Machine Learning Structural Equation Modeling and Falsificatory Data Analysis

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Conclusion

- Confirmatory and Exploratory Data Analysis are about what **is** out there
- Falsificatory Data Analysis is about what **is not** out there
- 3 Claims:
  1. FDA side-steps the problem of over-fitting
  2. ML-SEM has no equal in performing FDA
  3. FDA: Advance theories through their *Zone of Impossibility*

Today's Outline

1. What is Machine Learning? Causal Modeling? Predictive Modeling?
2. Machine Learning Structural Equation Modelling
3. Falsificatory Data Analysis
4. I-GSCA Trees and Falsificatory Data Analysis

1. What is Machine Learning? Causal Modeling? Predictive Modeling?

I. Concepts: Causal vs. Predictive Modeling
II. Archetypes of Causal Modeling
III. Pros/Cons of Causal Modeling
IV. Archetypes of Predictive Modeling
V. Pros/Cons of Predictive Modeling

I. Concepts: Causal vs. Predictive Modeling

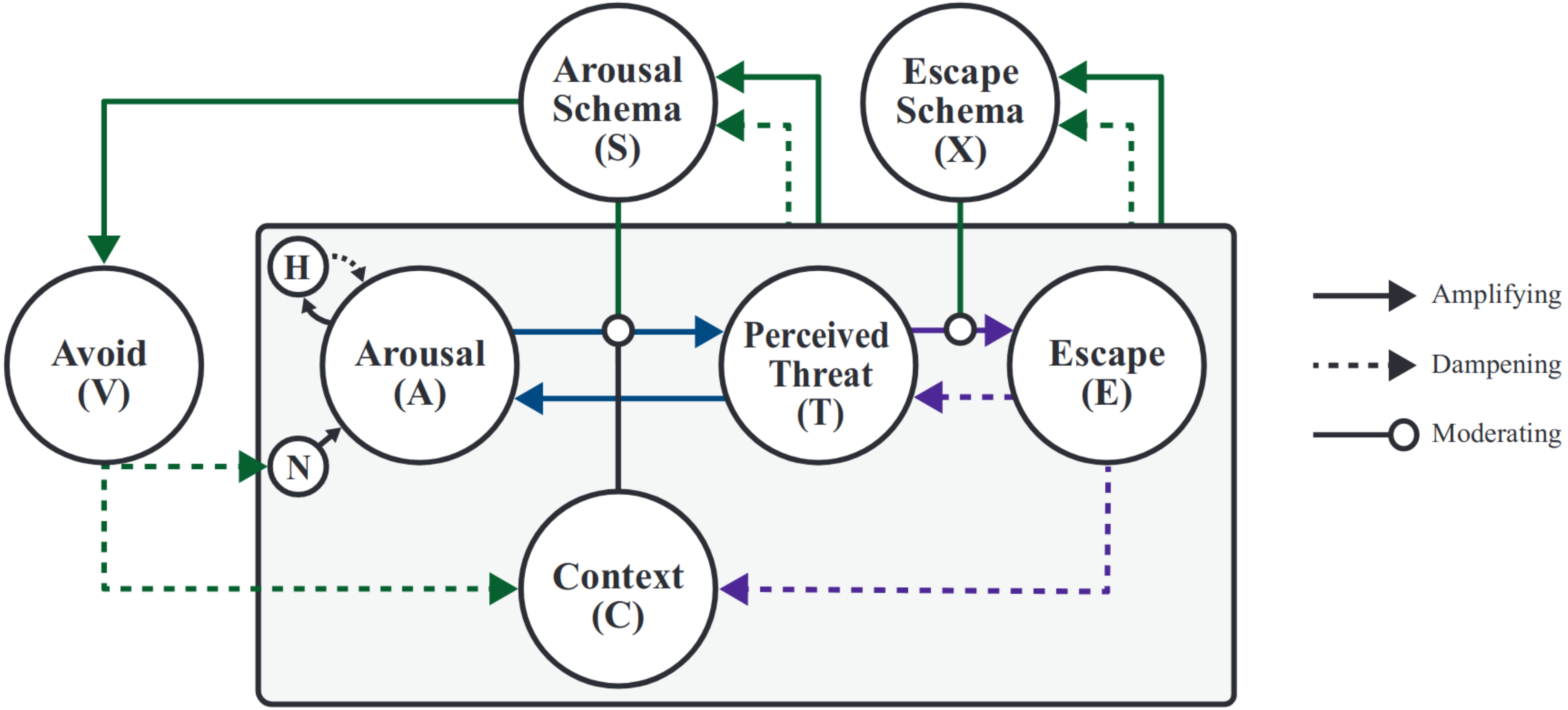
- Causal Modeling:
  - Change *X*, *Y* change?
- Predictive Modeling:
  - See *X*, *Y* is?

- Roughly, predictive modelling trades (**1**) mechanistic plausibility and interpretability for (**2**) utility and replicability
  - Neuro-genetic cognitive causal model to explain binge drinking @ 16
  - *Smoking @ 14 to predict binge drinking @ 16*

Pearl and Mackenzie, 2018; Shmueli, 2010; Yarkoni & Westfall, 2017

II. Archetypes of Causal Modeling

Causal Diagram (ABM) for Panic Stress Disorder



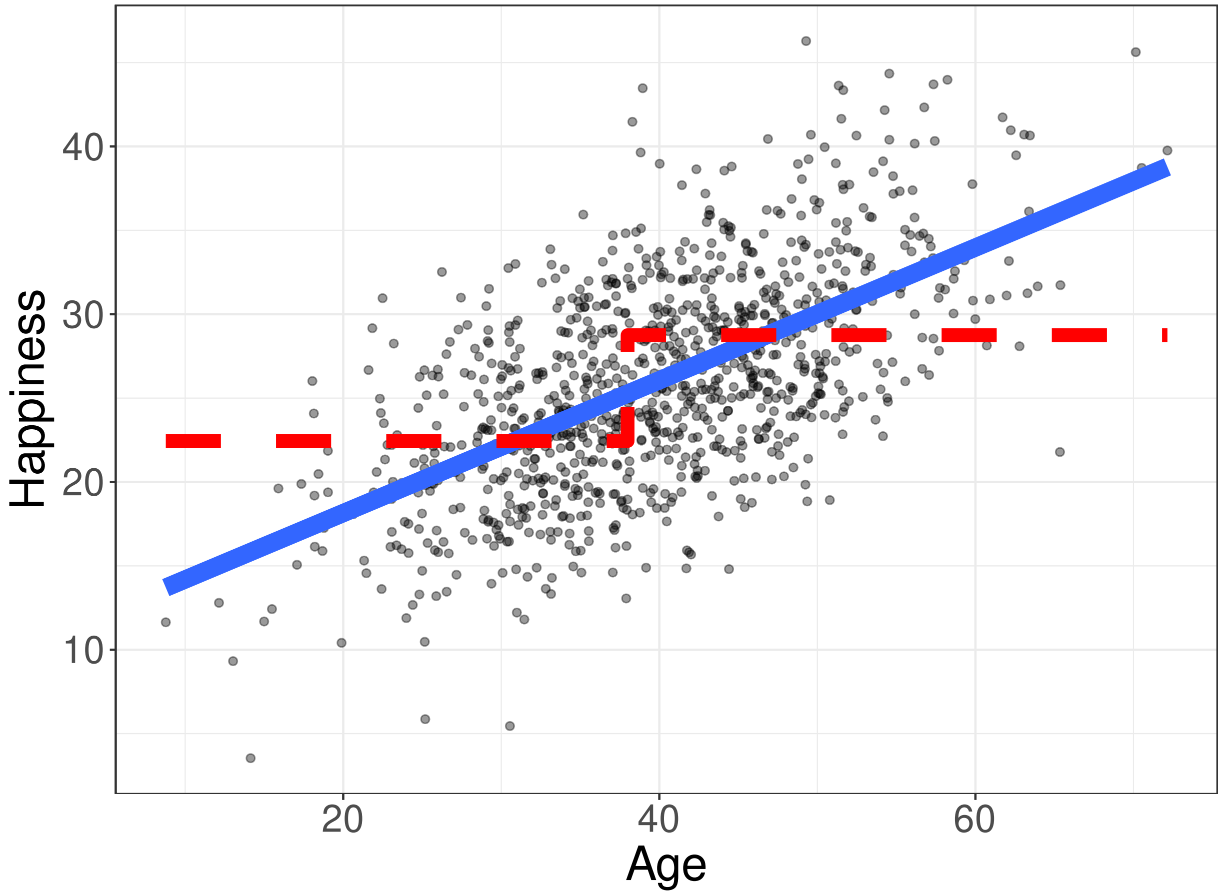
(N: Noise; H: Homeostatic Feedback)

