
Principal Components Analysis and Exploratory Factor Analysis

PSYC 943: Fundamentals
of Multivariate Modeling
Lecture 15: December 11, 2013

Today's Class

- “Advanced” matrix operations
- Principal Components Analysis
- Methods for exploratory factor analysis (EFA)
 - Principal Components-based (TERRIBLE)

The Logic of Exploratory Analyses

- Exploratory analyses attempt to discover hidden structure in data with little to no user input
 - Aside from the selection of analysis and estimation
- The results from exploratory analyses can be misleading
 - If data do not meet assumptions of model or method selected
 - If data have quirks that are idiosyncratic to the sample selected
 - If some cases are extreme relative to others
 - If constraints made by analysis are implausible
- Sometimes, exploratory analyses are needed
 - Must construct an analysis that capitalizes on the known features of data
 - There are better ways to conduct such analyses
- Often, exploratory analyses are not needed
 - But are conducted anyway – see a lot of reports of scale development that start with the idea that a construct has a certain number of dimensions

ADVANCED MATRIX OPERATIONS

A Guiding Example

- To demonstrate some advanced matrix algebra, we will make use of some data
- I collected data SAT test scores for both the Math (SATM) and Verbal (SATV) sections of 1,000 students
- The descriptive statistics of this data set are given below:

Statistic	SATV	SATM
Mean	499.3	498.3
SD	49.8	81.2

Correlation

SATV	1.00	0.78
SATM	0.78	1.00

Matrix Trace

- For a square matrix Σ with v rows/columns, the trace is the sum of the diagonal elements:

$$tr\Sigma = \sum_{v=1}^V a_{vv}$$

- For our data, the trace of the correlation matrix is 2
 - For all correlation matrices, the trace is equal to the number of variables because all diagonal elements are 1
- The trace will be considered the total variance in principal components analysis
 - Used as a target to recover when applying statistical models

Matrix Determinants

- A square matrix can be characterized by a scalar value called a determinant:

$$\det \Sigma = |\Sigma|$$

- Calculation of the determinant by hand is tedious
 - Our determinant was 0.3916
 - Computers can have difficulties with this calculation (unstable in cases)
- The determinant is useful in statistics:
 - Shows up in multivariate statistical distributions
 - Is a measure of “generalized” variance of multiple variables
- If the determinant is positive, the matrix is called **positive definite**
 - Is invertable
- If the determinant is not positive, the matrix is called **non-positive definite**
 - Not invertable

Matrix Orthogonality

- A square matrix $\mathbf{\Lambda}$ is said to be orthogonal if:

$$\mathbf{\Lambda}\mathbf{\Lambda}^T = \mathbf{\Lambda}^T\mathbf{\Lambda} = \mathbf{I}$$

- Orthogonal matrices are characterized by two properties:
 1. The dot product of all row vector multiples is the zero vector
 - ♦ Meaning vectors are orthogonal (or uncorrelated)
 2. For each row vector, the sum of all elements is one
 - ♦ Meaning vectors are “normalized”
- The matrix above is also called **orthonormal**
 - **The diagonal is equal to 1 (each vector has a unit length)**
- Orthonormal matrices are used in principal components and exploratory factor analysis

Eigenvalues and Eigenvectors

- A square matrix Σ can be decomposed into a set of eigenvalues λ and a set of eigenvectors \mathbf{e}

$$\Sigma \mathbf{e} = \lambda \mathbf{e}$$

- Each eigenvalue has a corresponding eigenvector
 - The number equal to the number of rows/columns of Σ
 - The eigenvectors are all orthogonal
- Principal components analysis uses eigenvalues and eigenvectors to reconfigure data

Eigenvalues and Eigenvectors Example

- In our SAT example, the two eigenvalues obtained were:

$$\lambda_1 = 1.78$$

$$\lambda_2 = 0.22$$

- The two eigenvectors obtained were:

$$\mathbf{e}_1 = \begin{bmatrix} 0.71 \\ 0.71 \end{bmatrix}; \mathbf{e}_2 = \begin{bmatrix} 0.71 \\ -0.71 \end{bmatrix}$$

- These terms will have much greater meaning in one moment (principal components analysis)

Spectral Decomposition

- Using the eigenvalues and eigenvectors, we can reconstruct the original matrix using a spectral decomposition:

$$\mathbf{\Sigma} = \sum_{v=1}^V \lambda_v \mathbf{e}_v \mathbf{e}_v^T$$

- For our example, we can get back to our original matrix:

$$\mathbf{R}_1 = \lambda_1 \mathbf{e}_1 \mathbf{e}_1^T = 1.78 \begin{bmatrix} .71 \\ .71 \end{bmatrix} \begin{bmatrix} .71 & .71 \end{bmatrix} = \begin{bmatrix} .89 & .89 \\ .89 & .89 \end{bmatrix}$$

$$\begin{aligned} \mathbf{R}_2 &= \mathbf{R}_1 + \lambda_2 \mathbf{e}_2 \mathbf{e}_2^T = \begin{bmatrix} .89 & .89 \\ .89 & .89 \end{bmatrix} + 0.22 \begin{bmatrix} .71 \\ -.71 \end{bmatrix} \begin{bmatrix} .71 & -.71 \end{bmatrix} \\ &= \begin{bmatrix} 1.00 & 0.78 \\ 0.78 & 1.00 \end{bmatrix} \end{aligned}$$

Additional Eigenvalue Properties

- The matrix trace is the sum of the eigenvalues:

$$tr\mathbf{\Sigma} = \sum_{v=1}^V \lambda_v$$

- In our example, the $tr\mathbf{R} = 1.78 + .22 = 2$

- The matrix determinant can be found by the product of the eigenvalues

$$|\mathbf{\Sigma}| = \prod_{v=1}^V \lambda_v$$

- In our example $|\mathbf{R}| = 1.78 * .22 = .3916$

AN INTRODUCTION TO PRINCIPAL COMPONENTS ANALYSIS

PCA Overview

- Principal Components Analysis (PCA) is a method for re-expressing the covariance (or often correlation) between a set of variables
 - The re-expression comes from creating a set of new variables (linear combinations) of the original variables
- PCA has two objectives:
 1. Data reduction
 - ♦ Moving from many original variables down to a few “components”
 2. Interpretation
 - ♦ Determining which original variables contribute most to the new “components”

