

# Focus! SEM Trees and Forests for Identifying Moderators in Structural Equation Models

DAGStat 2025

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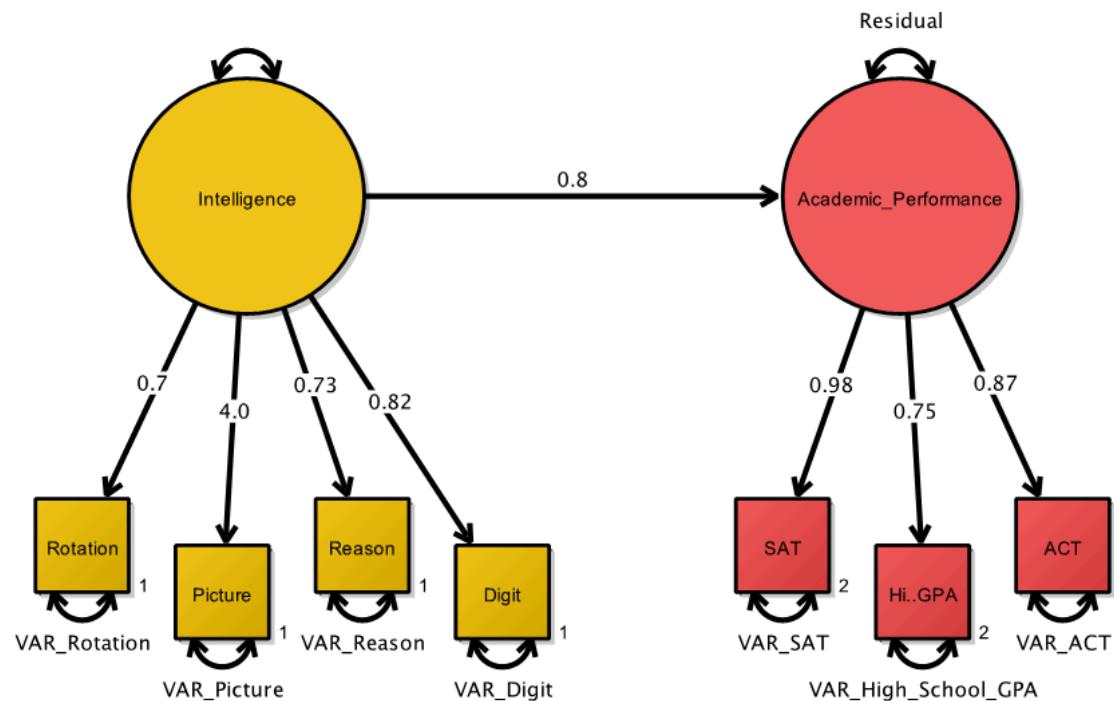
March 27, 2025

**Question: “Given a (theory-based) multivariate model, which predictors/covariates/moderators are relevant?**

# SEM + Decision Trees + Focus Parameters + Random Forests + Variable Importance

Roadmap

# SEM = Structure + Measurement



# SEM

- More formally, we assume that we have  $l$  variables of which  $p$  are latent variables
- In RAM notation, we define:
  - a covariance matrix  $\mathbf{S} \in \mathbb{R}^{l \times l}$  (“symmetric relations”),
  - a structural matrix  $\mathbf{A} \in \mathbb{R}^{l \times l}$  (“asymmetric relations”),
  - and a filter matrix  $\mathbf{F} \in \mathbb{R}^{p \times l}$  to filter out only observed variables

# SEM

Then, the model-implied covariance matrix becomes:

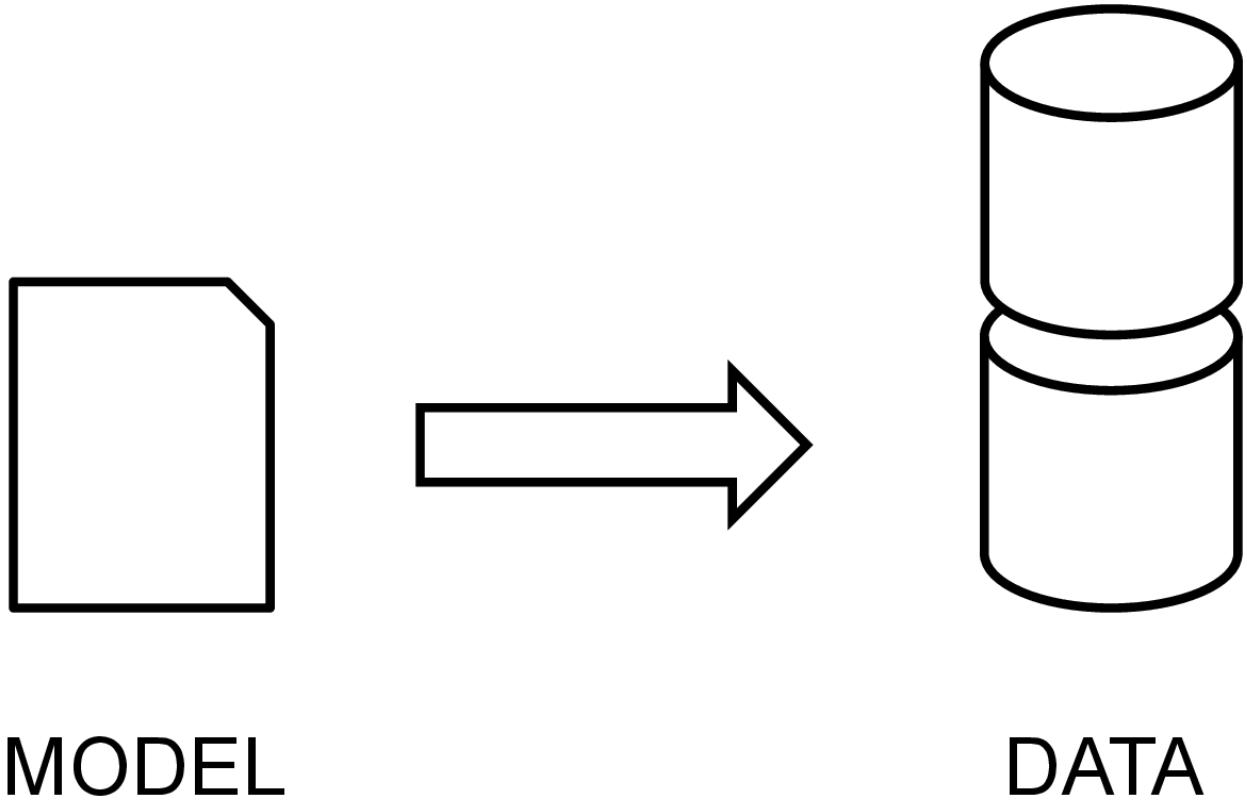
$$\Sigma = \mathbf{F}(\mathbf{I}_l - \mathbf{A})^{-1}\mathbf{S}(\mathbf{I}_l - \mathbf{A})^{-\mathbf{T}}\mathbf{F}^{\mathbf{T}}$$

And (covariance) likelihood fit function (based on multivariate normal assumption) of observed covariance  $S$ :

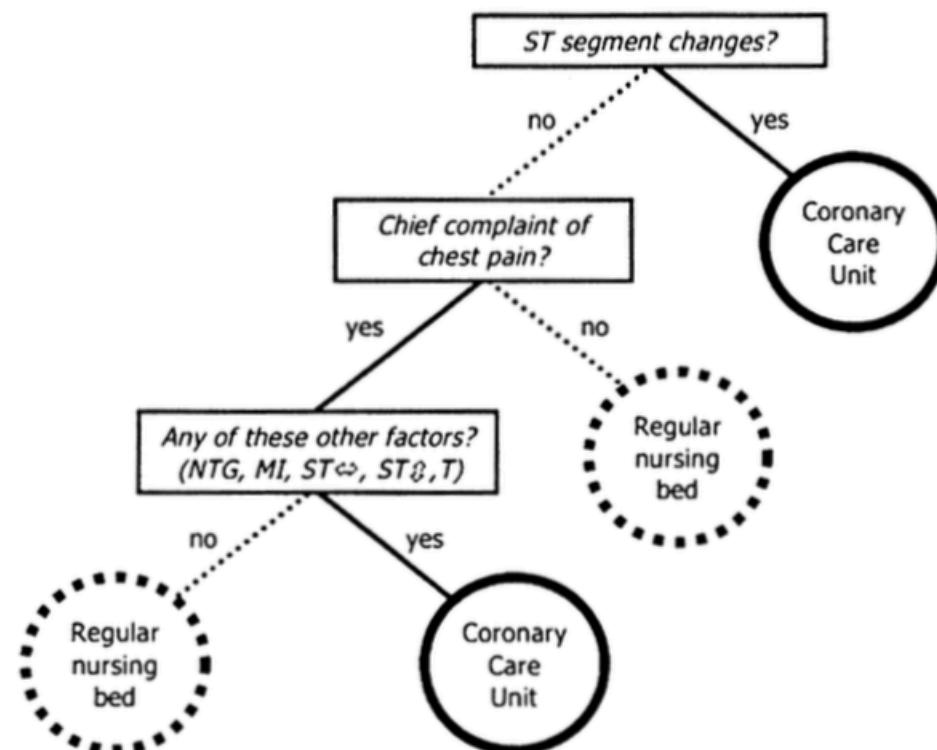
$$-2LL = \ln|\Sigma| + \text{tr}(\Sigma^{-1}\mathbf{S}) - \ln|\mathbf{S}| - p$$

(for multiple independent groups, the log-likelihoods sum up; means omitted here)