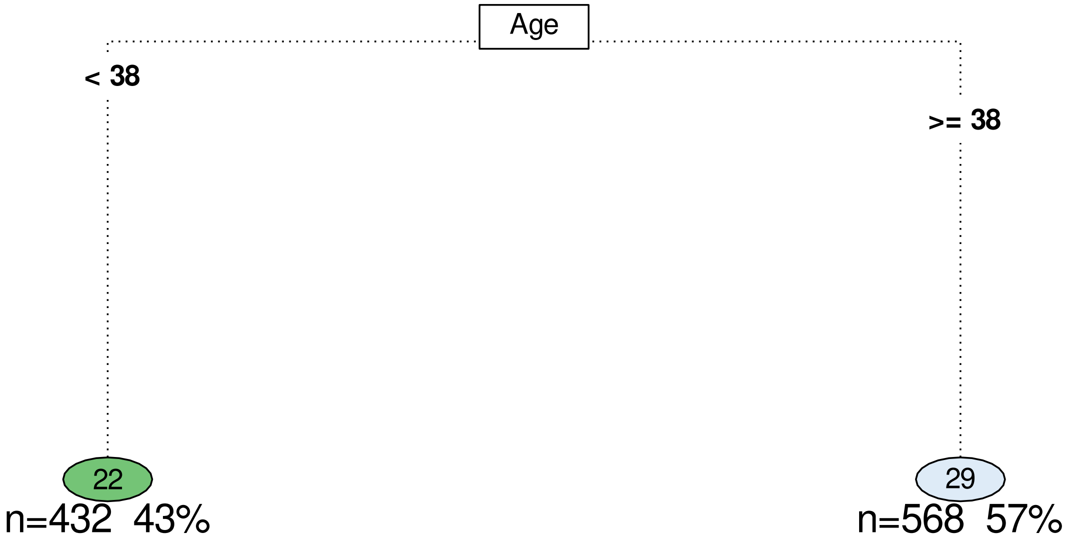
Robinaugh et al. 2019, Figure 1

III. Pros/Cons of Causal Modeling

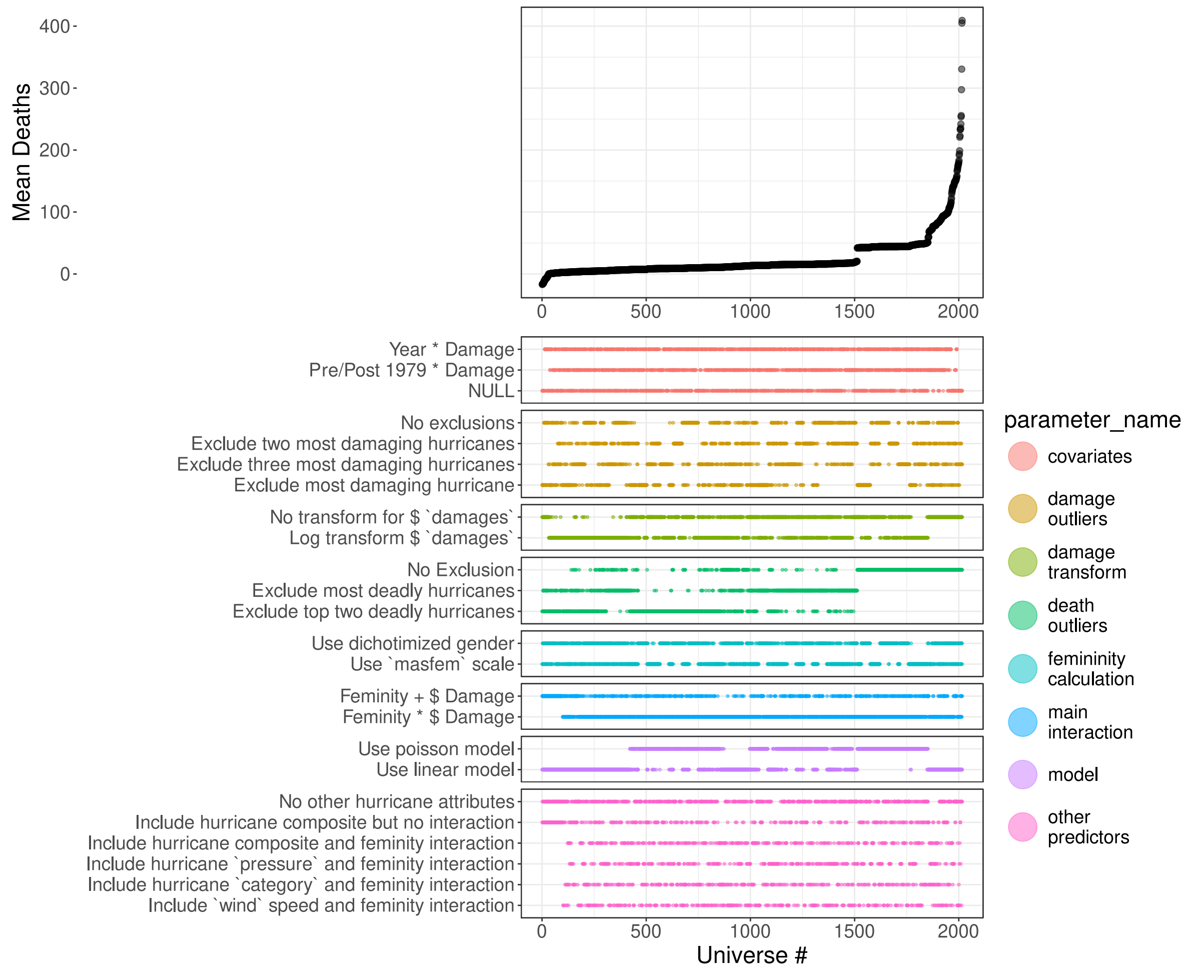
- Pros
  - Logical coherence between different datasets
  - Understanding
  - Successful Intervention
- Cons
  - Weak theory, weak model
  - N < J is tough
  - Measurability of relevant constructs?