Goals of PCA

- The goal of PCA is to find a set of k principal components (composite variables) that:
 - Is much smaller in number than the original set of V variables
 - Accounts for nearly all of the total variance
 - ♦ Total variance = trace of covariance/correlation matrix
- If these two goals can be accomplished, then the set of k principal components contains almost as much information as the original V variables
 - Meaning – the components can now replace the original variables in any subsequent analyses

Questions when using PCA

- PCA analyses proceed by seeking the answers to two questions:
 1. How many components (new variables) are needed to “adequately” represent the original data?
 - The term adequately is fuzzy (and will be in the analysis)
 2. (once #1 has been answered): What does each component represent?
 - The term “represent” is also fuzzy

PCA Features

- PCA often reveals relationships between variables that were not previously suspected
 - New interpretations of data and variables often stem from PCA
- PCA usually serves as more of a means to an end rather than an end in itself
 - Components (the new variables) are often used in other statistical techniques
 - ◆ Multiple regression/ANOVA
 - ◆ Cluster analysis
- Unfortunately, PCA is often intermixed with Exploratory Factor Analysis
 - Don't. Please don't. Please make it stop.

PCA Details

- Notation: Z are our new components and \mathbf{Y} is our original data matrix (with N observations and V variables)

- We will let p be our index for a subject

- The new components are linear combinations:

$$Z_{p1} = \mathbf{e}_1^T \mathbf{Y} = e_{11}Y_{p1} + e_{21}Y_{p2} + \cdots + e_{V1}Y_{pV}$$

$$Z_{p2} = \mathbf{e}_2^T \mathbf{Y} = e_{12}Y_{p1} + e_{22}Y_{p2} + \cdots + e_{V2}Y_{pV}$$

$$\vdots$$

$$Z_{pV} = \mathbf{e}_V^T \mathbf{Y} = e_{1V}Y_{p1} + e_{2V}Y_{p2} + \cdots + e_{VV}Y_{pV}$$

- The weights of the components (e_{jk}) come from the eigenvectors of the covariance or correlation matrix for component k and variable j

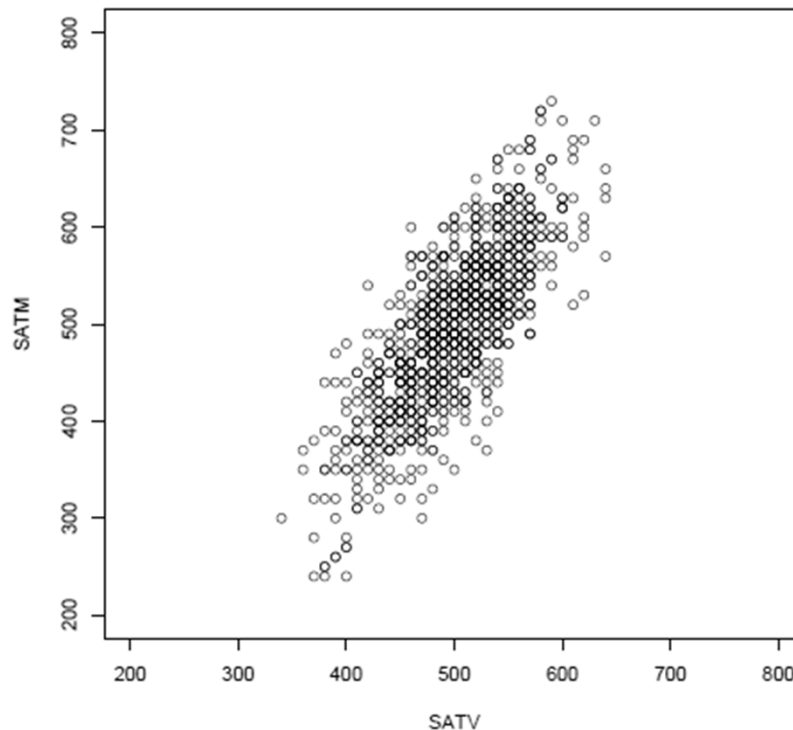
Details About the Components

- The components (Z) are formed by the weights of the eigenvectors of the covariance or correlation matrix of the original data
 - The variance of a component is given by the eigenvalue associated with the eigenvector for the component
- Using the eigenvalue and eigenvectors means:
 - Each successive component has lower variance
 - ♦ $\text{Var}(Z_1) > \text{Var}(Z_2) > \dots > \text{Var}(Z_v)$
 - All components are uncorrelated
 - The sum of the variances of the principal components is equal to the total variance:

$$\sum_{v=1}^V \text{Var}(Z_v) = \text{tr}\mathbf{\Sigma} = \sum_{v=1}^V \lambda_v$$

PCA on our Example

- We will now conduct a PCA on the **correlation matrix** of our sample data
 - This example is given for demonstration purposes – typically we will not do PCA on small numbers of variables



PCA in SAS

- The SAS procedure that does principal components is called PROC PRINCOMP
 - Mplus does not compute principal components

```
PROC PRINCOMP DATA=sat OUT=pcsat;  
VAR satv satm;  
RUN;
```

