Exploratory Factor Analysis and Principal Component Analysis

- Today's topics:
  - What are EFA and PCA for?
  - Planning a factor analytic study
  - Analysis steps:
    - Extraction methods
    - How Many Factors
    - Rotation and Interpretation
    - Factor Scores
  - Wrapping Up…

Where we are headed…

- The rest of the course is dedicated to specific kinds of measurement models…
  - Confirmatory factor models (≈ linear factor models)
  - Item response models (≈ nonlinear factor models)
- This week we'll stop by EFA and PCA to illustrate how these devices are similar to and different than confirmatory factor models.
  - Hitting the major points only
  - But it could be a whole semester if you let it…

EFA vs. PCA

- 2 very different schools of thought on exploratory factor analysis (EFA) vs. principal components analysis (PCA):
  1. EFA and PCA are TWO ENTIRELY DIFFERENT THINGS… How dare you even put them into the same sentence!
  2. PCA is a special kind (or extraction type) of EFA… although they are often used for different purposes, the results turn out the same a lot anyway, so what's the big deal?
- My world view:
  - I'll describe them via school of thought #2. I want you to know what their limitations are. I want you to know that they are not really testable models.

Primary Purposes of EFA and PCA

- **EFA**: "Determine nature and number of latent variables that account for observed variation and covariation among set of observed indicators (≈ items or variables)"
  - In other words, what causes these observed responses?
  - Summarize patterns of correlation among indicators
  - Solution is an end (i.e., is of interest) in and of itself
- **PCA**: "Reduce multiple observed variables into fewer components that summarize their variance"
  - In other words, how can I abbreviate this set of variables?
  - Solution is usually a means to an end

EFA and PCA, continued

- Tabachnick & Fidell also suggest the purpose of EFA/PCA is to:
  - Provide an operational definition for an underlying process using observed variables (= indicators)
  - Test a theory about the nature of an underlying process
  - But as we will see, there is very little 'testing' involved…
- But then they point out the problems of these methods:
  - No criterion against which to test the solution
  - After extraction, there are an infinite number of available equivalent rotations
  - EFA is often used to "save" bad experiments, so it has a relatively poor reputation

Planning a Factor Analytic Study
(from Tabachnick and Fidell)

- Hypothesize the number of factors you are trying to measure (but 5-6 is recommended for a stable solution)
  - Make sure to include "all relevant related constructs" or else what's missing can inadvertently mess up your solution
  - **Do not expect the program to be able to tell you this part!!!!**
- Get 5-6 good indicators (items or variables) per factor
  - At least some should be 'marker indicators'
  - Avoid complex (multidimensional) indicators
  - Is helpful (imperative, even) to know a priori which factor each indicator should be representing…
  - Watch out for 'outlier indicators' – If an indicator is not related to the others, it will not be part of a useful factor solution

Planning a Factor Analytic Study
(from Tabachnick and Fidell)

- Sample size requirements
  - Get a sample with sufficient variability
    - Hard to work with correlations among constants…
    - Avoid pooling across groups or across time → implies invariance
  - Get a 'big enough' sample (more indicators → more people)
    - "At least 5 people per indicator"
    - Somewhere past 200 or so…"300 is comforting"
    - In reality this also depends on how well your factors hold together

Planning a Factor Analytic Study
(from Tabachnick and Fidell)

- Data requirements (for making inferences, anyway)
  - Indicators should be multivariate normally distributed
    - It's harder to test for multivariate normality than univariate normality, but you basically want to watch out for any univariate normal problems and deal with them prior to factor analysis (i.e., remove outliers, transform to fix skewness, etc).
  - Indicators should be correlated at least .30 or so…
    - **If they aren't correlated in the first place… game over**.
    - Assuming linear relationships among indicators, too
  - …But watch out for extreme multicolinearity/singularity
    - Not a problem for PCA
    - Will mess up an EFA

Steps in EFA (and PCA)

1. **Choose an estimator/extraction method**
2. Determine number of factors
3. Select a rotation
4. Interpret solution (may need to repeat steps 2 and 3)
5. If needed, generate factor scores

