelihood techniques assume residuals are normally distributed around zero and thus we need to fit any correlated residuals.
   - Introducing correlated residuals (the many minor factors) makes the models fail.
   - Is the overestimation of a general factor due to this improper specification?
2. Simulations with no minor factors show the same problem.
   - The bias is slightly less for the case of 6 variables and two group factors compared to 12 variables and 3 group factors

Finding ω_g from 12 variables, 3 group factors, and no minor factors



Finding ω_g from 6 variables, 2 group factors, and no minor factors



Exploratory Factor Analysis procedures for estimating the general factor saturation

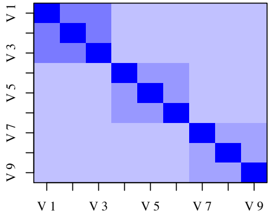
Three step procedure (implemented in the *psych* package in R).

1. Exploratory Factor Analysis with an oblique transformation (extract at least two factors, preferably three or more)
   - Factor extraction can be Maximum Likelihood, Minimal Residual, Principal Axis, etc.
   - Transformations can be promax, oblimin, simplimax, bentlerQ, geominQ or biquartimin
2. Extract one higher order factor from the matrix of correlations of the lower order factors
3. Apply the Schmid-Leiman transformation to find loadings of the general on the items

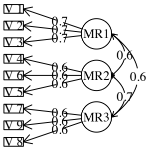
Can also take this EFA model and then fit a pure g + cluster solution using CFA.

Three steps in finding a general factor

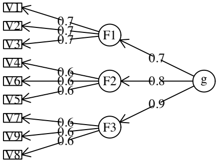
9 variables, 3 group factors



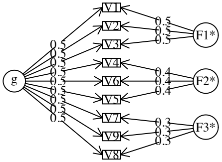
Oblique Factor Solution



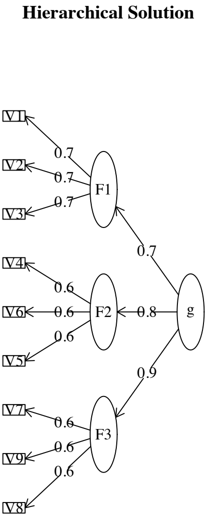
Hierarchical Solution

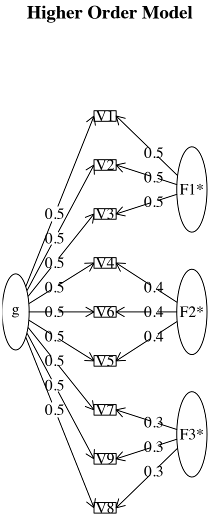


Higher Order Model



The Schmid-Leiman transformation finds the general factor loadings for a higher order model given a hierarchical model.





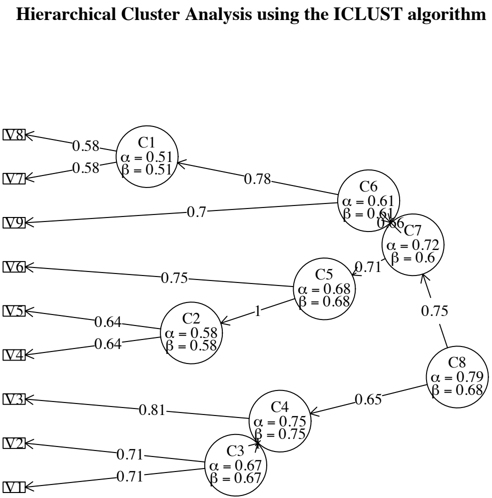
Hierarchical Cluster Analysis and Coefficient β

Given the definition of a general factor as representing what is common to *all* items, then the worst split half correlation of a set of items or tests reflects just this general variance (Revelle, 1979). Although combinatorially complex to find the worst split, one way to estimate the worst split half is through hierarchical cluster analysis.

1. Find the correlation/covariance matrix
2. Find the most similar pair of items based upon the correlations
3. Combine them to form a new item composite.
4. Find the split half reliability (β) of this composite based upon the correlation between the two parts.
5. Repeat steps 2-4 until *beta* fails to increase.

To estimate *beta* of an entire test, ignore step 5.

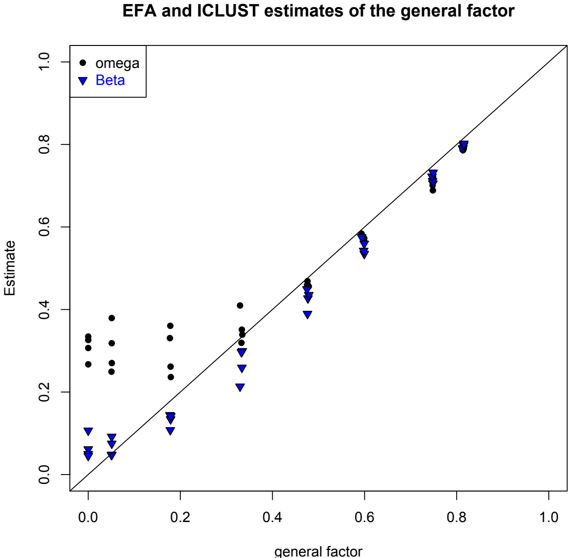
A hierarchical cluster analysis estimates ω_g by finding β