Eigenvalues of the Correlation Matrix

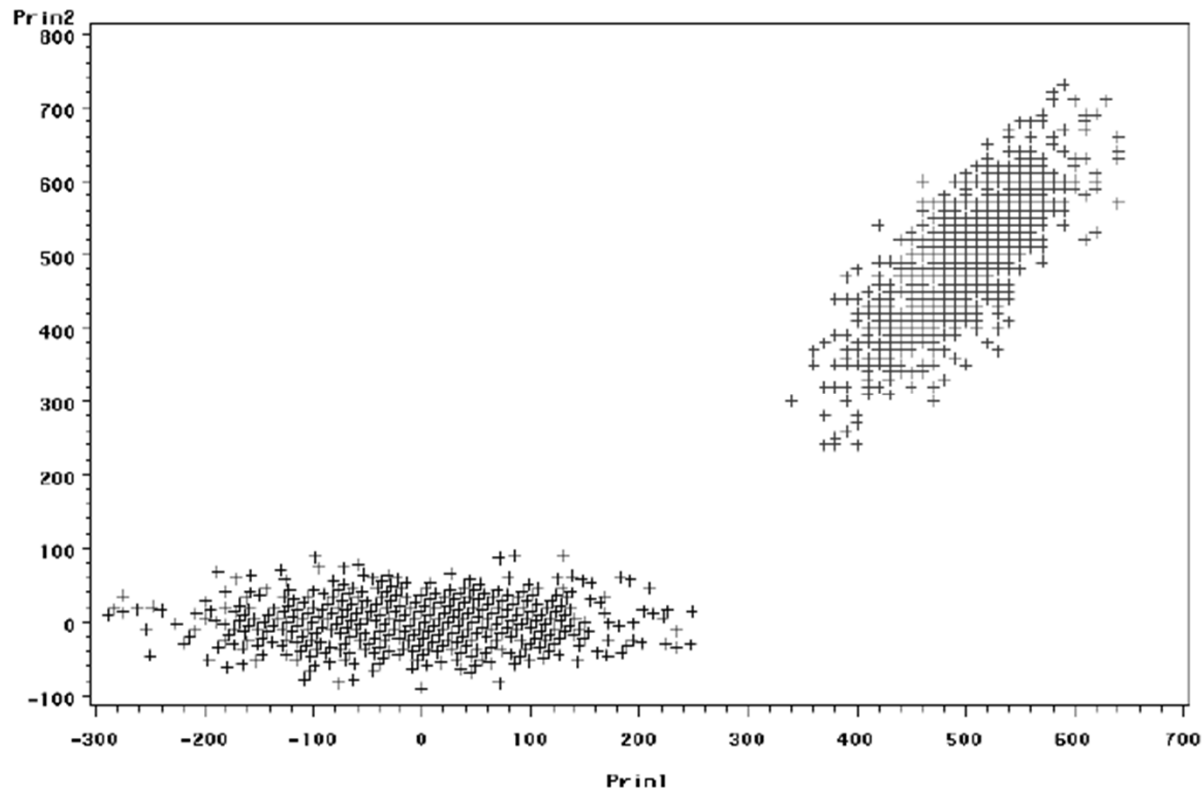
	Eigenvalue	Difference	Proportion	Cumulative
1	1.77522381	1.55044763	0.8876	0.8876
2	0.22477619		0.1124	1.0000

Eigenvectors

	Prin1	Prin2
SATV	0.707107	0.707107
SATM	0.707107	-0.707107

Graphical Representation

- Plotting the components and the original data side by side reveals the nature of PCA:
 - Shown from PCA of covariance matrix



The Growth of Gambling Access

- In past 25 years:
 - An exponential increase in the accessibility of gambling
 - An increased rate of with problem or pathological gambling (Volberg, 2002, Welte et al., 2009)
- Hence, there is a need to better:
 - Understand the underlying causes of the disorder
 - Reliably identify potential pathological gamblers
 - Provide effective treatment interventions



Pathological Gambling: DSM Definition

- To be diagnosed as a pathological gambler, an individual must meet 5 of 10 defined criteria:
 1. Is preoccupied with gambling
 2. Needs to gamble with increasing amounts of money in order to achieve the desired excitement
 3. Has repeated unsuccessful efforts to control, cut back, or stop gambling
 4. Is restless or irritable when attempting to cut down or stop gambling
 5. Gambles as a way of escaping from problems or relieving a dysphoric mood
 6. After losing money gambling, often returns another day to get even
 7. Lies to family members, therapist, or others to conceal the extent of involvement with gambling
 8. Has committed illegal acts such as forgery, fraud, theft, or embezzlement to finance gambling
 9. Has jeopardized or lost a significant relationship, job, educational, or career opportunity because of gambling
 10. Relies on others to provide money to relieve a desperate financial situation caused by gambling

Research on Pathological Gambling

- In order to study the etiology of pathological gambling, more variability in responses was needed
- The Gambling Research Instrument (Feasel, Henson, & Jones, 2002) was created with 41 Likert-type items
 - Items were developed to measure each criterion
- Example items (ratings: Strongly Disagree to Strongly Agree):
 - I worry that I am spending too much money on gambling (C3)
 - There are few things I would rather do than gamble (C1)
- The instrument was used on a sample of experienced gamblers from a riverboat casino in a Flat Midwestern State
 - Casino patrons were solicited after playing roulette

The GRI Items

- The GRI used a 6-point Likert scale
 - 1: Strongly Disagree
 - 2: Disagree
 - 3: Slightly Disagree
 - 4: Slightly Agree
 - 5: Agree
 - 6: Strongly Agree
- To meet the assumptions of factor analysis, we will treat these responses as being continuous
 - This is tenuous at best, but often is the case in factor analysis
 - Later we will discuss how to treat these as categorical items
 - ◆ Hint: Item Response Models

The Sample

- Data were collected from two sources:
 - 112 “experienced” gamblers
 - ♦ Many from an actual casino
 - 1192 college students from a “rectangular” midwestern state
 - ♦ Many never gambled before
- Today, we will combine both samples and treat them as homogenous – one sample of 1304 subjects
 - Later we will test this assumption – measurement invariance (called differential item functioning in item response theory literature)

Final 10 Items on the Scale

Item	Criterion	Question
GRI1	3	I would like to cut back on my gambling.
GRI3	6	If I lost a lot of money gambling one day, I would be more likely to want to play again the following day.
GRI5	2	I find it necessary to gamble with larger amounts of money (than when I first gambled) for gambling to be exciting.
GRI9	4	I feel restless when I try to cut down or stop gambling.
GRI10	1	It bothers me when I have no money to gamble.
GRI13	3	I find it difficult to stop gambling.
GRI14	2	I am drawn more by the thrill of gambling than by the money I could win.
GRI18	9	My family, coworkers, or others who are close to me disapprove of my gambling.
GRI21	1	It is hard to get my mind off gambling.
GRI23	5	I gamble to improve my mood.

