simsem: SIMulated Structural Equation Modeling in R

Alexander M. Schoemann
Sunthud Pornprasertmanit
Patrick J. Miller

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KU CENTER FOR RESEARCH METHODS & DATA ANALYSIS
College of Liberal Arts & Sciences

Monte Carlo Simulations

- Monte Carlo simulations are a popular tool for methodologists with many uses
  - Determine the accuracy of new methods
  - Compare different methods
  - Perform power analyses
  - Determine model fit in SEM

Monte Carlo Simulations

- General steps in a Monte Carlo Simulation
  1. Specify population parameters
  2. Create a sample of size N, based on population parameters
  3. Analyze sample data from step 2 with chosen statistical method(s).
  4. Repeat steps 2 and 3 for each of r replications.

Software Options for Monte Carlo Simulations with SEM

- Mplus
- EQS
- PRELIS/LISREL
- SAS
- lavaan
- Other R packages (sem, OpenMx)
- Others?

simsem

- A new R package designed to automate Monte Carlo Simulations using SEM
- simsem can:
  - Generate data
  - Modify generated data
  - Analyze data
  - Summarize results
  - Use multiple processors across simulations

simsem Features

- Data generation
  - Currently only continuous data are generated.
    - By default data are generated from a multivariate normal distribution
    - Both manifest and latent variables can have non-normal distributions
  - Data can be generated from a covariance matrix and mean vector or through a series of linear equations.

simsem Features

- Data generation (continued)
  - Data can be generated with population misfit
  - Data can be generated with continuously varying parameters
  - Generating and analysis models are specified using LISREL matrices

simsem Features

- Data modification
  - Many type of missing data mechanisms can be simulated
    - MCAR
    - MAR
    - Planned missing data designs
      - “3” Form Design
      - “2” Method Design

simsem Features

- Data analysis
  - All models are fit using lavaan (Rosseel, 2012)
    - Robust ML estimators are available
    - Equality constraints can be included
    - FIML is used when data are missing
  - Multiple imputation of missing data is performed with Amelia (Honaker, King & Blackwell, 2011)
    - Data are imputed, analyzed and results are combined with Rubin’s Rules for each replication

simsem Features

- Summarizing Results
  - Results from a simulation can be automatically summarized
  - Results for each model parameter include:
    - Parameter bias
    - Standard error bias
    - Confidence interval coverage
    - Power