# Theory-driven modeling

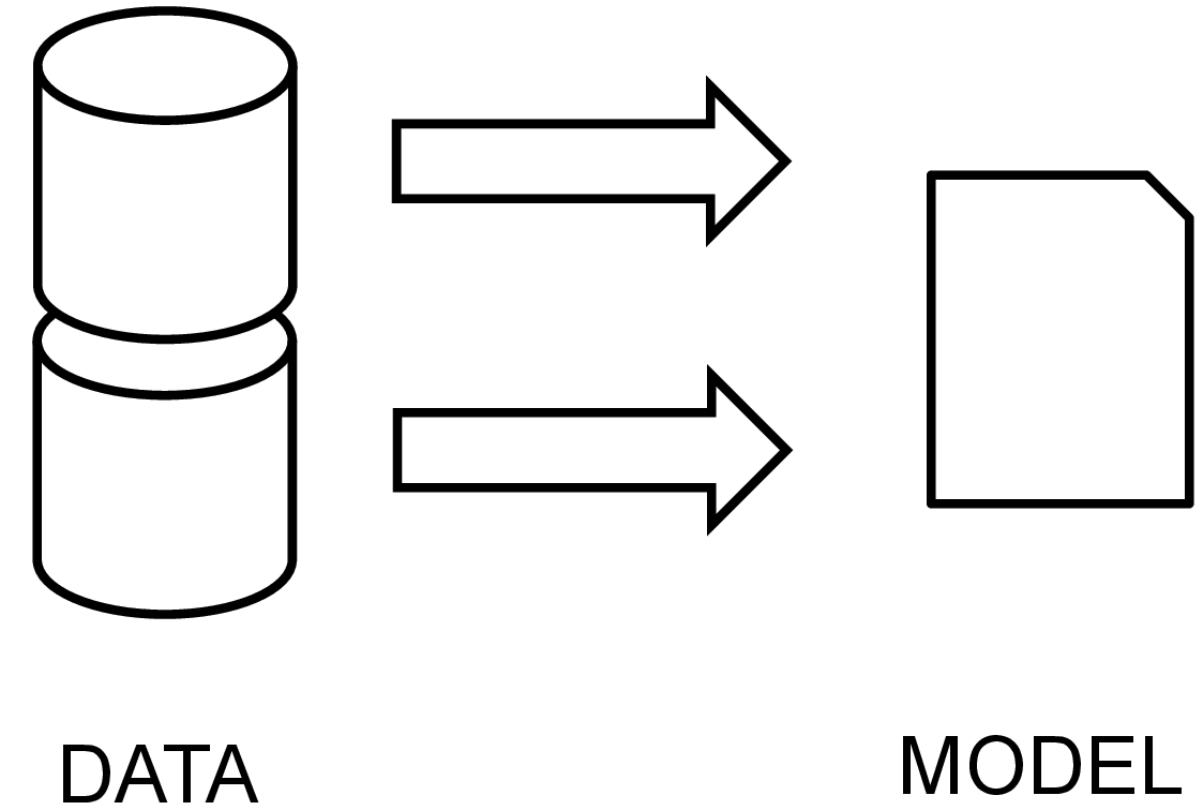


# Decision Trees



Gigerenzer and Kurzenhaeuser (2005)