Estimator/Extraction Methods

- Estimator/Extraction Methods
  - Most common: Principal Components (PCA), Principal Factors (PF; also known as Principal Axes), Maximum Likelihood (ML)
  - Less common EFA methods: Image Factoring, Alpha Factoring, Unweighted Least Squares, Weighted Least Squares
- The point: Obtain a set of (orthogonal) components or factors that combine to reproduce the observed correlation matrix among the indicators
  - Differ by criteria used to establish the solution
    - Maximizing variance
    - Minimizing residuals

Extraction Methods

(School of Thought #1, please don't hurt me)

- The Question: How many factors do I need to reproduce the observed correlation matrix among the indicators?
  - **But 'which' correlation matrix are we starting from???**
- Primary difference between PCA and EFA:
  - **PCA**: Analyze **ALL** the variance in the indicators
    - On the diagonal of the analyzed correlation matrix are 1's
  - **EFA**: Analyze **COMMON** variance (covariance) in the indicators
    - On the diagonal of the correlation matrix are essentially the R^2 for each indicator being predicted by all the other indicators
    - These R^2 values are called **commonalities** (H^2)
    - Means that the leftover non-common variance (which we'll eventually call error variance) gets dropped prior to analysis

Extraction Methods: PCA

(school of thought #1, please don't hurt me)

- PCA: Extracts # COMPONENTS = # indicators
  - Will perfectly reproduce original correlation matrix
  - Unique mathematical solution
  - Components are uncorrelated (orthogonal)
  - Extracted in order of most variance accounted for in indicators
  - Provides component loadings (the L's) that relate each observed indicator (the I's) to each extracted component (the C's)
- Example with 5 indicators:
  - $C_1 = L_{11}I_1 + L_{12}I_2 + L_{13}I_3 + L_{14}I_4 + L_{15}I_5$
  - $C_2 = L_{21}I_1 + L_{22}I_2 + L_{23}I_3 + L_{24}I_4 + L_{25}I_5$
  - $C_3 = L_{31}I_1 + L_{32}I_2 + L_{33}I_3 + L_{34}I_4 + L_{35}I_5$
  - $C_4 = L_{41}I_1 + L_{42}I_2 + L_{43}I_3 + L_{44}I_4 + L_{45}I_5$
  - $C_5 = L_{51}I_1 + L_{52}I_2 + L_{53}I_3 + L_{54}I_4 + L_{55}I_5$

Keep all components?
= Full Component Solution

Keep fewer components?
= Truncated Component Solution

PCA, continued

- Consider the corr matrix on the right
- Obviously there are 2 kinds of information among these 4 indicators
  - X_1 & X_2 X_3 & X_4
- Looks like the PCs should be formed as

	X_1	X_2	X_3	X_4
X_1	1.0			
X_2	.7	1.0		
X_3	.3	.3	1.0	
X_4	.3	.3	.5	1.0

$C_1 = L_{11}X_1 + L_{12}X_2$ -- capturing the information in X_1 & X_2

$C_2 = L_{23}X_3 + L_{24}X_4$ -- capturing the information in X_3 & X_4

- But remember, PCA extraction isn't trying to "group indicators" -- it is trying to "reproduce variance"
  - Note the "cross correlations" between the "groups" of indicators

PCA, continued

- So, because of the cross correlations, in order to maximize the variance reproduced, C_1 will be formed more like ...

  $C_1 = .5X_1 + .5X_2 + .4X_3 + .4X_4$
  - Notice that all the variables contribute to defining C_1
  - Notice the slightly higher loadings for X_1 & X_2
- Because C_1 didn't focus on the X_1 & X_2 indicator group or X_3 & X_4 indicator group, there will still be variance to account for in both, and C_2 will be formed, probably something like …

  $C_2 = .3X_1 + .3X_2 - .4X_3 - .4X_4$
  - Notice that all the variables contribute to defining C_2
  - Notice the slightly higher loadings for X_3 & X_4