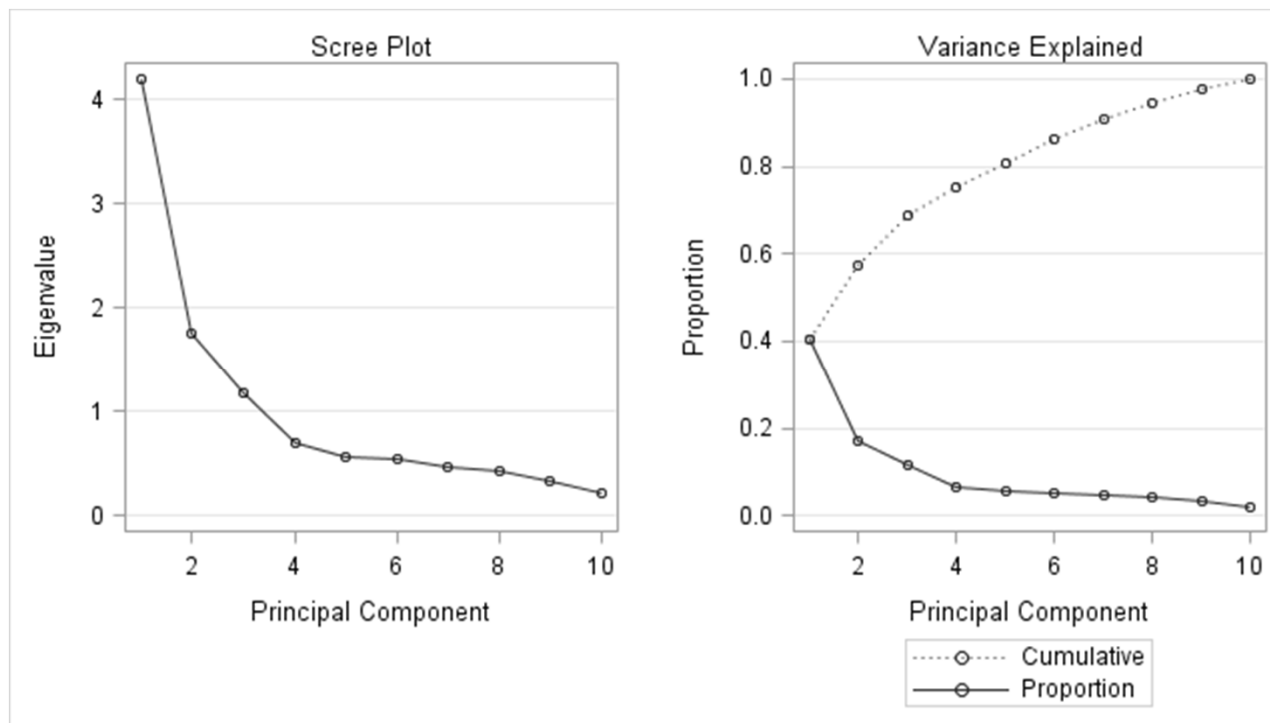
PCA with Gambling Items

- To show how PCA works with a larger set of items, we will examine the 10 GRI items (the ones that fit a one-factor CFA model)
- **TO DO THIS YOU MUST IMAGINE:**
 - THESE WERE THE ONLY 10 ITEMS YOU HAD
 - YOU WANTED TO REDUCE THE 10 ITEMS INTO 1 OR 2 COMPONENT VARIABLES
 - CAPITAL LETTERS ARE USED AS YOU SHOULD NEVER DO A PCA AFTER RUNNING A CFA – THEY ARE FOR DIFFERENT PURPOSES!
- I will use SAS for this analysis but will switch to Mplus for ML EFA (see this and the next class)

```
PROC PRINCOMP DATA=gri10 COV OUT=princomp;  
VAR GRI1 GRI3 GRI5 GRI9 GRI10 GRI13 GRI14 GRI18 GRI21 GRI23;  
RUN;
```

Question #1: How Many Components?

- To answer the question of how many components, two methods are used:
 - Scree plot of eigenvalues (looking for the “elbow”)
 - Variance accounted for (should be > 70%)
- We will go with 4 components: (variance accounted for VAC = 75%)
- Here variance accounted for is for the **total sample variance**



Question #2:

What Does Each Component Represent?

- To answer question #2 – we look at the weights of the eigenvectors (here is the unrotated solution)

	Eigenvectors			
	Prin1	Prin2	Prin3	Prin4
GRI1	0.31	0.10	0.17	0.84
GRI3	0.23	0.08	0.18	0.13
GRI5	0.32	0.09	0.23	-0.03
GRI9	0.24	0.09	0.16	-0.03
GRI10	0.28	0.09	0.24	-0.08
GRI13	0.33	0.16	0.19	-0.22
GRI14	0.45	-0.86	-0.23	-0.01
GRI18	0.35	0.40	-0.83	0.03
GRI21	0.27	0.14	0.06	-0.20
GRI23	0.33	0.10	0.14	-0.42

Final Result: Four Principal Components

- Using the weights of the eigenvectors, we can create four new variables – the four principal components
 - SAS does this for our standardized variables

Prin1	Prin2	Prin3	Prin4
2.544888869	1.2879589791	1.5823332302	1.8230315368
-2.185140823	0.364612547	0.1984710943	-0.264276829
0.6179049702	0.6644431285	0.2403178049	-0.378428365
-0.144307756	1.126940873	1.5393138875	0.1311429292
-0.144307756	1.126940873	1.5393138875	0.1311429292
-2.185140823	0.364612547	0.1984710943	-0.264276829
-2.185140823	0.364612547	0.1984710943	-0.264276829
-2.185140823	0.364612547	0.1984710943	-0.264276829
-1.872493616	0.469205857	0.364758028	0.5794583213
-1.872493616	0.469205857	0.364758028	0.5794583213

- Each of these is uncorrelated with each other
 - The variance of each is equal to the corresponding eigenvalue
- We would then use these in subsequent analyses

PCA Summary

- PCA is a **data reduction** technique that relies on the mathematical properties of eigenvalues and eigenvectors
 - **Used to create new variables (small number) out of the old data (lots of variables)**
 - The new variables are principal components (they are not factor scores)
- PCA appeared first in the psychometric literature
 - Many “factor analysis” methods used variants of PCA before likelihood-based statistics were available
- Currently, PCA (or variants) methods are the default option in SPSS and SAS (PROC FACTOR)