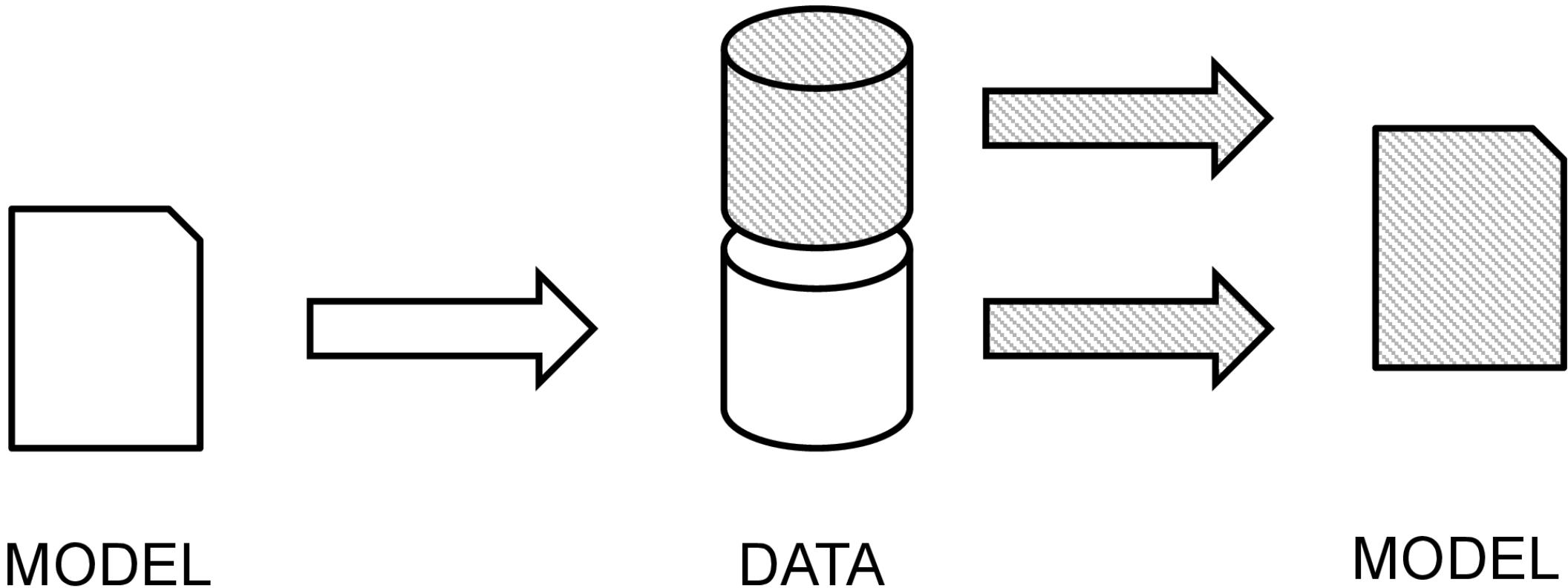
# Data-driven modeling



# SEM Trees

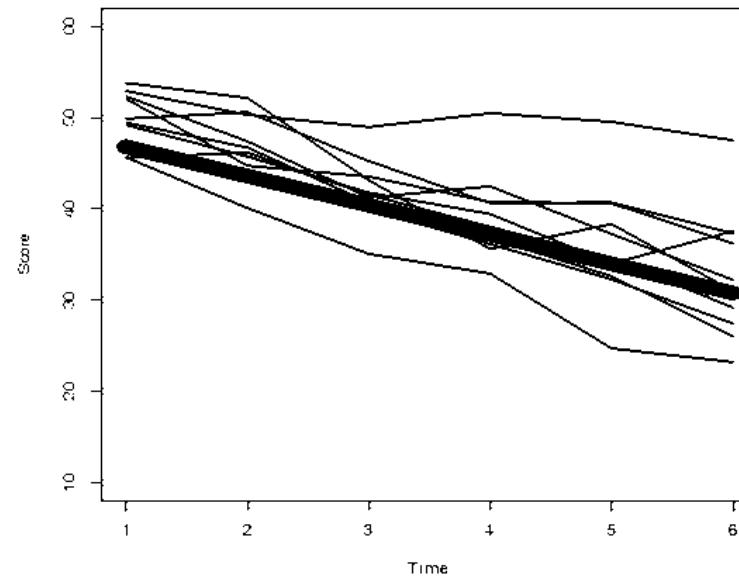
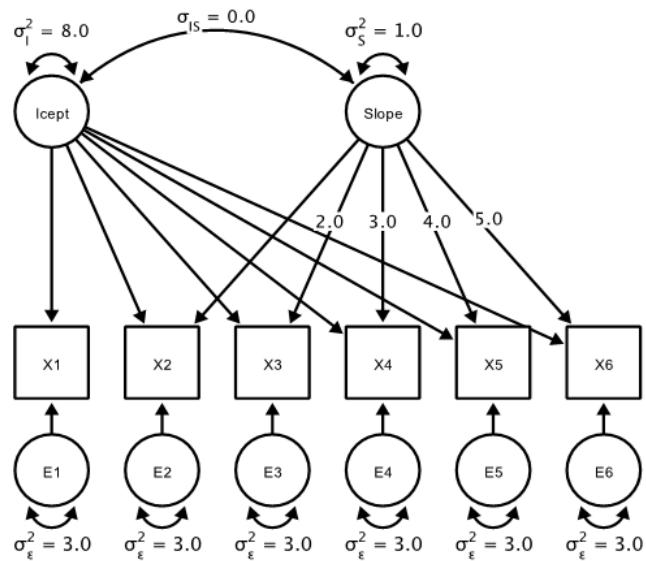
an instance of model-based recursive partitioning (Zeileis, Hothorn, and Hornik, 2008; Brandmaier, von Oertzen, McArdle, and Lindenberger, 2013)

# Theory-guided exploration



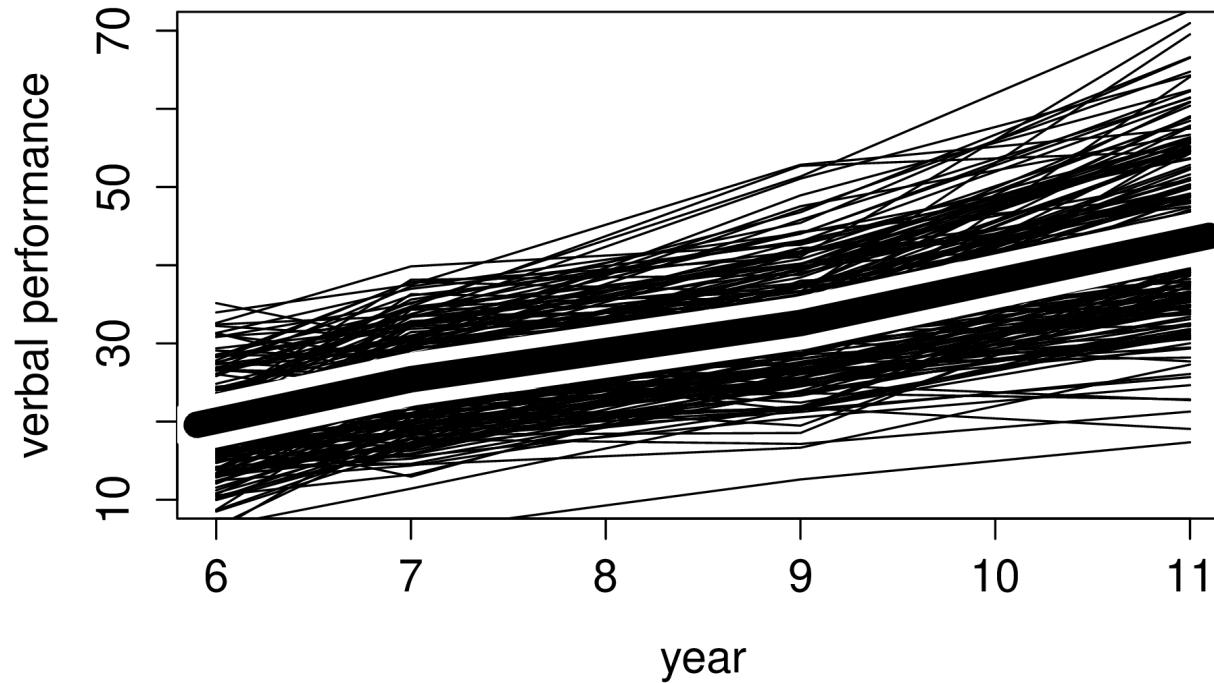
Brandmaier, Prindle, McArdle, and Lindenberger (2016)