PCA, continued

- While this set of components will account for lots of the indicators' variance, it doesn't provide a very satisfactory interpretation
  - C_1 is a unipolar general factor
    - Unipolar: All indicators load 'substantially' in the same direction
  - C_2 is a bipolar general factor (even though all the variables are positively correlated with each other)
    - Bipolar: Some load positively and some load negatively
- The point here was to show what PCA does (maximize variance accounted for) and what it doesn't do (find groups of indicators)
- Later we will see how "rotation" provides the link between extraction (to max variance) and our goal of identifying "groups of indicators"

PCA Component Matrices

- Component matrix represents all the information resulting from an extraction
  - Each column represents one component
  - Each row represents one of the indicators
  - Each value is the correlation between that component and that indicator
- Information gained from the component matrix:
  - Total variance accounted for by each component
  - Communality of each indicator (assuming orthogonality)

PCA Component Matrices, continued

	C_1	C_2
I_1	.8	-.2
I_2	.7	-.1
I_3	.2	.5
I_4	.2	.4

- If you square and sum down a column, you get the eigenvalue for that component
  Eigen C_1 → $.8^2 + .7^2 + .2^2 + .2^2 = 1.21$
- Eigen / # indicators = variance accounted for by that component
  % C_1 → 1.21 / 4 = .3025 or 30.25%

- If you square and sum across a row, you get the extracted communality for that indicator (originally started at 1 in PCA):
  V^1 -- $.8^2 + -.2^2 = .68$ or 68% of its variance
  – Note this won't work unless the solution stays orthogonal…
- Same exact logic and procedure applies to EFA loading matrices, too, but they are called "Factor Matrices" instead

EFA Extraction Methods: PF vs. ML

- <u>PF = Principal Factors = Principal Axis</u>
  – No model fit, but no multivariate normality required
  – Iterative procedure to get communalities
    - Starts as R^2 from prediction by other indicators ("Initial")
    - Ends up with R^2 from prediction by all the factors ("Extraction")
    - Watch out for "Heywood cases" → $R^2 > 1$
  – Goal is to maximize variance extracted
- <u>ML = Maximum Likelihood</u>
  – Assessment of model fit, but multivariate normality required
  – Focuses on coming up with 'best guesses' for loadings and error variances, not directly for communalities
  – Is closest to CFA, so is recommended if heading there

Other EFA Extraction Methods

- <u>Image Factoring</u>
  – Like Principal Factors, in that it uses communalities of 'common' variance on the diagonal of the analyzed correlation matrix
    - Loadings based on covariances, though
  – Like PCA, in that communalities are non-iterative – are actual fixed R^2 values (so is mathematically unique solution)
- <u>Alpha Factoring</u>
  – Concerned w/ reliability of the common factors
  – Communalities are derived to maximize coefficient alpha
- <u>Unweighted Least Squares</u>
  – Minimize squared differences between observed and reproduced corr matrices
  – Only considers off-diagonal differences, communalities are derived after-the-fact
- <u>Weighted Least Squares</u>
  – Minimizes off-diagonal squared differences between observed and reproduced correlation matrices by applying weights
  – Variables with substantial shared variances are weighted more than substantial unique variances

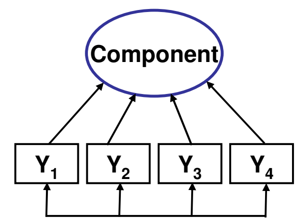
PCA vs. EFA, continued

- So if the difference between EFA and PCA is just in the communalities…
  – **PCA**: **All** variance in indicators is analyzed
    - No separation of common variance from error variance
    - Yields components that are uncorrelated
  – **EFA**: Only **common** variance in indicators is analyzed
    - Separates common variance from error variance
    - Yelds factors that may be uncorrelated or correlated
- Why the controversy?
  – Why is EFA considered to be about underlying structure, while PCA is supposed to be used only for data reduction?
  – The answer lies in the theoretical model underlying each…

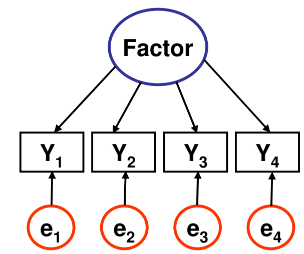
Big Conceptual Difference between PCA and EFA