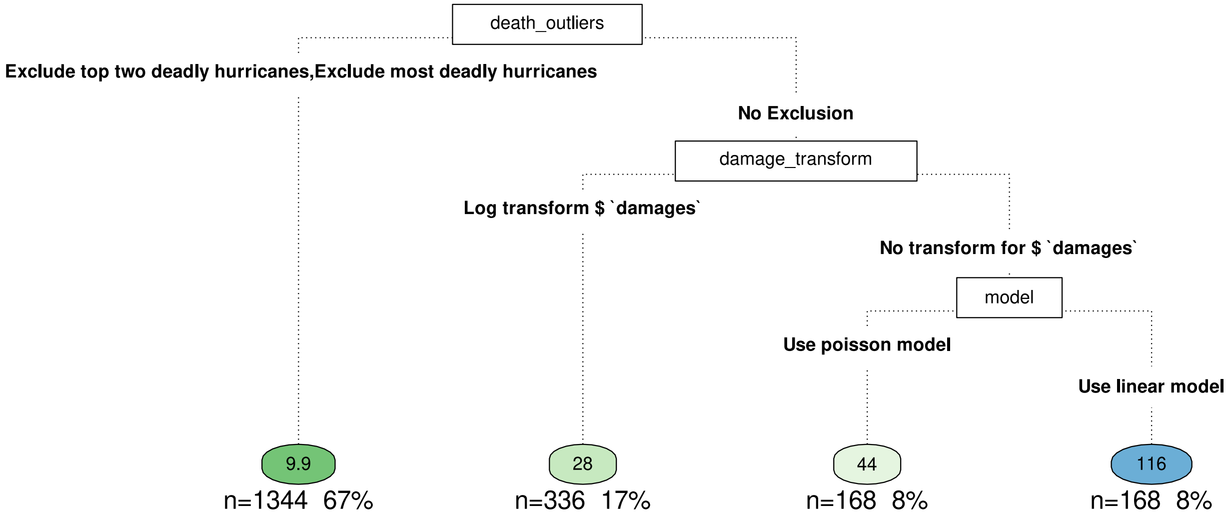
IVA. Archetypes of Predictive Modeling





IVB. Archetypes of Predictive Modeling





See our poster for more!

Data and Code Associated with Sarma et al. (2022) based on Jung et al. (2014) and Simonsohn et al. (2020)

V. Pros/Cons of Predictive Modeling

- Pros
  - Replicability
  - Utility
  - Handles N < J
  - Comparable predictive ability to true causal model (Shmueli 2010)
  - Beyond A > B, A < B… to A is *here* and B is *there*: **why**?
- Cons
  - Causally uninterpretable/incorrect (McElreath, 2020; Pearl & Mackenzie, 2018)
  - Interpretability? (c.f., Henninger et al., 2023)

Fuse ML + SEM???

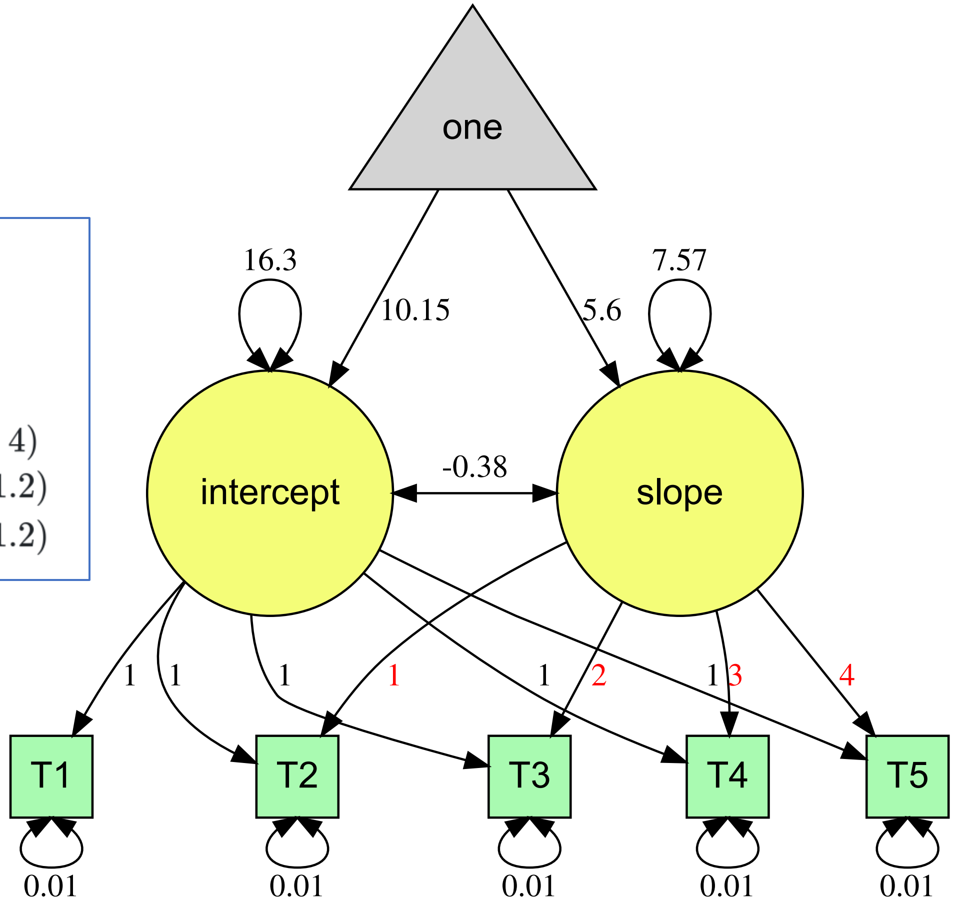
Off-set weaknesses and get best of both worlds for free?!