# A Simple Example: Wechsler Intelligence Scale for Children



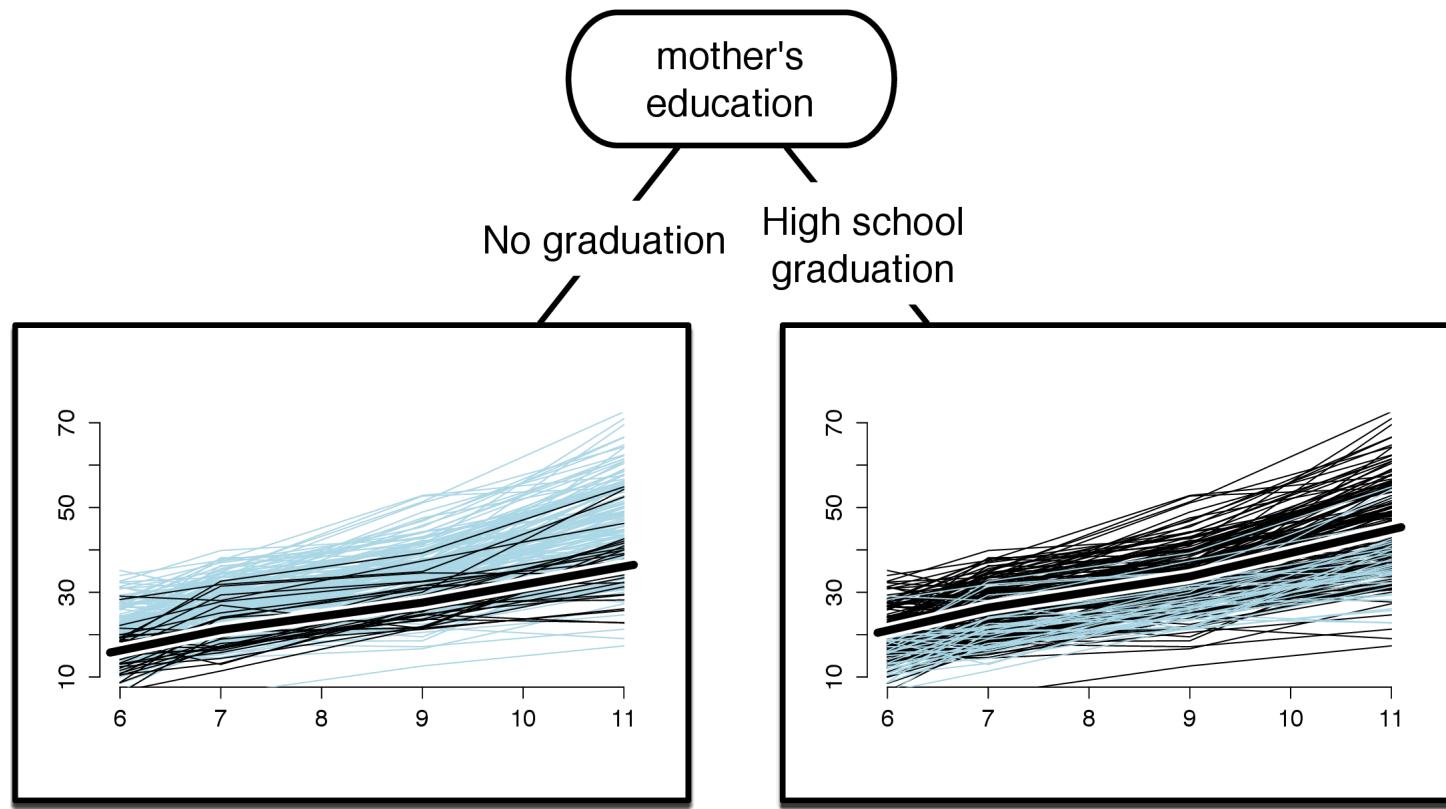
Brandmaier, von Oertzen, McArdle et al. (2013)