- In PCA, we get components that are **outcomes** built from linear combinations of the indicators:
  - $\mathbf{C_1} = L_{11}I_1 + L_{12}I_2 + L_{13}I_3 + L_{14}I_4 + L_{15}I_5$
  - $\mathbf{C_2} = L_{21}I_1 + L_{22}I_2 + L_{23}I_3 + L_{24}I_4 + L_{25}I_5$
  - … and so forth – note that C is the **OUTCOME**
    - **This is not a testable measurement model per se.**
- In EFA, we get factors that are thought to be the **cause** of the observed indicators (here, 5 indicators, 2 factors):
  - $I_1 = L_{11}\mathbf{F_1} + L_{12}\mathbf{F_2} + e_1$
  - $I_2 = L_{21}\mathbf{F_1} + L_{22}\mathbf{F_2} + e_1$
  - $I_3 = L_{31}\mathbf{F_1} + L_{32}\mathbf{F_2} + e_1$
  - … and so forth… but note that F is the **PREDICTOR → testable**

PCA vs. EFA/CFA



This is not a testable measurement model, because how do we know if we've combined stuff "correctly"?



This IS a testable measurement model, because we are trying to predict the observed covariances between the indicators by creating a factor.

Big Conceptual Difference between PCA and EFA

- In **PCA**, the component is just the sum of the parts, and there is no inherent reason why the parts should be correlated (they just are)
  - But it's helpful if they are (otherwise, there's no point in trying to build components to summarize the variables → "component" = "variable")
  - The type of construct measured by a component is often called an '**emergent**' construct – i.e., it emerges from the indicators.
  - Examples: "Free time", "SES", "Support/Resources"
- In **EFA**, the indicator responses are caused by the factors, and thus should be uncorrelated once controlling for the factors
  - The type of construct that is measured by a factor is often called a '**reflective**' construct – i.e., the indicators are a reflection of your status on the latent variable.
  - Examples: Pretty much everything else…

Steps in EFA (and PCA)

1. Choose an estimator/extraction method
2. **Determine number of factors**
3. Select a rotation
4. Interpret solution (may need to repeat steps 2 and 3)
5. If needed, generate factor scores

How many factors/components?

- In other words, “How many constructs am I measuring?”
  – *Now do you see why the computer shouldn’t be telling you this?*
- Rules about the number of factors or components needed are based on Eigenvalues:
  – Eigenvalues = how much of ‘total’ variance in observed indicators is accounted for by each factor or component
    - In PCA, ‘total’ is really out of total possible variance
    - In EFA, ‘total’ is just out of total possible *common* variance
- 3 proposed methods
  – Kaiser-Guttman Rules (eigenvalues over 1)
  – Scree test (ok, “scree plot”, really)
  – Parallel analysis (ok, “parallel plot”, really)

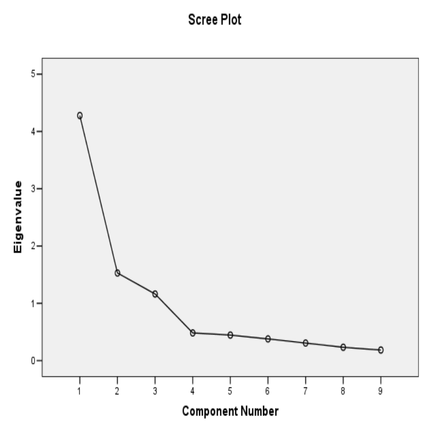
How many factors?

- Kaiser-Guttman Rule:
  – Keep any factors with Eigenvalues over 1
    - Supposed to be on non-reduced correlation matrix (i.e., the one with the 1’s in the diagonal for all the variance, not just the common variance), but people use it for the reduced EFA corr matrices, too
  – Logic: Eigenvalues are amount of variance accounted for by factor (where total variance = total # indicators)
    - At the bare minimum, the factor should account for as much variance as one of the original indicators did (i.e., its own variance)
    - Again, this logic only makes sense if you’re talking about the total, non-reduced matrix… but this appears ambiguous
  – But whatever: Most sources suggest this rule doesn’t work well, anyway… (and of course it is the default in many programs)

How many factors?