2. Machine Learning Structural Equation Modelling

I. The Case of SEM Trees
II. I-GSCA
III. I-GSCA Trees
IV. Pace: Capitalizing on Chance

IA. The Case of SEM Trees

$$\begin{aligned} N &= 1000 \\ N_{G1} &\sim 500 \\ N_{G2} &\sim 500 \\ Timepoints &= 5 \\ \beta_0 &\sim N(\mu = 10, \sigma = 4) \\ \beta_{slope(G1)} &\sim N(\mu = 3, \sigma = 1.2) \\ \beta_{slope(G2)} &\sim N(\mu = 8, \sigma = 1.2) \end{aligned}$$

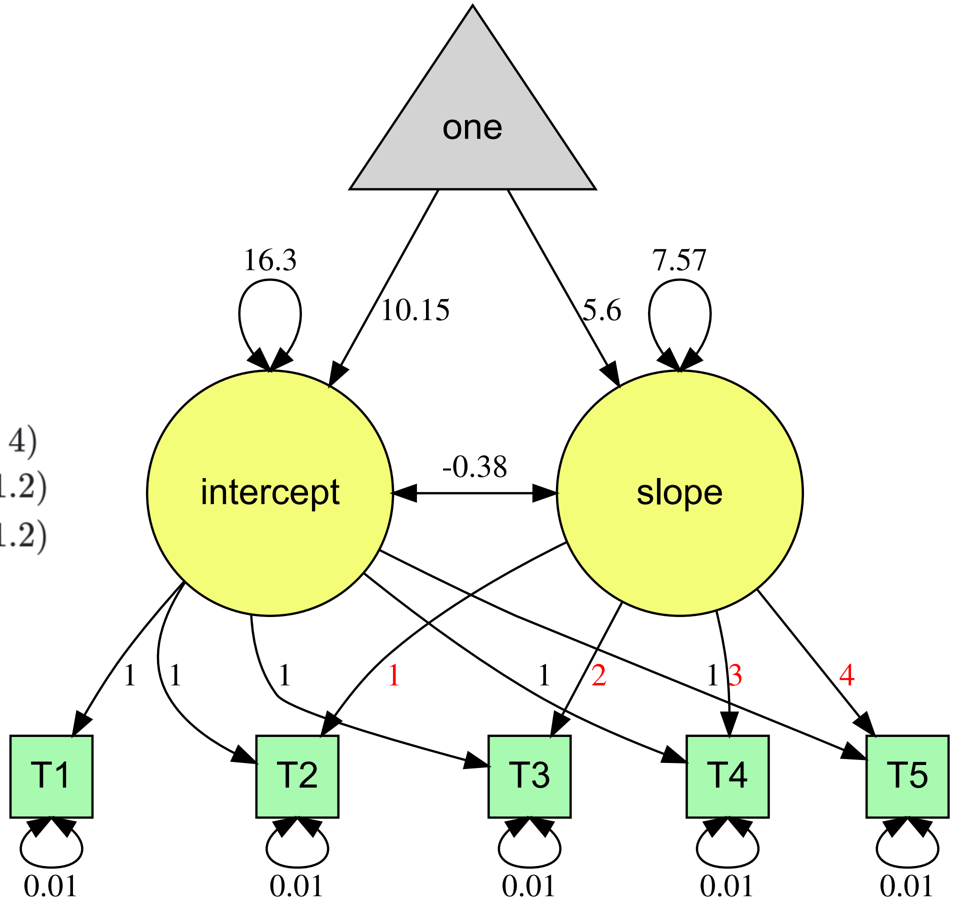


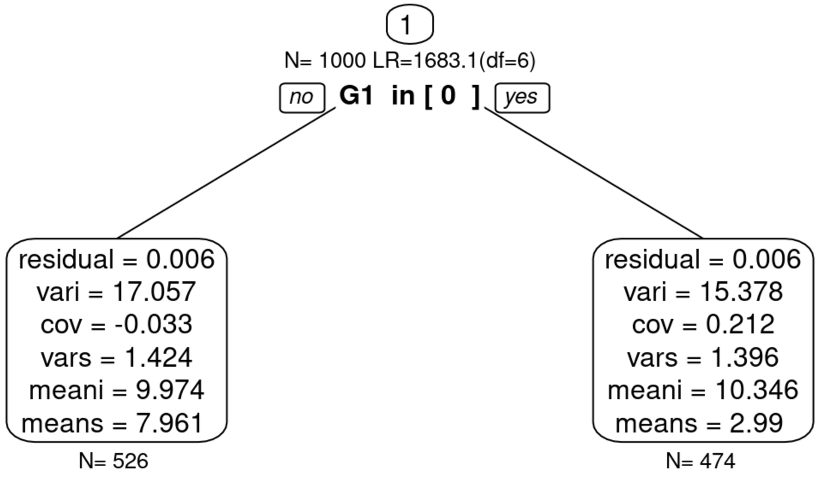
- Use DT to split data on predictor (group)
- Best fitting multi-group model?

semtree vignette: Getting Started with the semtree package

IB. The Case of SEM Trees

$$N = 1000$$
$$N_{G1} \sim 500$$
$$N_{G2} \sim 500$$
$$Timepoints = 5$$
$$\beta_0 \sim N(\mu = 10, \sigma = 4)$$
$$\beta_{slope(G1)} \sim N(\mu = 3, \sigma = 1.2)$$
$$\beta_{slope(G2)} \sim N(\mu = 8, \sigma = 1.2)$$