# A Simple Example: WISC

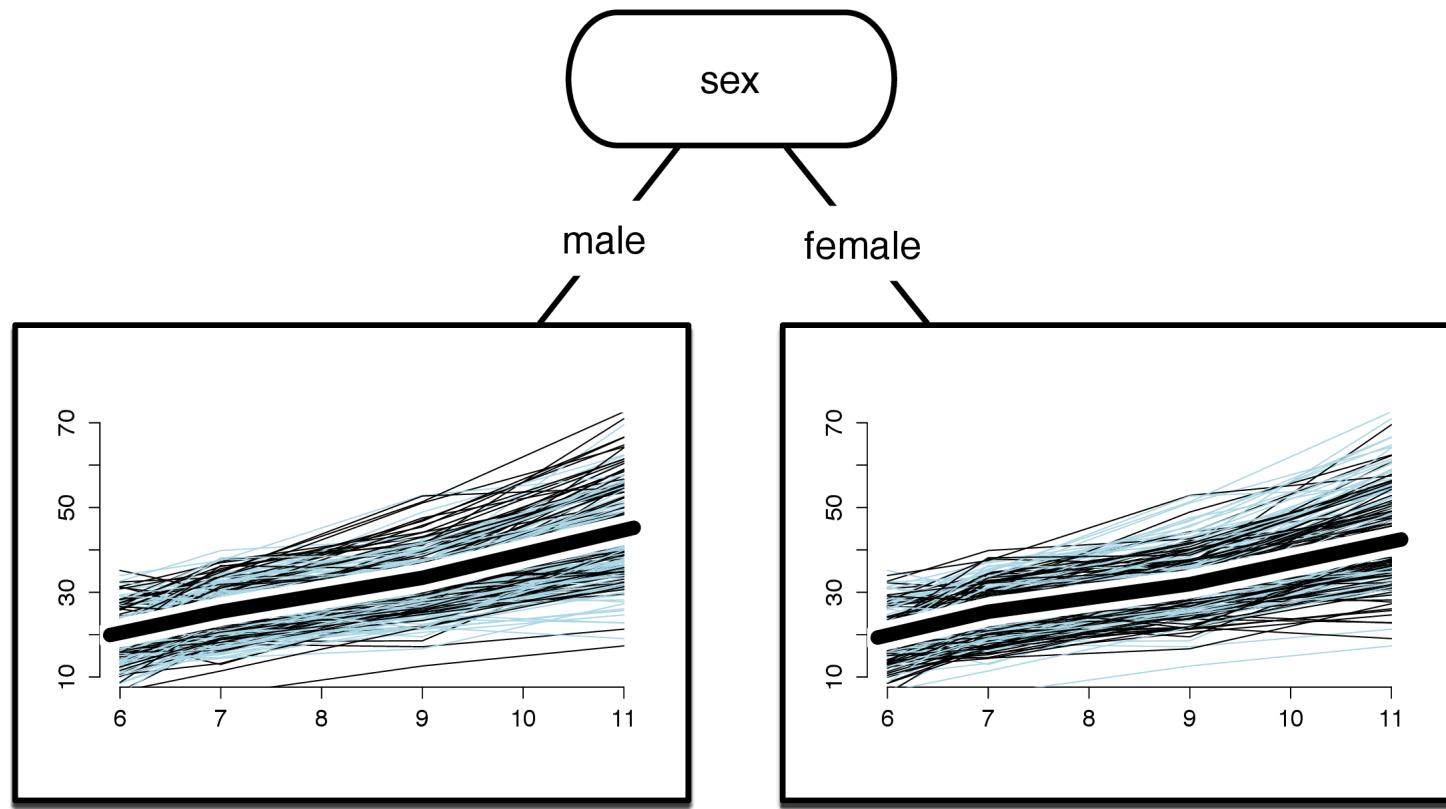


N=204 children, McArdle & Epstein, 1987

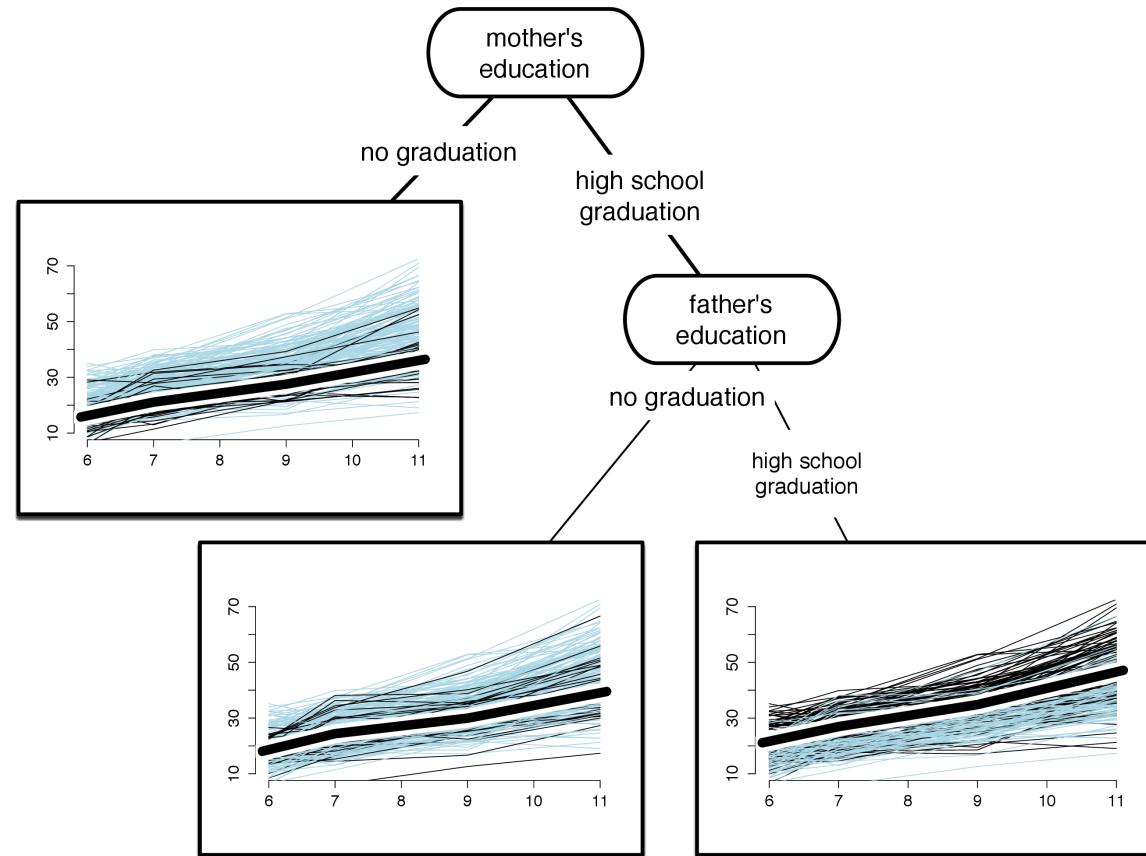
# A Simple Example: WISC



# A Simple Example: WISC



# A Simple Example: WISC



# What do splits represent?

Splits in an LGCM may represent any combination of:

- Differences in mean within-person changes
- Differences in interindividual differences in within-person change
- Differences in the mean of the intercept
- Differences in interindividual differences in the intercept
- Differences in the correlation of intercept and within-person change
- Differences in reliability or growth curve misfit (differences in measurement error as part of the model residual variance)

# Evaluating Splits in (SEM) Trees

# Testing for group differences

Brandmaier, von Oertzen, McArdle et al. (2013) proposed old-school likelihood ratio test for *split selection*:

Given a parametric model  $M$  with ML parameter estimates  $\hat{\theta}$  and data  $X$ , which is exhaustively split into  $X_1$  and  $X_2$  with corresponding maximum likelihood estimates  $\hat{\theta}_1$  and  $\hat{\theta}_2$ :

$$LR = -2LL\left(X_1|M(\hat{\theta}_1)\right) - 2LL\left(X_2|M(\hat{\theta}_2)\right) + 2LL\left(X|\hat{\theta}\right)$$

which is asymptotically  $\chi^2$ -distributed if  $H_0$  is true (i.e., no group differences) with  $df = \dim(\theta)$