Example 1: Power Analysis

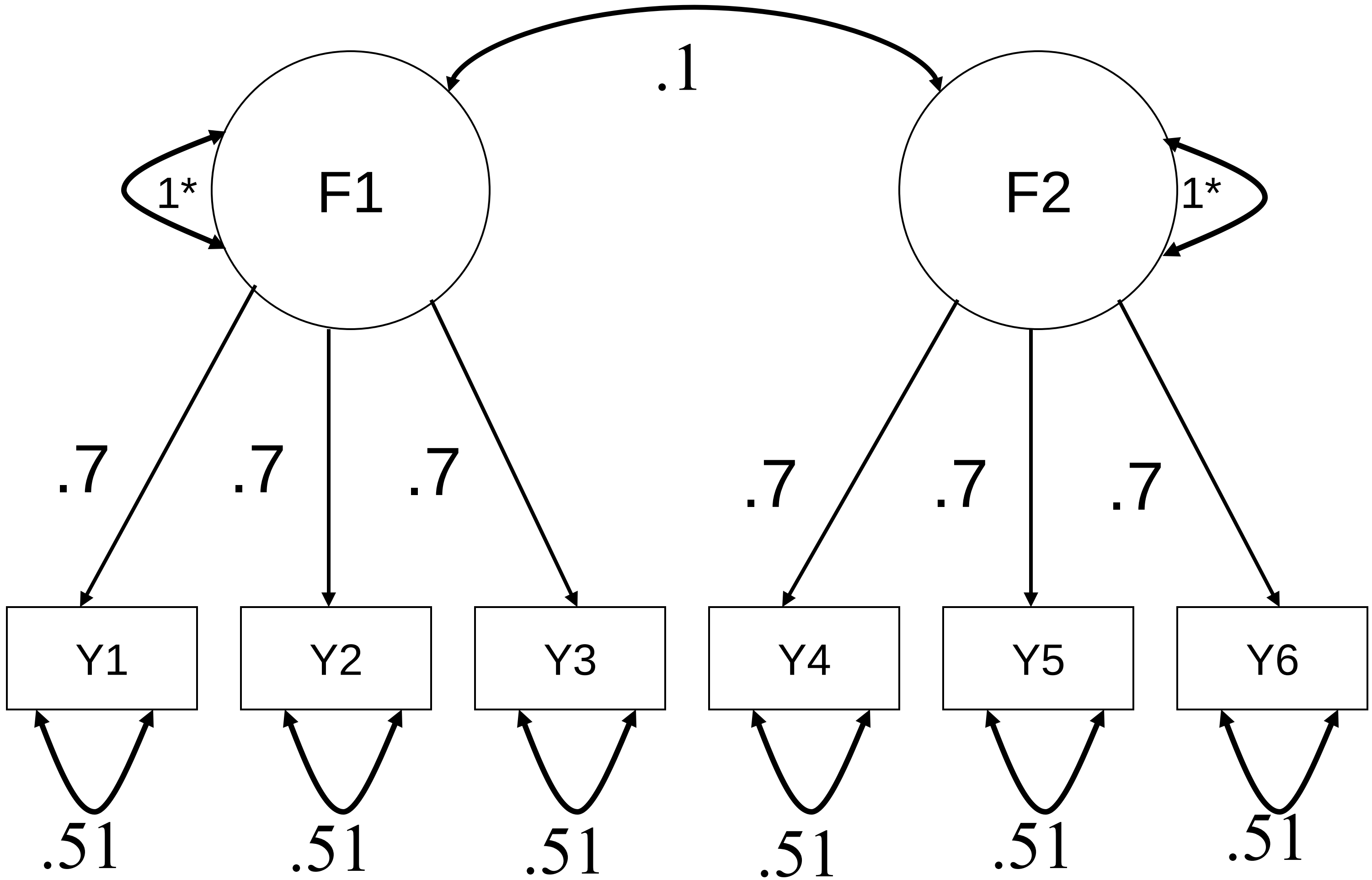
- Given population parameters, what sample size will result in a given level of power (e.g., .80)?
  - Continuously varying sample size approach
    - Specify model and a range of sample sizes
    - Generate 3000 replications varying sample size across replications
    - Record each parameter’s significance for each replication (0 not sig., 1 sig.)

Example 1: Power Analysis

- Given population parameters, what sample size will results in a given level of power (e.g., .80)?
  - Use logistic regression to predict a parameter's significance (across all replications) from the sample size of each replication.
  - The predicted probability from the logistic regression at a given N is power for that parameter at that N