Scree “Test” → Scree plot

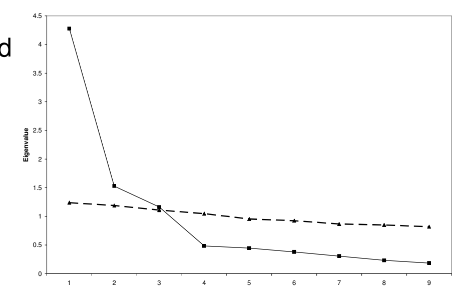
- Plot factor number on x-axis, its Eigenvalue on y-axis
- Look for ‘break’ in the curve where the slope changes, and retain the number of factors before that break
- Available in most programs
- Research suggests it works ‘most of the time’



How many factors?

Parallel “Test” → Parallel plot

- Plot Eigenvalues from your solution against those obtained from simulated data using randomly generated numbers
  – Use mean across simulations (same sample size, same # indicators, same # factors)
- Find point where real data crosses fake data – retain # factors above that point
- Not available in SPSS
  – Available SAS code reference given in Brown chapter 3



Intermediate Summary…

- PCA and EFA are both exploratory techniques geared loosely towards examining the structure underneath a series of continuous indicators (items or subscales):
  - PCA: How do indicators linearly combine to produce a set of uncorrelated linear composite outcomes?
  - EFA: What is the structure of the latent factors that produced the covariances among the observed indicators (factor = predictor)?
- Involves sequence of sometimes ambiguous decisions:
  - Extraction method
  - Number of factors
  - Next up: rotation, interpretation, and factor scores…

Steps in EFA (and PCA)

1. Choose an estimator/extraction method
2. Determine number of factors/components
3. **Select a rotation**
4. Interpret solution (may need to repeat steps 2 and 3)
5. If needed, generate factor scores

What is Rotation For?

- Although the component or factor matrix has the loadings of each indicator for each component or factor, those original loadings hardly ever get used directly to interpret the factors
- Instead, we often 'rotate' the factor solution
- **Rotation results in an equivalently-fitting, but different interpreted model solution**
- What this means is that factor loadings are NOT unique – for every solution there is an infinite number of possible sets of factor loadings, each as 'right' as the next

Goal of Rotation: Simple Structure

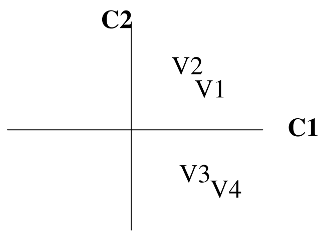
- The idea of rotation is to redefine the factor loadings to obtain simple structure
  - Each factor should have indicators with strong loadings
    - Obvious which indicators measure it (+/-) and which don't
  - Each indicator should load strongly on only one factor
    - Know what each item is 'for'
    - Construct measured is readily identifiable
    - Indicators should have large communalities
- Two kinds of rotations:
  - Orthogonal (uncorrelated factors)
  - Oblique (correlated factors)

"Simple Structure" via Rotation

- We're usually factoring to find "groups of variables", but the extraction process is trying to "reproduce variance"
- Factor Rotations -- changing the "viewing angle" of the factor space -- are the major approach to providing simple structure
- Simple Structure = the factor vectors spear the variable clusters

Unrotated

	C_1	C_2
V_1	.7	.5
V_2	.6	.6
V_3	.6	-.5
V_4	.7	-.6

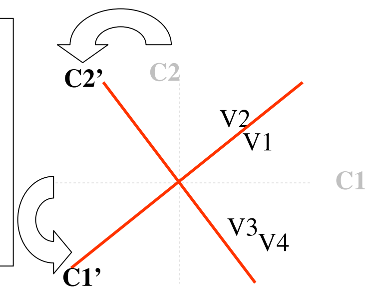


"Simple Structure" via Rotation

- Factor Rotations -- changing the "viewing angle" of the factor space -- are the major approach to providing simple structure
  - Structure is "simplified" if the factor vectors "spear" the variable clusters