Potentially Solvable Statistical Issues in PCA

- The typical PCA analysis also has a few statistical concerns
 - Some of these can be solved if you know what you are doing
 - The typical analysis (using program defaults) does not solve these
- Missing data is omitted using listwise deletion – biases possible
 - Could use ML to estimate covariance matrix, but then would have to assume multivariate normality
- The distributions of variables can be anything...but variables with much larger variances will look like they contribute more to each component
 - Could standardize variables – but some can't be standardized easily (think gender)
- The lack of standard errors makes the component weights (eigenvector elements) hard to interpret
 - Can use a resampling/bootstrap analysis to get SEs (but not easy to do)

My (Unsolvable) Issues with PCA

- My issues with PCA involve the two questions in need of answers for any use of PCA:
 1. The number of components needed is not based on a statistical hypothesis test and hence is subjective
 - Variance accounted for is a descriptive measure
 - No statistical test for whether an additional component significantly accounts for more variance
 2. The relative meaning of each component is questionable at best and hence is subjective
 - Typical packages provide no standard errors for each eigenvector weight (can be obtained in bootstrap analyses)
 - No definitive answer for component composition
- In sum, I feel it is very easy to be mislead (or purposefully mislead) with PCA

EXPLORATORY FACTOR ANALYSIS

Primary Purpose of EFA

- **EFA:** “Determine nature and number of latent variables that account for observed variation and covariation among set of observed indicators (\approx 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
- Compared with **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

Methods for EFA

- You will see many different types of methods for “extraction” of factors in EFA
 - Many are PCA-based
 - Most were developed before computers became relevant or likelihood theory was developed

- You can ignore all of them and focus on one:

Only Use Maximum Likelihood for EFA

- The maximum likelihood method of EFA extraction:
 - Uses the same log-likelihood as confirmatory factor analyses/SEM
 - ◆ Default assumption: multivariate normal distribution of data
 - Provides consistent estimates with good statistical properties (assuming you have a large enough sample)
 - Missing data using all the data that was observed (MAR)
 - Is consistent with modern statistical practices

Questions when using EFA

- EFAs proceed by seeking the answers to two questions:
(the same questions posed in PCA; but with different terms)
- 1. How many latent factors are needed to “adequately” represent the original data?
 - “Adequately” = does a given EFA model fit well?
- 2. (once #1 has been answered): What does each factor represent?
 - The term “represent” is fuzzy

The Syntax of Factor Analysis

- Factor analysis works by hypothesizing that a set of latent factors helps to determine a person's response to a set of variables

- This can be explained by a system of simultaneous linear models
- Here Y = observed data, p = person, v = variable, F = factor score (Q factors)

$$Y_{p1} = \mu_{y_1} + \lambda_{11}F_{p1} + \lambda_{12}F_{p2} + \cdots + \lambda_{1Q}F_{pQ} + e_{p1}$$

$$Y_{p2} = \mu_{y_2} + \lambda_{21}F_{p1} + \lambda_{22}F_{p2} + \cdots + \lambda_{2Q}F_{pQ} + e_{p2}$$

\vdots

$$Y_{pV} = \mu_{y_V} + \lambda_{V1}F_{p1} + \lambda_{V2}F_{p2} + \cdots + \lambda_{VQ}F_{pQ} + e_{pV}$$

- μ_{y_v} = mean for variable v
- λ_{vf} = factor loading for variable v onto factor f (regression slope)
 - Factors are assumed distributed MVN with zero mean and (for EFA) identity covariance matrix (uncorrelated factors – to start)
- e_{pv} = residual for person p and variable v
 - Residuals are assumed distributed MVN (across items) with a zero mean and a diagonal covariance matrix Ψ containing the unique variances
- Often, this gets shortened into matrix form:

$$\mathbf{Y}_p = \boldsymbol{\mu}_Y + \boldsymbol{\Lambda}\mathbf{F}_p^T + \mathbf{e}_p$$

How Maximum Likelihood EFA Works

- Maximum likelihood EFA assumes the data follow a multivariate normal distribution
 - The basis for the log-likelihood function (same log-likelihood we have used in every analysis to this point)
- The log-likelihood function depends on two sets of parameters: the mean vector and the covariance matrix
 - Mean vector is saturated (just uses the item means for item intercepts) – so it is often not thought of in analysis
 - ♦ Denoted as $\mu_Y = \mu_I$
 - Covariance matrix is what gives “factor structure”
 - ♦ EFA models provide a structure for the covariance matrix

The EFA Model for the Covariance Matrix

- The covariance matrix is modeled based on how it would look if a set of hypothetical (latent) factors had caused the data
- For an analysis measuring F factors, each item in the EFA:
 - Has 1 unique variance parameter
 - Has F factor loadings
- The initial estimation of factor loadings is conducted based on the assumption of uncorrelated factors
 - Assumption is dubious at best – yet is the cornerstone of the analysis

Model Implied Covariance Matrix

- The factor model implied covariance matrix is $\Sigma_Y = \Lambda\Phi\Lambda^T + \Psi$
 - Where:
 - ♦ Σ_Y = model implied covariance matrix of the observed data (size $I \times I$)
 - ♦ Λ = matrix of factor loadings (size $I \times F$)
 - In EFA: all terms in Λ are estimated
 - ♦ Φ = factor covariance matrix (size $F \times F$)
 - In EFA: $\Phi = \mathbf{I}$ (all factors have variances of 1 and covariances of 0)
 - In CFA: this is estimated
 - ♦ Ψ = matrix of unique (residual) variances (size $I \times I$)
 - In EFA: Ψ is diagonal by default (no residual covariances)
 - Therefore, the EFA model-implied covariance matrix is:
$$\Sigma_Y = \Lambda\Lambda^T + \Psi$$

EFA Model Identifiability

- Under the ML method for EFA, the same rules of identification apply to EFA as to Path Analysis
 - T-rule: Total number of EFA model parameters must not exceed unique elements in saturated covariance matrix of data
 - ♦ For an analysis with a number of factors F and a set number of items I there are $F*I + I = I(F + 1)$ EFA model parameters
 - ♦ As we will see, there must be $\frac{F(F-1)}{2}$ constraints for the model to work
 - ♦ Therefore, $I(F + 1) - \frac{F(F-1)}{2} < \frac{I(I+1)}{2}$
 - Local-identification: each portion of the model must be locally identified
 - ♦ With all factor loadings estimated local identification fails
 - No way of differentiating factors without constraints