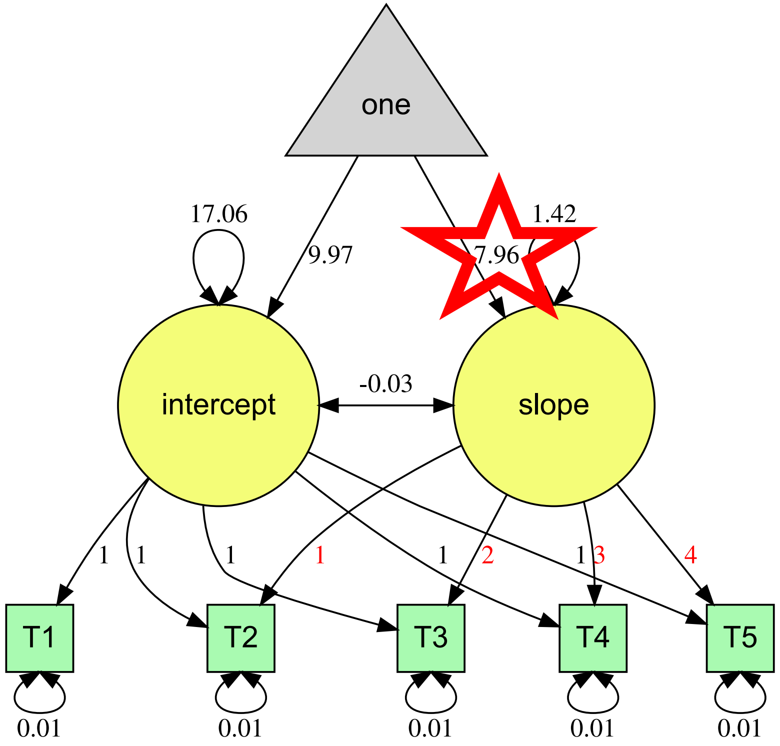


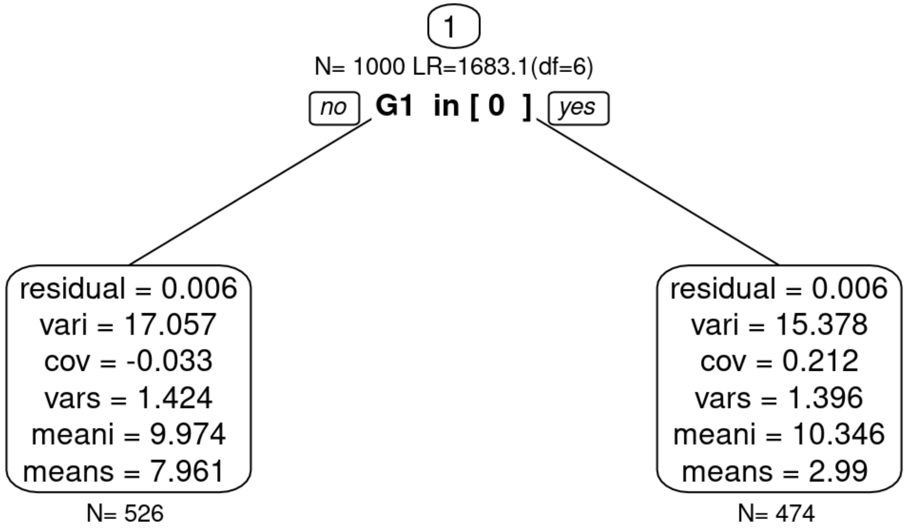


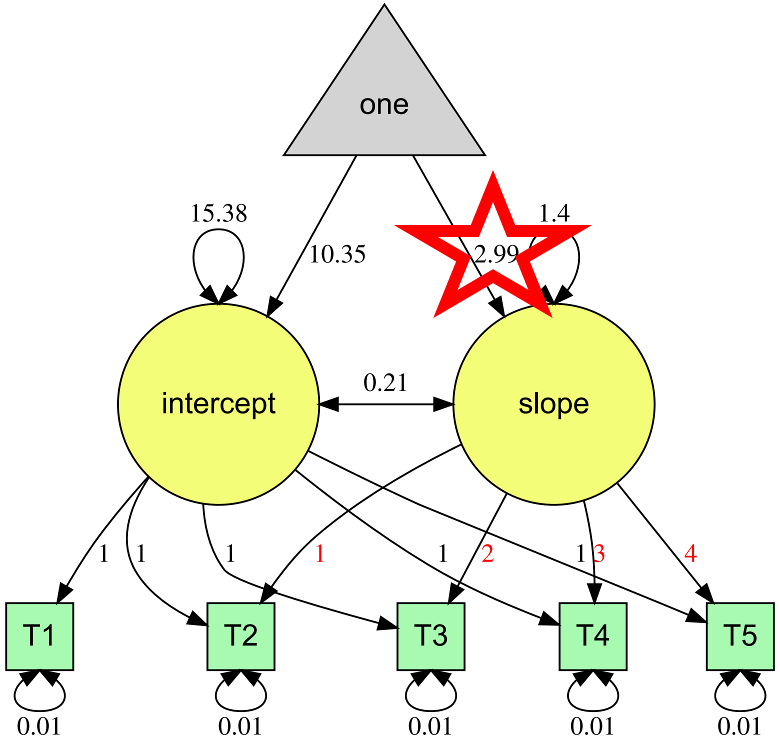
semtree vignette: Getting Started with the semtree package

semtree vignette: Getting Started with the semtree package
Brandmaier et al. (2013B, Equation 4)
Brandmaier & Jacobucci, 2023

IC. The Case of SEM Trees







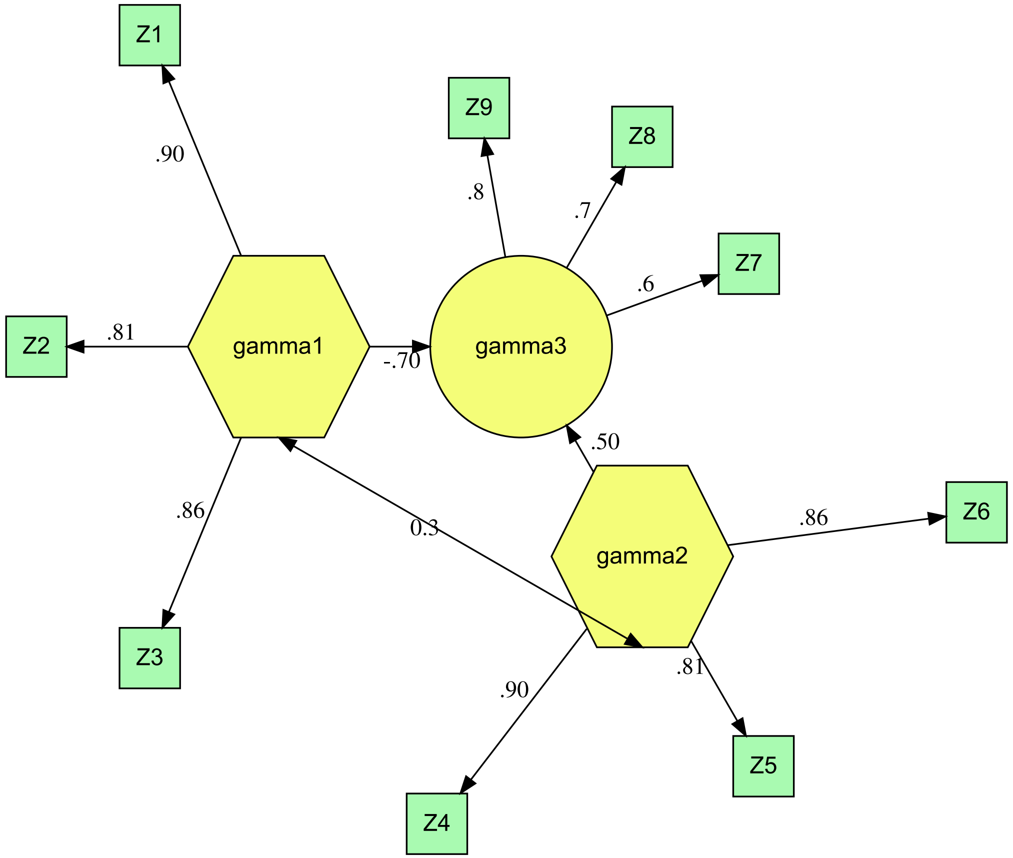
$$\Lambda = \sum_{i=0}^{k} \mathcal{LL}(\hat{\theta}_i | D_i) - \mathcal{LL}(\hat{\theta}_F | D_F)$$

$$\Lambda \sim \chi^2(df = (k-1)m)$$

II. I-GSCA: Integrated-Generalized Structured Component Analysis

- Alternative to CSA

- Combines GSCA and GSCA_m
- Unbiased loadings + paths
- No convergence problems
- Global optimization criterion + FIT statistic