Unrotated

	C_1	C_2
V_1	.7	.5
V_2	.6	.6
V_3	.6	-.5
V_4	.7	-.6



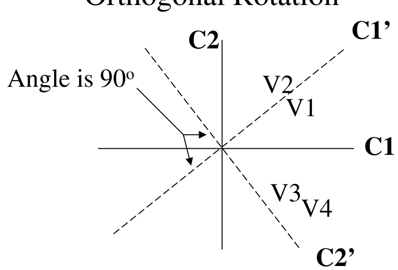
Rotated

	C_1	C_2
V_1	.7	-.1
V_2	.7	.1
V_3	.1	-.5
V_4	.2	-.6

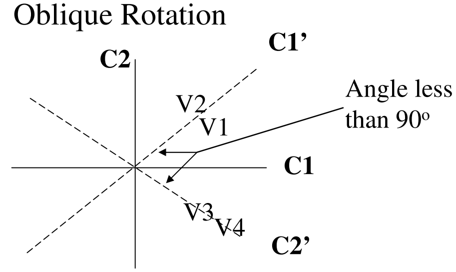
Major Types of Rotation

- Orthogonal Rotation -- resulting factors are uncorrelated
  - More parsimonious & efficient, but less "natural"
- Oblique Rotation -- resulting factors are correlated
  - More "natural" & better "spearing", but more complicated

Orthogonal Rotation



Oblique Rotation



Major Types of **Orthogonal** Rotation

- **Varimax** -- most commonly used and common default
  - "Simplifies factors" by maximizing variance of loadings within factors (high loadings → higher, low loadings → lower)
  - Tends to produce group factors (factors are more equitable)
- **Quartimax**
  - "Simplifies indicators" by maximizing variance of loadings within indicators (minimizes #factors each indicator loads on)
  - Tends to "move" indicators from extraction less than varimax
  - Tends to produce a general and small group factors
- **Equimax**
  - Designed to "balance" varimax and quartimax tendencies
  - Didn't work very well (particularly if you don't know how many factors you should have) -- can't do simultaneously -- whichever is done first dominates the final structure

Major Types of **Oblique** Rotation

- **Direct Oblimin:**
  – Spearing indicator clusters as well as possible to produce lowest occurrence of cross-loading indicators
  – Depends on value of "allowed correlation" (δ in SPSS, Γ also):
    - δ = -4 solution is orthogonal
    - δ < 0 solutions are increasingly orthogonal
    - δ = 0 factors are fairly highly correlated (Direct Quartimin)
    - δ = 1 factors are very highly correlated
    - This parameter matters, so try a few versions…
- **Promax**
  – Computes best orthogonal solution and then "relaxes" orthogonality constraints to better "spear" indicator clusters with factor vectors (give simpler structure)

Differences with Oblique Rotation

- Note: If the factors aren't correlated, the oblique solution will look similar to an orthogonal one solution, so I'd pry recommend using an oblique rotation to start with.
  – Reasonable to assume things will be related somewhat…
- Although overall model fit is the same…
  – Now get an additional matrix of factor correlations
  – Eigenvalues will be different (are re-dispersed)
  – Communalities will be the same, but they cannot be computed from the factor matrix directly (because of factor correlations)
  – But FUN NEW MATRICES to interpret…

Steps in EFA (and PCA)

1. Choose an estimator/extraction method
2. Determine number of factors/components
3. Select a rotation
4. **Interpret solution** (may need to repeat steps 2 and 3)
5. If needed, generate factor scores

Interpreting Factors...

- Interpretation is the process of "naming factors" based on the indicators that "load on" them
- Which indicators "load" is decided based on a "cutoff"
  - Cutoffs usually range from .3 to .4 (+/-)
  - Note that significance tests of loadings are not usually given!!
    - Although can be obtained separately though other procedures… (see Browne, Cudeck, Tateneni, & Mels, 1998; Tateneni, 1998)
- Higher cutoffs decrease # loading indicators
  - Factors may be ill-defined, some indicators may not load
- Lower cutoffs increase # loading indicators
  - Indicators more likely to be load on more than one factor

Which Set of Loadings?