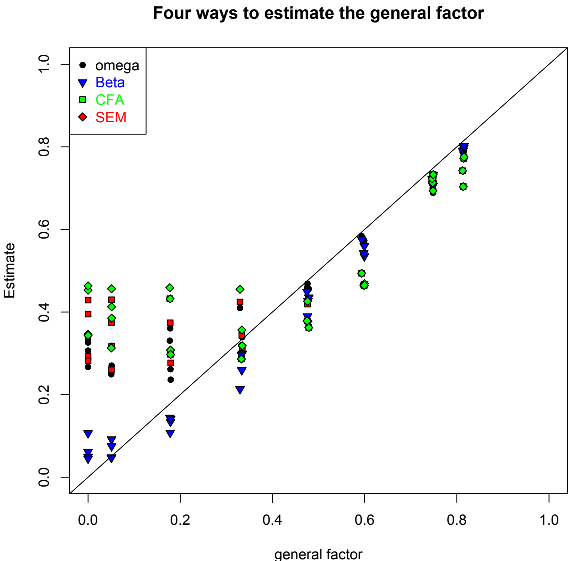
Four approaches to estimate a general factor

1. CFA/SEM based upon an a priori model
2. CFA based upon trial and error model fitting
   - (Do we really think some of those correlated residuals were specified a priori?)
3. EFA approach to finding ω_h through a Schmid Leiman transformation
4. Cluster analytical approach to find β.
5. Comparison of these approaches using simulation methodology discussed on slide 23.
   - Comparison of EFA with Schmid Leiman using the `omega` function to ICLUST using the `iclust` function.
   - Comparison of both of these with the CFA procedures.

Exploratory approaches to estimate a general factor

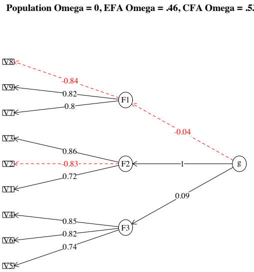


Comparing four ways to estimate a general factor



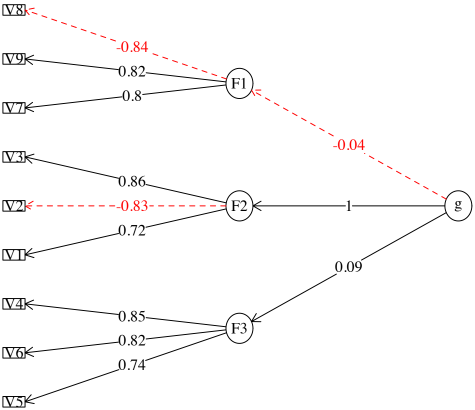
Failures of EFA/CFA approaches for low values of ω_g

1. EFA and CFA approaches have a large ($\approx .2 - .4$) positive bias when $\omega_g < .3$. Why?
   - Mindless application of these methods does not work. They all will report a value even though examination of the graphic output shows the problem.
   - One needs to examine the paths carefully to recognize the problem.
   - Consider the result with an $\omega_g = .46$ (The graphic is intentionally too small to emphasize the problem!)



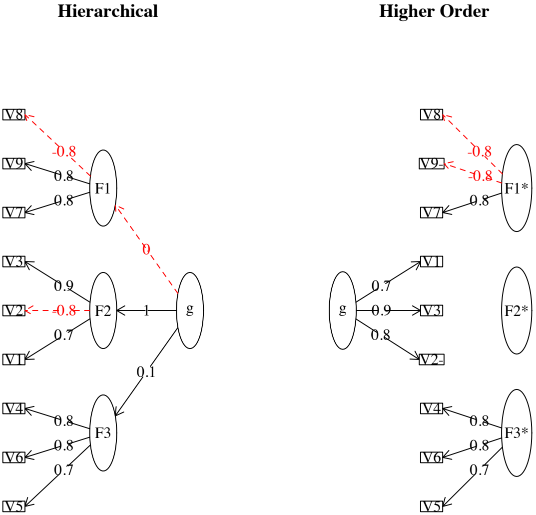
An example of a poor solution that actually looks good

Population Omega = 0, EFA Omega = .46, CFA Omega = .53



A better way to detect a bad solution

Clearly, the "good" value of ω_g was based entirely on one group



How to estimate a general factor

1. What works?
   1. Confirmatory Factor Analysis
      - Direct estimation of higher order models based upon strong theory
      - Requires graphical inspection of the solution
   2. Exploratory Factor Analysis
      - Estimation based upon the data (doesn't require theoretical prediction)
      - Schmid Leiman Transformations and Coefficient ω_h
      - Requires graphical inspection of the solution
   3. Hierarchical Cluster Analysis and Coefficient β
2. What doesn't work
   1. First unrotated factor loadings
   2. First factor from Bifactor rotations
   3. Eigen values of first factor

What about statistical measures of fit?

1. Common misapprehension that only SEM/CFA give goodness of fit tests
   - Comparative Fit, RMSEA, SRMR, BIC, etc.
2. Fit is merely a function of the residuals and of the adequacy of the fitting function
   - Modern EFA functions will find these fit indices (e.g., `fa`, `omega`, `omegaSem` in the *psych* package (Revelle, 2012) in R.

Carroll, J. B. (1993). *Human cognitive abilities: A survey of factor-analytic studies*. New York, NY, US: Cambridge University Press.

Cattell, R. B. (1957). *Personality and motivation structure and measurement*. Oxford, England: World Book Co.

Cattell, R. B. (1966). *The scientific analysis of personality*. Chicago,: Aldine Pub. Co.

Cronbach, L. J. (1951). Coefficient alpha and the internal structure of tests. *Psychometrika*, *16*, 297–334.

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