# Split selection

- Starting at the root of a tree, find best split by greedy search
- Depending on measurement scale
  - all possible split points for ordinal and metric variables (linear costs)
  - all possible dichotomizations for nominal variables (exponential costs)
- Continue splitting if difference is significant

Effects of interest can be in any subset of model parameters

# Focus parameters with LR tests

For  $\chi^2$ -based tests, instead of:

$$LR = -2LL\left(X_1|M(\hat{\theta}_1)\right) - 2LL\left(X_2|M(\hat{\theta}_2)\right) + 2LL\left(X|\hat{\theta}\right)$$

we estimate *loss of fit due to constraining only focus parameters* to identity across groups:

$$LR = -2LL\left(X_1 \mid M(\hat{\theta}_1)\right) - 2LL\left(X_2 \mid M(\hat{\theta}_2)\right) - 2LL\left(X_1 \mid M(\hat{\theta}'_1)\right) - 2LL\left(X_2 \mid M(\hat{\theta}'_2)\right)$$

with focus parameters constrained to be identical across groups for  $\theta'_1$  and  $\theta'_2$

# Focus parameters

This is more expensive because we need to obtain maximum likelihood estimates for every possible split:

$$\operatorname{argmin}_{\theta'_1, \theta'_2} -2LL(X_1|M(\theta'_1)) - 2LL(X_2|M(\theta'_2))$$

subject to focus parameters being identical

In total, we need one more iterative optimization process per each potential split point (with potentially more convergence issues)