- Orthogonal Rotation:
  – "**Rotated Factor** (or Component) **Matrix**"
  – Correlation of indicator with the factor… the end.
- Oblique Rotations: 3 different matrices are relevant
  – Loadings in "**Pattern Matrix**": Partial correlation of indicator with the factor, controlling for the other factors
    - Most often used to interpret the solution
  – Loadings in "**Structure Matrix**": Bivariate correlation of indicator with the factor
    - Loadings will pry be higher than in the pattern matrix
  – "Factor Correlation Matrix": Correlations among factors
  – Pattern Matrix * Factor Correlation Matrix = Structure Matrix

About Factor Solutions

- Trade-off between "parsimony" and "specificity" of solutions
  - Influences the #factors and cutoff decisions which then influence factor interpretation
  - General and "larger" group factors include more indicators, account for more variance -- are more parsimonious
  - Unique and "smaller" group factors include fewer indicators and may be more focused -- are often more specific
- When there is a general or large group factor, be careful about subsequent smaller group factors
  - They may be "left-over" parts of multivocal indicators
  - Factors may not represent the "named" parts of the indicators
  - Keeping and rotating "too many" factors will increase the chances of finding ill-defined factors

'Bad' Kinds of Factors

- Because EFA starts with correlations, any item properties (besides their construct) that influence correlation can influence the factor solution
- These include:
  – Differential skewness → lower correlation
  – Difficulty factors → indicators with higher means group together
  – Wording direction → reverse-coded indicators may group together
  – Common method → indicators from same source of observation or about the same object may group together

'Bad' Kinds of Indicators

- What if an indicator loads on 2 (or more) factors?
  – Is your construct more complicated than you thought?
    - Does the indicator just happen to measure two things?
    - Or do you have a 'third construct' that is different than, but related to, the factors it is currently loading on?
  – What happens if you change the number of factors?
    - If fewer, do the factors with multivocal items come together?
    - If more, do the multivocal items split into a new factor?
  – Two perspectives:
    1. Multivocal items are BAD. DROP THEM.
    2. Multivocal items are theoretically informative – explore them further, even though this may mean more research adding additional indicators that help resolve some of these issues.

Steps in EFA (and PCA)

1. Choose an estimator/extraction method
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4. Interpret solution (may need to repeat steps 2 and 3)
5. If needed, **generate factor scores**

Computing Factor Scores

- Regression approach - Best among computational methods
  - Capitalizes on chance relationships, so factor scores are biased
  - Factor scores can be correlated even if supposed to be orthogonal
- Bartlett method
  - Factor scores only correlate with their own factors; are unbiased
  - Factor scores can be correlated even if supposed to be orthogonal
- Anderson-Rubin approach
  - Uncorrelated factor scores even if factors are correlated
  - Best if goal is an orthogonal score
- Empirical Bayes Estimation
  - What's done in SEM frameworks…
  - But stay tuned for the problems in doing this…

Factor Scores… Do you even need them?

- Factor Indeterminacy (see Grice, 2001):
  - There is an infinite number of possible factor scores that all have the same mathematical characteristics
  - Different approaches can yield very different results
- A simple, yet effective solution is simply sum the items that load highly on a factor…"Unit-weighting"
  - Research has suggested that this 'simple' solution is more effective when applying the results of a factor analysis to different samples – factor loadings don't replicate all that well
  - Just make sure to standardize the indicators first if they are on different numerical metrics
- Use SEM – you don't need the factor scores.

Wrapping Up: "Exploratory" Factor Analysis

- *Exploring* means trying alternatives
  - # factors, rotations, cutoffs for loadings, factor scores…
- Best-case scenario: we get about the same answer regardless of solution choices
  - More realistic scenario: we have to pick one and defend it
  - Report all factor loadings so that readers have same information you did to make their own decisions…
- Then comes replication with another similar sample…
  - THEN it's time for confirmatory factor analysis so we can actually test alternative models, not just describe a correlation matrix…
  - **Or start with CFA if you have an idea of what you are measuring in the first place!**