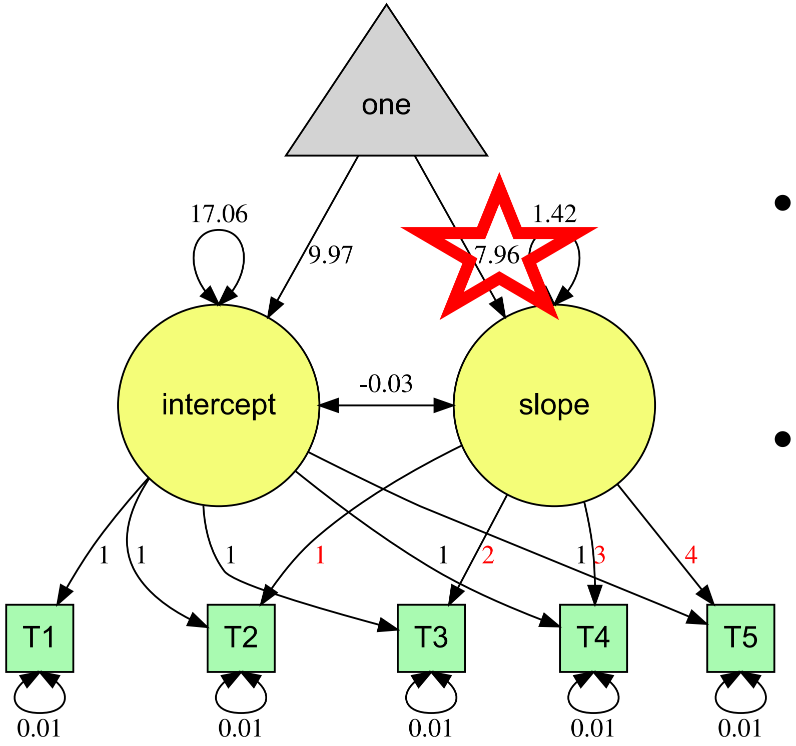
Based on Hwang et al. (2021, Figure 1)

III. I-GSCA Trees

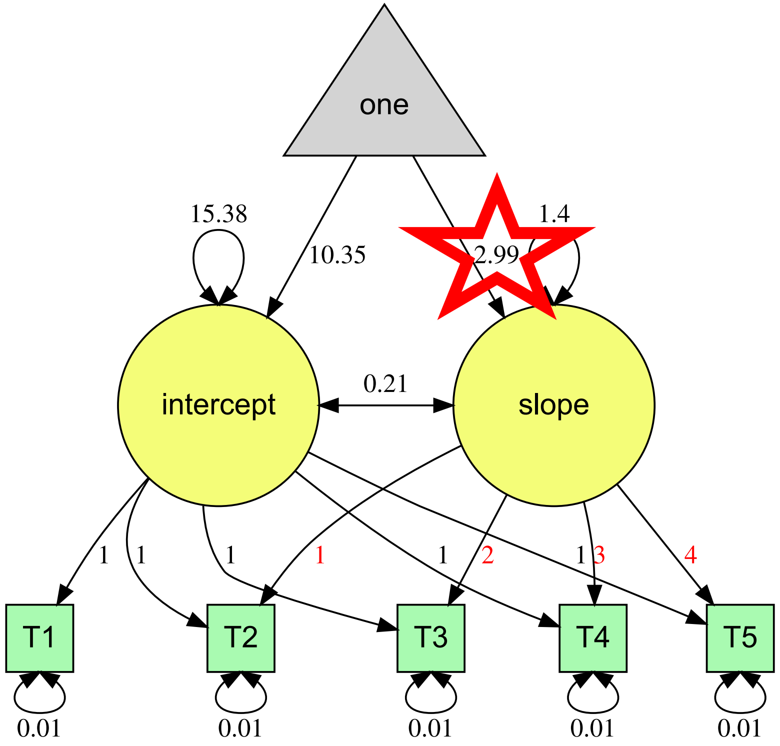
- FIT ~ Proportion of Explained Variance
- Like SEM Trees, choose multi-group models with significantly greater FIT than single group

semtree vignette: Getting Started with the semtree package
Brandmaier & Jacobucci, (2023)
MacCallum et al. (1992)

V. *Pace*: Capitalizing on Chance



- SEM may or may not vary with income, but so what? (c.f., Gelman & Carlin, 2014)
- Technology vs Theoretical purpose
- How many times has the collection of data meaningfully affected psychological theory?



Falsificatory Data Analysis

I. Confirm. Explore! Falsify?
II. Falsificatory Data Analysis' Gambit
III. Related Ideas & Guaranteed Returns

I. Confirm. Explore! Falsify?

- What is out there? Is ____ TRUE?
  - CDA
  - EDA

- *Instead, in FDA*:
  - What do you think is impossible?
  - What do you refuse to believe?
  - What would you need to see to change your mind?
  - When should the data be rejected?

- A theory that says that everything is possible is no theory at all

Similar to Meehl's Description of Popper's Work in 1989 Philosophical Psychology Lectures; terminologically similar, but different from, Gelman's Distinction

II. Falsificatory Data Analysis' Gambit

- Data-driven falsification of causal model: Theory Invariance
  - Predictors and Anti-Predictors
  - Height varies by country… But difference by a factor of 100X?
    - Unit conversion error? Cm to M?
    - Willingness to say that the data is incorrect and must be thrown away
    - Scientific grounds, not statistical

- Advance theories through their *Zone of Impossibility*
  - *Gambit*: Zone of Impossibility is much smaller than Zone of Possibility
  - Claim: Zone of Impossibility != Conditions for Refutation
  - Advantage: Focusing on impossible observations emphasizes link between theory and observation, not theory and statistics

These ideas are similar to those in Becker et al. (2013), but these are more extreme

III. Related Ideas & Guaranteed Returns

- Related Ideas
    - Equivalence Testing
    - Regression Diagnostics
    - Exploratory Data Analysis

- Guaranteed Minimum: Data Quality Checks
    - Number of measurements
    - Unit conversion error
    - Measurement validity
    - *Becker et al. (2013)*

I-GSCA Trees and Falsificatory Data Analysis

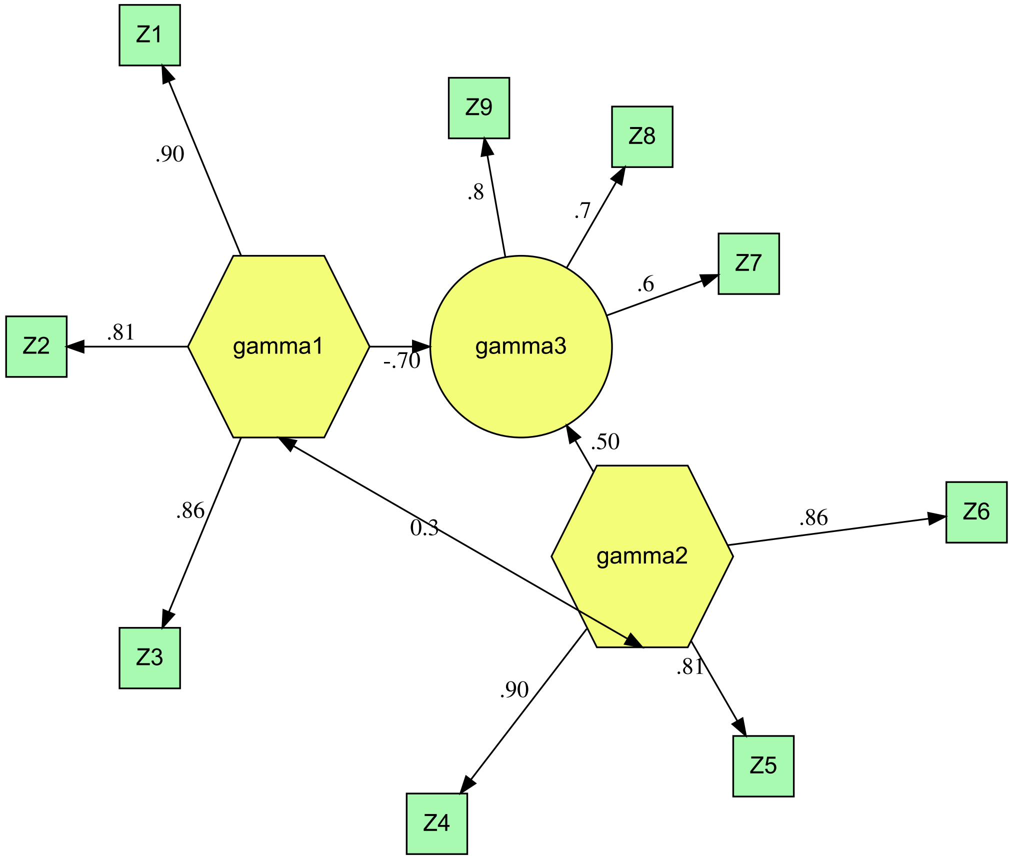
1. Monte Carlo Simulation
2. How well?
3. Future Directions