$$p = \frac{e^{B_0 + B_1 N}}{1 + e^{B_0 + B_1 N}}$$

Example 1: Power Analysis



Example 1: Power Analysis

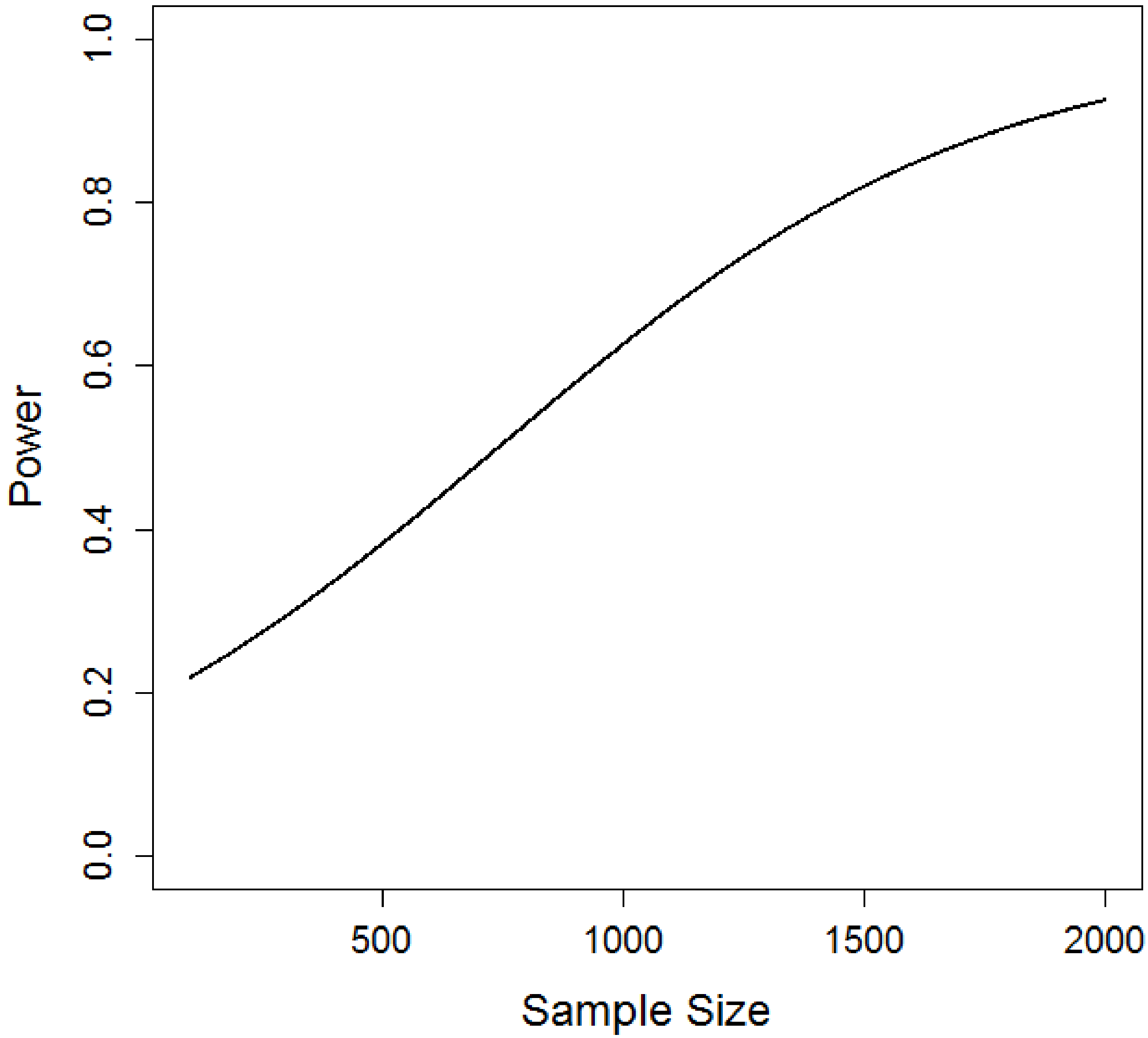
$$LY = \begin{matrix} 0.7 & 0 \\ 0.7 & 0 \\ 0.7 & 0 \\ 0 & 0.7 \\ 0 & 0.7 \\ 0 & 0.7 \end{matrix}$$

$$PS = \begin{matrix} 1 & 0.1 \\ 0.1 & 1 \end{matrix}$$

$$TE = \begin{matrix} 0.51 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0.51 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0.51 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0.51 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0.51 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0.51 \end{matrix}$$

Example 1: Power Analysis

- Results: What sample size results in power for the latent correlation of .80?
  - 3000 replications, randomly varying N between 100-2000
  - logit(power) = $\beta_0 + \beta_1 N$
  - Power = .80 when N = 1436