Constraints to Make EFA in ML Identified

- The EFA model imposes the following constraint:

$$\Lambda^T \Psi \Lambda = \Delta$$

such that Δ is a diagonal matrix

- This puts $\frac{F(F-1)}{2}$ constraints on the model (that many fewer parameters to estimate)
- This constraint is not well known – and how it functions is hard to describe
 - For a 1-factor model, the results of EFA and CFA will match
- Note: the other methods of EFA “extraction” avoid this constraint by not being statistical models in the first place
 - PCA-based routines rely on matrix properties to resolve identification

The Nature of the Constraints in EFA

- The EFA constraints provide some detailed assumptions about the nature of the factor model and how it pertains to the data

- For example, take a 2-factor model (one constraint):

$$\sum_{v=1}^V \psi_v^2 \prod_{f=1}^{Q=2} \lambda_{vf} = 0$$

- In short, some combinations of factor loadings and unique variances (across and within items) cannot happen
 - This goes against most of our statistical constraints – which must be justifiable and understandable (therefore testable)
 - This constraint is not testable in CFA

The Log-Likelihood Function

- Given the model parameters, the EFA model is estimated by maximizing the multivariate normal log-likelihood

➤ For the data

$$\log L = \log \left[(2\pi)^{-\frac{NV}{2}} |\mathbf{\Sigma}|^{-\frac{N}{2}} \exp \left[\sum_{p=1}^N -\frac{(\mathbf{Y}_p - \boldsymbol{\mu}_y)^T \mathbf{\Sigma}^{-1} (\mathbf{Y}_p - \boldsymbol{\mu}_y)}{2} \right] \right] =$$

$$-\frac{NV}{2} \log(2\pi) - \frac{N}{2} \log(|\mathbf{\Sigma}|) - \sum_{p=1}^N \frac{(\mathbf{Y}_p - \boldsymbol{\mu}_y)^T \mathbf{\Sigma}^{-1} (\mathbf{Y}_p - \boldsymbol{\mu}_y)}{2}$$

- Under EFA, this becomes:

$$\log L$$

$$= -\frac{NV}{2} \log(2\pi) - \frac{N}{2} \log(|\mathbf{\Lambda}\mathbf{\Lambda}^T + \mathbf{\Psi}|)$$

$$- \sum_{p=1}^N \frac{(\mathbf{Y}_p - \boldsymbol{\mu}_I)^T (\mathbf{\Lambda}\mathbf{\Lambda}^T + \mathbf{\Psi})^{-1} (\mathbf{Y}_p - \boldsymbol{\mu}_I)}{2}$$

Benefits and Consequences of EFA with ML

- The parameters of the EFA model under ML retain the same benefits and consequences of any model (i.e., CFA)
 - Asymptotically (large N) they are consistent, normal, and efficient
 - Missing data are “skipped” in the likelihood, allowing for incomplete observations to contribute (assumed MAR)
- Furthermore, the same types of model fit indices are available in EFA as are in CFA
- As with CFA, though, an EFA model must be a close approximation to the saturated model covariance matrix if the parameters are to be believed
 - This is a marked difference between EFA in ML and EFA with other methods
 - quality of fit is statistically rigorous

FACTOR LOADING ROTATIONS IN EFA

Rotations of Factor Loadings in EFA

- Transformations of the factor loadings are possible as the matrix of factor loadings is only unique up to an orthogonal transformation
 - Don't like the solution? Rotate!
- Historically, rotations use the properties of matrix algebra to adjust the factor loadings to more interpretable numbers
- Modern versions of rotations/transformations rely on “target functions” that specify what a “good” solution should look like
 - The details of the modern approach are lacking in most texts

Types of Classical Rotated Solutions

- Multiple types of rotations exist but two broad categories seem to dominate how they are discussed:
- **Orthogonal rotations:** rotations that force the factor correlation to zero (orthogonal factors). The name orthogonal relates to the angle between axes of factor solutions being 90 degrees. The most prevalent is the varimax rotation.
- **Oblique rotations:** rotations that allow for non-zero factor correlations. The name orthogonal relates to the angle between axes of factor solutions not being 90 degrees. The most prevalent is the promax rotation.
 - These rotations provide an estimate of “factor correlation”

How Classical Orthogonal Rotation Works

- Classical orthogonal rotation algorithms work by defining a new rotated set of factor loadings Λ^* as a function of the original (non-rotated) loadings Λ and an orthogonal rotation matrix \mathbf{T}

$$\Lambda^* = \Lambda \mathbf{T}$$

where: $\mathbf{T}\mathbf{T}^T = \mathbf{T}^T\mathbf{T} = \mathbf{I}$

- These rotations do not alter the fit of the model as

$$\Sigma_Y = \Lambda^* \Lambda^{*T} + \Psi = \Lambda \mathbf{T} (\Lambda \mathbf{T})^T + \Psi = \Lambda \mathbf{T} \mathbf{T}^T \Lambda^T + \Psi = \Lambda \Lambda^T + \Psi$$

Modern Versions of Rotation

- Most studies using EFA use the classical rotation mechanisms, likely due to insufficient training
- Modern methods for rotations rely on the use of a target function for how an optimal loading solution should look

$$\mathbf{L} = \begin{bmatrix} x & 0 & 0 \\ x & 0 & 0 \\ x & 0 & 0 \\ x & 0 & 0 \\ 0 & x & 0 \\ 0 & x & 0 \\ 0 & 0 & x \\ 0 & 0 & x \\ 0 & 0 & x \end{bmatrix}$$

From Browne (2001)

Rotation Algorithms

- Given a target function, rotation algorithms seek to find a rotated solution that simultaneously:
 1. Minimizes the distance between the rotated solution and the original factor loadings
 2. Fits best to the target function
- Rotation algorithms are typically iterative – meaning they can fail to converge
- Rotation searches typically have multiple optimal values
 - Need many restarts

EFA IN MPLUS

EFA in Mplus

- Mplus has an extensive set of rotation algorithms
 - The default is the Geomin rotation procedure
- The Geomin procedure is the default as it was shown to have a good performance for a classic Thurstone data set (see Browne, 2001)
- We could spend an entire semester on rotations, so I will focus on the default option in Mplus and let the results generalize across most methods