I. Monte Carlo Simulation

- Our model should not vary much based on location
  - Anti-Predictor: Location

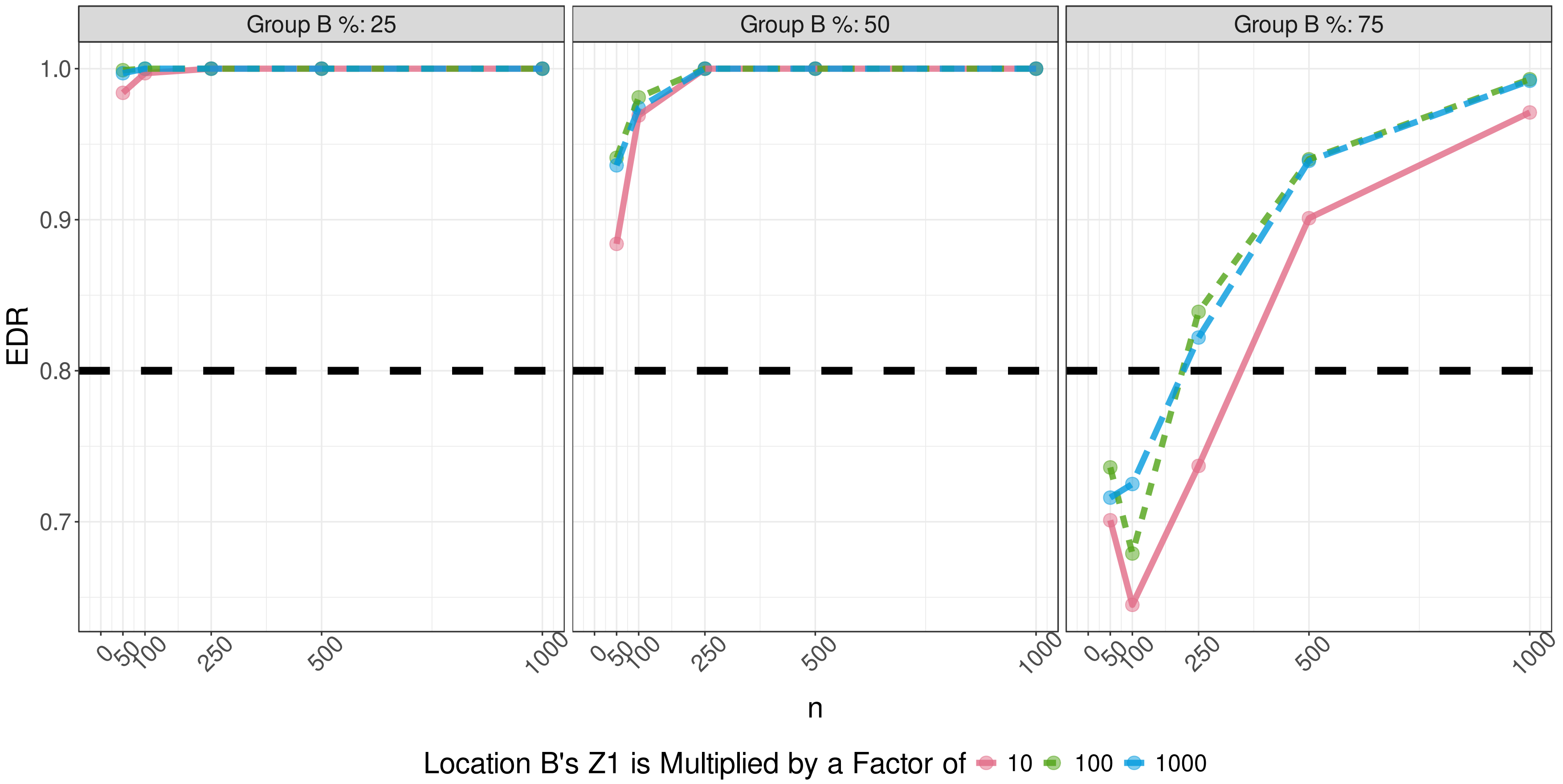
- BUT, data entry error on Z1!

- Generate MVN ~ standardized data
- Random assignment of location
- +5 all indicators
- Multiply Z1 by 1, 10, 100 or 1000



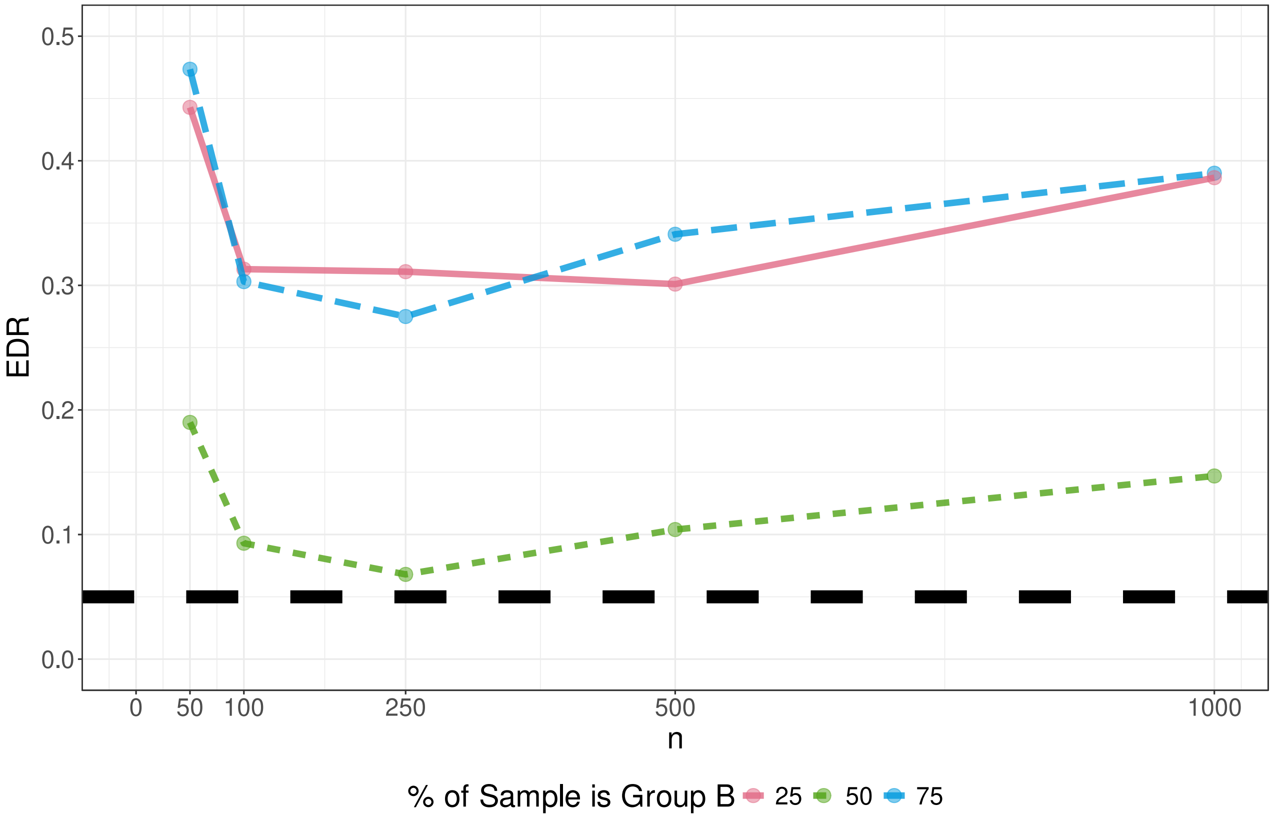
Based on Hwang et al. (2021, Figure 1)