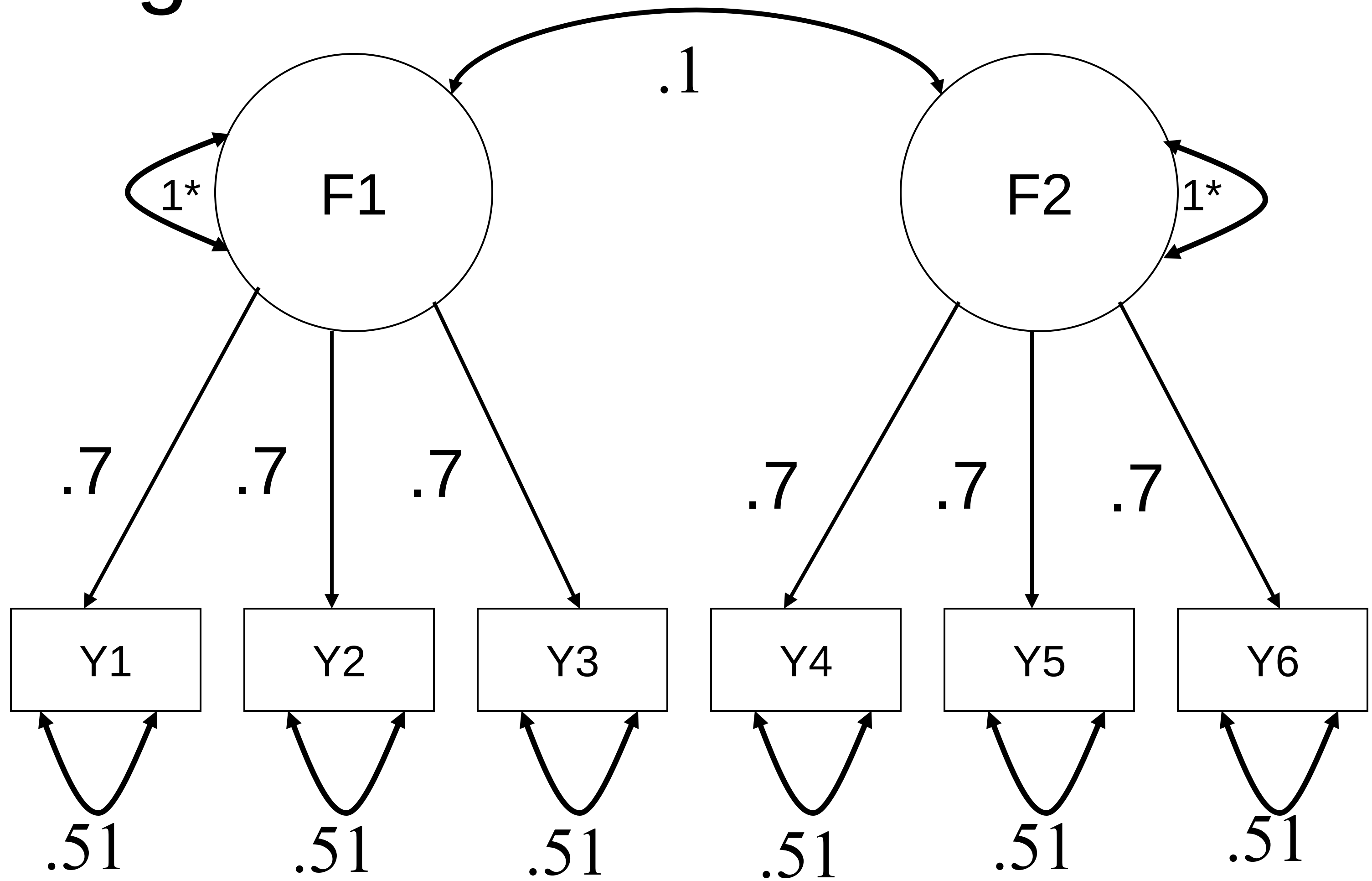

Power
0.0
0.2
0.4
0.6
0.8
1.0
500
1000
1500
2000
Sample Size

Example 2: Planned Missing Data Design

- Investigate power and bias in a 3 form planned missing data design

Form	Common Set X	Variable Set A	Variable Set B	Variable Set C
1	¼ of items	¼ of items	¼ of items	Missing
2	¼ of items	¼ of items	Missing	¼ of items
3	¼ of items	Missing	¼ of items	¼ of items

Example 2: Planned Missing Data Design



Example 2: Planned Missing Data Design

- Planned missing design:
  - X block:Y1 and Y4
  - A block: Y2 and Y5
  - B block: Y3
  - C Block: Y4
- Missing data is handled through 5 imputations in Amelia
- N = 500
- 1000 replications

Example 2: Results

```
========= Fit Indices Cutoffs ============
              0.1      0.05      0.01     0.001      Mean
Chi        14.793    18.995    27.851    43.315     5.420
AIC      7962.256  7986.963  8049.541  8076.073  7846.052
BIC      8042.333  8067.041  8129.618  8156.151  7926.130
RMSEA       0.041     0.052     0.070     0.094     0.010
CFI         0.984     0.974     0.949     0.881     0.996
TLI         0.970     0.951     0.905     0.776     1.014
SRMR        0.041     0.044     0.050     0.056     0.032
```