Steps in an ML EFA Analysis

- To determine number of factors:
 1. Run a 1-factor model (note: same fit as CFA model)
 - ♦ Check model fit (RMSEA, CFI, TLI) – stop if model fits adequately
 2. Run a 2-factor model
 - ♦ Check model fit (RMSEA, CFI, TLI) – stop if model fits adequately
 3. Run a 3-factor model (if possible – remember maximum number of parameters possible)
 - ♦ Check model fit (RMSEA, CFI, TLI) – stop if model fits adequately
 - And so on...
- One huge note: unlike in PCA analyses, there are no model-based eigenvalues to report (nor VAC for the whole model)
 - These are no longer useful in determining the number of factors
 - Mplus will give you a plot (PLOT command, TYPE=PLOT2)
 - ♦ These are from the H1 model correlation matrix

10 Item GRI: EFA Using ML in Mplus

- The 10 item GRI has a $\frac{10(10+1)}{2} = 55$ unique parameters in the H1 (saturated) covariance matrix
 - The limit of parameters possible in an EFA model
 - In theory, we could estimate 6 factors
 - ♦ In practice, 6 factors is impossible with 10 items

Factors	Factor Loadings	Unique Variances	Constraints	Total Covariance Parameters
1	10	10	0	20
2	20	10	1	29
3	30	10	3	37
4	40	10	6	46
5	50	10	10	50
6	60	10	15	55

Mplus Syntax

```
TITLE:
    Gambling Research Instrument Items
    Data from 1192 College Students/144 Gamblers
    41 Likert Items (1-6): GRI1-GRI41
    12 SOGS items (SOGS4-SOGS15), mostly dichotomous
    =====
    Identification: Marker Item Factor Variance, Zero Factor Mean
    =====
    All 41 Items: EFA Analysis

DATA:
    FILE = gamblingdata.csv;

VARIABLE:
    NAMES = GRI1-GRI41 SOGS4-SOGS15 Student ID;
    USEVARIABLES = GRI1 GRI3 GRI5 GRI9 GRI10 GRI13
                   GRI14 GRI18 GRI21 GRI23;
    IDVARIABLE = ID;
    MISSING = ALL(99);

ANALYSIS:
    TYPE = EFA 1 6;
    ROTATION = GEOMIN;
    RSTARTS = 100;

PLOT:
    TYPE = PLOT1 PLOT2 PLOT3;

OUTPUT:
    SAMPSTAT;
```

Model Comparison: Fit Statistics

F	Log-Likelihood	#Ptrs	AIC	BIC	SSA BIC	RMSEA	CFI	TLI
1	-16,648.054	30	33,356.108	33,512.031	33,416.735	.052	.969	.961
2	-16,595.511	39	33,269.021	33,471.721	33,347.835	.029	.993	.987
3	-16,581.715	47	33,257.431	<u>33,501.710</u>	<u>33,352.412</u>	.021	.997	.994
4	-16.572.437	54	<u>33,252.873</u>	33,533.535	33,362.001	.000	1.000	1.001
5	-16,568.963	60	33,257.925	33,569.771	33,379.178	.000	1.000	1.004
6	-16.567.438	65	33,264.875	33,602.709	33,396.232	.000	1.000	1.000

Model Comparison: Likelihood Ratio Tests

- Model 1 v. Model 2: $\chi^2_9 = 105.086, p < .001$
- Model 2 v. Model 3: $\chi^2_8 = 27.592, p < .001$
- Model 3 v. Model 4: $\chi^2_7 = 18.556, p = .010$
- Model 4 v. Model 5: $\chi^2_6 = 6.948, p = .323$
- Likelihood ratio tests suggest a 4-factor solution
 - However, RMSEA, CFI, and TLI all would be acceptable under one factor

Mplus Output: A New Warning

- A new warning now appears in the Mplus output:

```
WARNING:  IN EXPLORATORY FACTOR ANALYSIS WITH 4 FACTOR(S)  
  
THE CONDITION NUMBER OF THE ROTATED SOLUTION IS 0.288D-09.  
THE OPTIMAL ROTATION MAY BE POORLY IDENTIFIED.  
CHANGING THE ROTATION METHOD MAY RESOLVE THIS PROBLEM.
```

- The GEOMIN rotation procedure uses an iterative algorithm that attempts to provide a good fit to the non-rotated factor loadings while minimizing a penalty function
 - It may not converge
 - It may converge to a local minimum
 - It may converge to a location that is not well identified (as is our problem)
- Upon looking at our 4-factor results, we find some very strange numbers
 - So we will stick to the 3-factor model for our explanation
 - In reality you shouldn't do this (but you shouldn't do EFA)

Mplus EFA 3-Factor Model Output

- The key to interpreting EFA output is the factor loadings:

	GEOMIN ROTATED LOADINGS		
	1	2	3
GRI1	0.485	0.088	0.043
GRI3	0.471	0.058	0.021
GRI5	0.527	0.225	-0.015
GRI9	0.008	0.971	0.009
GRI10	0.491	0.254	0.008
GRI13	0.223	0.056	0.504
GRI14	0.446	-0.007	-0.038
GRI18	0.084	-0.048	0.429
GRI21	-0.015	0.015	0.778
GRI23	0.405	-0.033	0.332

- Historically, the standard has been if the factor loading is bigger than .3, then the item is considered to load onto the factor
 - This is different under ML – as we can now use Wald tests

Wald Tests for Factor Loadings

- Using the Wald Tests, we see a different story (absolute value must be great than 2 to be significant)

	Est./S.E. GEOMIN ROTATED LOADINGS		
	1	2	3
GRI1	2.802	0.445	0.518
GRI3	2.678	0.305	0.266
GRI5	1.921	0.698	-0.295
GRI9	1.746	3.551	0.535
GRI10	1.624	0.733	0.178
GRI13	1.659	0.500	4.537
GRI14	5.419	-0.084	-0.449
GRI18	0.703	-0.878	4.196
GRI21	-0.607	0.591	23.681
GRI23	4.325	-0.440	3.684