IIA. How well? Power



- Number of digits in unstandardized measurement?
- Stratified Bootstrap?

IIB. How well? Type 1 Error



- Better testing techniques?
- Is the use of significance tests incompatible with FDA?

III. Future Directions – mtruong@yorku.ca

- Falsificatory Data Analysis?
  - Philosophy of Science justifications?
  - Advantages and disadvantages
  - Likely requires counter-induction to be useful
    - *Feyerabend, 2020*
- IGSCA-Trees?
  - Complete implementation in R cSEM Package
    - Rademaker and Schuberth, 2020
  - More extensive MCS, compare with CSA, vary number of digits in unstandardized data
  - Random Forests?
    - *Brandmaier et al., 2016*
  - Better ways of group comparison? Stratified Bootstrapping?
  - Constrained Splits?
    - *Brandmaier et al., 2013*
  - M-Fluctuation Test? Un-Biased Splits?
    - *Hothorn et al., 2006; Strobl et al., 2007; Zeileis & Hornik, 2007*
  - $N < J$: Regularization? Bayes?
    - *Choi & Hwang, 2020; Hwang & Takane, 2014*

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Thanks does not imply endorsement

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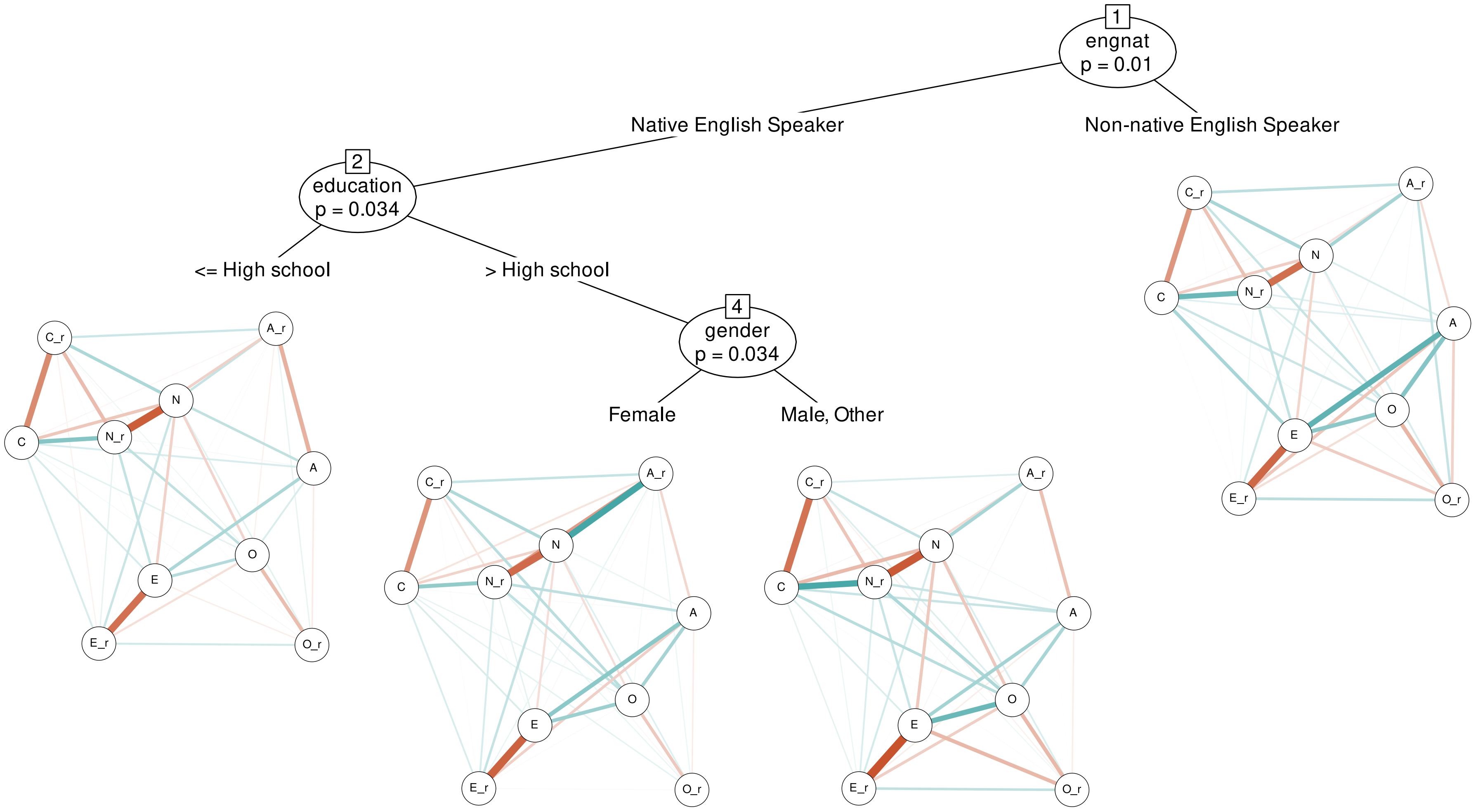
Data Generation Procedure

- Please see Cho and Choi (2020) and Hwang et al. (2021, Appendix B)
- Composite
  - Specify Var-Cov Mx of Indicators
  - Use both largest eigenvalue and parts of Var-Cov Mx to get Weights
  - Use Weights and Var-Cov Mx to get Loadings
- Factor
  - Use specified loadings matrix to get variance of residuals
- Construct Var-Cov Mx
  - Use path-coefficients, and construct covariances to derive Var-Cov Mx
- Population Var-Cov Mx for Indicators
  - Use block-diagonalized loadings Mx, Construct Var-Cov Mx and residual Mxs to get pop var-cov Mx

Results Depend on... Research Assistant???



Jones et al. (2020) and Ten Item Personality Questionnaire Data from Open Psychometrics