Example 2: Results

========== Parameter Estimates and Standard Errors =============

	Estimate.Average	Estimate.SD	Average.SE	Power..Not.equal.0.	Std.Est	Std.Est.SD
LY1_1	0.699	0.063	0.060	1.000	0.700	0.055
LY2_1	0.703	0.066	0.067	1.000	0.704	0.055
LY3_1	0.701	0.068	0.067	1.000	0.702	0.056
LY4_2	0.699	0.060	0.061	1.000	0.700	0.052
LY5_2	0.701	0.069	0.067	1.000	0.704	0.057
LY6_2	0.704	0.068	0.067	1.000	0.703	0.055
PS2_1	0.098	0.068	0.067	0.317	0.098	0.068
TE1_1	0.503	0.077	0.073	0.994	0.506	0.078
TE2_2	0.499	0.078	0.076	1.000	0.502	0.077
TE3_3	0.502	0.080	0.076	0.999	0.504	0.079
TE4_4	0.505	0.075	0.073	0.995	0.507	0.074
TE5_5	0.496	0.078	0.076	1.000	0.501	0.079
TE6_6	0.501	0.076	0.077	0.999	0.502	0.077
TY1	0.000	0.045	0.045	0.052	0.000	0.045
TY2	0.001	0.055	0.053	0.061	0.001	0.055
TY3	0.000	0.052	0.053	0.052	0.000	0.052
TY4	0.000	0.044	0.045	0.051	0.000	0.044
TY5	0.000	0.055	0.053	0.061	0.000	0.055
TY6	0.001	0.052	0.053	0.049	0.001	0.052

Example 2: Results

	Average.Param	Average.Bias	Coverage	Average.FMI1	SD.FMI1	Average.FMI2	SD.FMI2
LY1_1	0.70	-0.001	0.939	0.325	0.160	0.356	0.177
LY2_1	0.70	0.003	0.936	0.443	0.168	0.485	0.182
LY3_1	0.70	0.001	0.928	0.446	0.175	0.487	0.190
LY4_2	0.70	-0.001	0.949	0.327	0.163	0.358	0.180
LY5_2	0.70	0.001	0.927	0.447	0.174	0.489	0.188
LY6_2	0.70	0.004	0.936	0.445	0.174	0.487	0.188
PS2_1	0.10	-0.002	0.944	0.218	0.117	0.237	0.131
TE1_1	0.51	-0.007	0.945	0.432	0.181	0.472	0.195
TE2_2	0.51	-0.011	0.941	0.496	0.175	0.541	0.186
TE3_3	0.51	-0.008	0.928	0.498	0.179	0.543	0.191
TE4_4	0.51	-0.005	0.947	0.434	0.185	0.474	0.200
TE5_5	0.51	-0.014	0.918	0.491	0.178	0.535	0.190
TE6_6	0.51	-0.009	0.943	0.499	0.179	0.544	0.191
TY1	0.00	0.000	0.948	0.000	0.000	0.000	0.000
TY2	0.00	0.001	0.939	0.265	0.135	0.290	0.151
TY3	0.00	0.000	0.948	0.267	0.132	0.292	0.148
TY4	0.00	0.000	0.949	0.000	0.000	0.000	0.000
TY5	0.00	0.000	0.939	0.273	0.133	0.299	0.149
TY6	0.00	0.001	0.951	0.271	0.131	0.296	0.147

Some Future Plans

- Multiple group models (coming soon!)
- Categorical indicators
- Multilevel SEM
- Non-linear constraints
- Additional analysis (e.g., OpenMx) and imputation packages (e.g, Mice)
- Latent interactions
- Syntax entry

Also…

- Another R package that may interest R users familiar with SEM
- semTools
  - Useful tools for conducting SEM in R
    - e.g., runMI, imputes missing data, runs each imputed data set, and combines results
  - An open source, community supported package
    - Have an idea for a function? Or a way to improve an existing function? Let us know!

Thank you. Questions?

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simsem: simsem.org
example code available at: simsem.org
email: schoemann@ku.edu

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