- Factor 2 has 1 item that significantly loads onto it
- Factor 3 has 4 items
- Factor 1 has 4 items
- Two items have no significant loadings at all

Factor Correlations

- Another salient feature in oblique rotations is that of the factor correlations
- Sometimes these values can exceed 1 (called factor collapse) so it is important to check

GEOMIN FACTOR CORRELATIONS			
	1	2	3
1	1.000		
2	0.677	1.000	
3	0.783	0.650	1.000

Where to Go From Here

- If this was your analysis, you would have to make a determination as to the number of factors
 - We thought 4 – but 4 didn't work
 - Then we thought 3 – but the solution for 3 wasn't great
 - Can anyone say 2?
- Once you have settled the number of factors, you must then describe what each factor means
 - Using the pattern of rotated loadings
- After all that, you should validate your result
 - You should regardless of analysis (but especially in EFA)

PCA VERSUS EFA

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...
 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
 - **It is not your data's job to tell you what constructs you are measuring!! If you don't have any idea, game over**

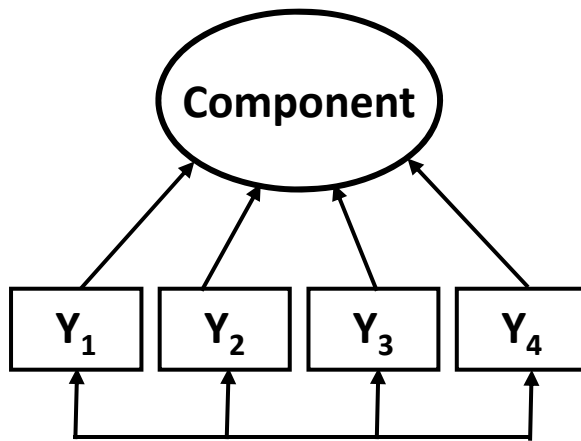
PCA vs. EFA, continued

- So if the difference between EFA and PCA is just in the communalities (the diagonal of the correlation matrix)...
 - PCA: All variance in indicators is analyzed
 - ◆ No separation of common variance from error variance
 - ◆ Yields components that are uncorrelated to begin with
 - EFA: Only common variance in indicators is analyzed
 - ◆ Separates common variance from error variance
 - ◆ Yields 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...

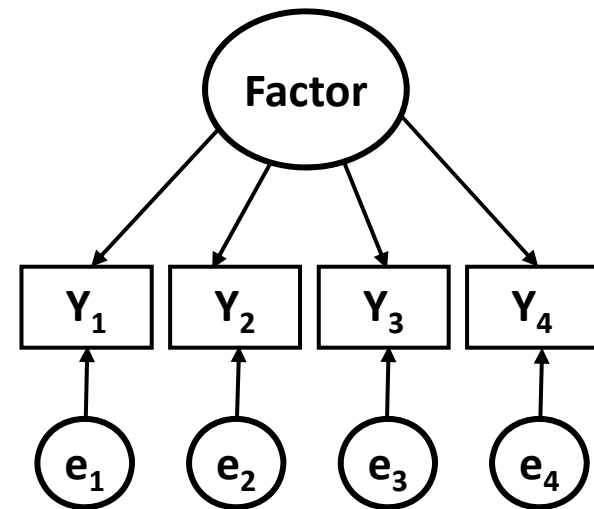
Big Conceptual Difference between PCA and EFA

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

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 they should be (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 (“**formative**”).
 - Examples: “Lack of Free time”, “SES”, “Support/Resources”
- In **EFA**, the indicator responses are caused by the factors, and thus should be uncorrelated once controlling for the factor(s)
 - 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...

My Issues with EFA

- Often a PCA is done and called an EFA
 - PCA is not a statistical model!
- No statistical test for factor adequacy
- Rotations are suspect
- Constraints are problematic

COMPARING CFA AND EFA

Comparing CFA and EFA

- Although CFA and EFA are very similar, their results can be very different for two or more factors
 - Results for the 1 factor are the same in both (use standardized factor identification in CFA)
- EFA typically assumes uncorrelated factors
- If we fix our factor correlation to zero, a CFA model becomes very similar to an EFA model
 - But...with one exception...

EFA Model Constraints

- For more than one factor, the EFA model has too many parameters to estimate
 - Uses identification constraints (where Δ is diagonal):
$$\Lambda' \Psi \Lambda = \Delta$$
- This puts $\frac{F(F-1)}{2}$ multivariate constraints on the model
- These constraints render the comparison of EFA and CFA useless for most purposes
 - Many CFA models do not have these constraints
- Under maximum likelihood estimators, both EFA and CFA use **the same likelihood function**
 - Multivariate normal
 - Mplus: full information

CFA Approaches to EFA

- We can conduct exploratory analysis using a CFA model
 - Need to set the right number of constraints for identification
 - We set the value of factor loadings for a few items on a few of the factors
 - ◆ Typically to zero (my usual thought)
 - ◆ Sometimes to one (Brown, 2002)
 - We keep the factor covariance matrix as an identity
 - ◆ Uncorrelated factors (as in EFA) with variances of one
- Benefits of using CFA for exploratory analyses:
 - CFA constraints remove rotational indeterminacy of factor loadings – no rotating is needed (or possible)
 - Defines factors with potentially less ambiguity
 - ◆ Constraints are easy to see
 - For some software (SAS and SPSS), we get much more model fit information

EFA with CFA Constraints

- To do EFA with CFA, you must:
 - Fix factor loadings (set to either zero or one)
 - ◆ Use “row echelon” form :
 - ◆ One item has only one factor loading estimated
 - ◆ One item has only two factor loadings estimated
 - ◆ One item has only three factor loadings estimated
 - Fix factor covariances
 - ◆ Set all to 0
 - Fix factor variances
 - ◆ Set all to 1

CONCLUDING REMARKS

Wrapping Up

- Today we discussed the world of exploratory factor analysis and found the following:
 - PCA is what people typically run when they are after EFA
 - ML EFA is a better option to pick (likelihood based)
 - ◆ Constraints employed are hidden!
 - ◆ Rotations can break without you realizing they do
 - ML EFA can be shown to be equal to CFA for certain models
 - Overall, CFA is still your best bet
 - ◆ Visit PSYC 948 next semester to learn more about why...