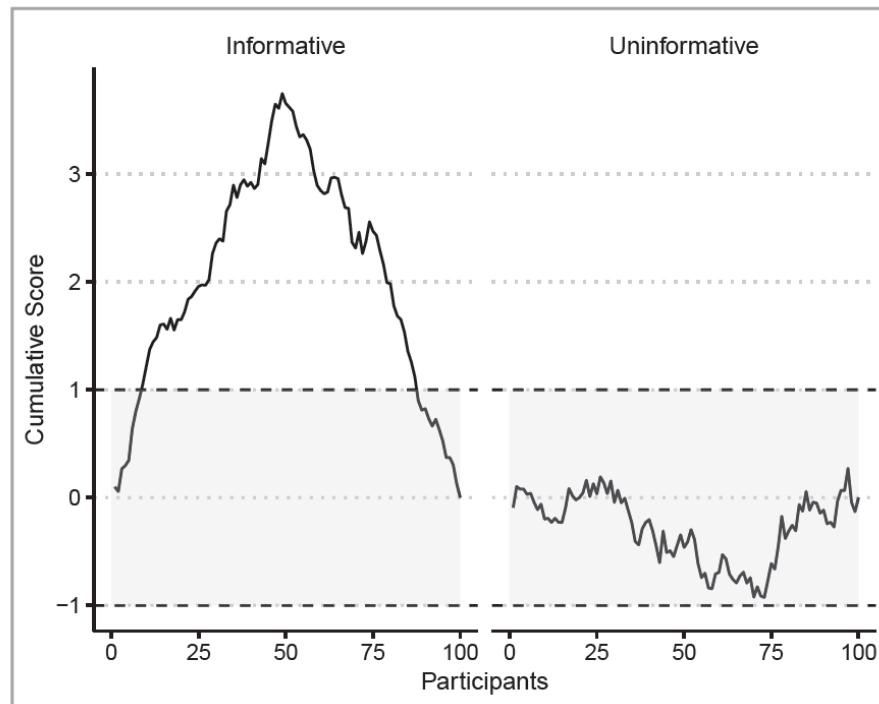


# Score-based Tests

- Likelihood ratio tests are computationally expensive, we get convergence problems, naive LR test suffer from multiple testing issues and variable selection bias like CART (Strobl, Boulesteix, Zeileis, and Hothorn, 2007)
- Let's use score tests (proposed for general model-based partitioning by Zeileis, Hothorn, and Hornik (2008))



# Score-based Tests

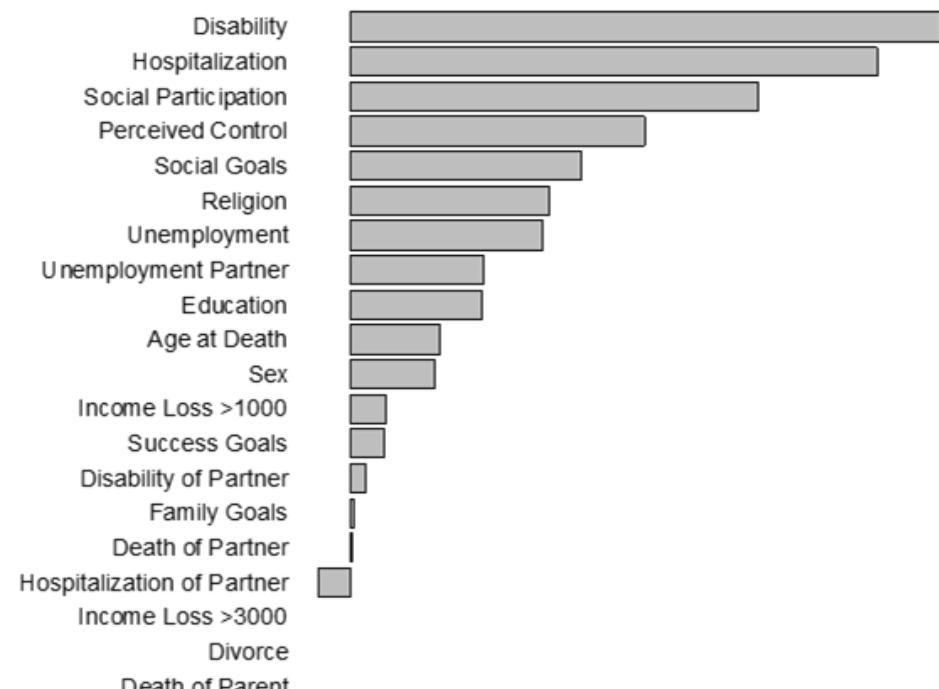


- Score based test statistics are functions of the case-wise derivatives of the (log)likelihood function
- Backbone of MOB in `party/partykit` and were also brought to SEM trees by (Arnold, Voelkle, and Brandmaier, 2021)
- Under H<sub>0</sub> (no informative split), the cumulative score process is a Brownian bridge
- Various statistics available (e.g. maximum Lagrange multiplier *maxLM*; double maximum for illustration on the left)
- By computing them on subsets of parameters, we get *focus parameters* for free

# Variable Importance

- Single trees are unstable
- Subsample data and predictors to create a forest with diverse predictor combinations
- Using a permutation approach, estimate contribution of each predictor to misfit (Brandmaier, Prindle, McArdle et al., 2016)
- ...but beware of marginal importance; (Strobl, Boulesteix, Kneib, Augustin, and Zeileis, 2008)

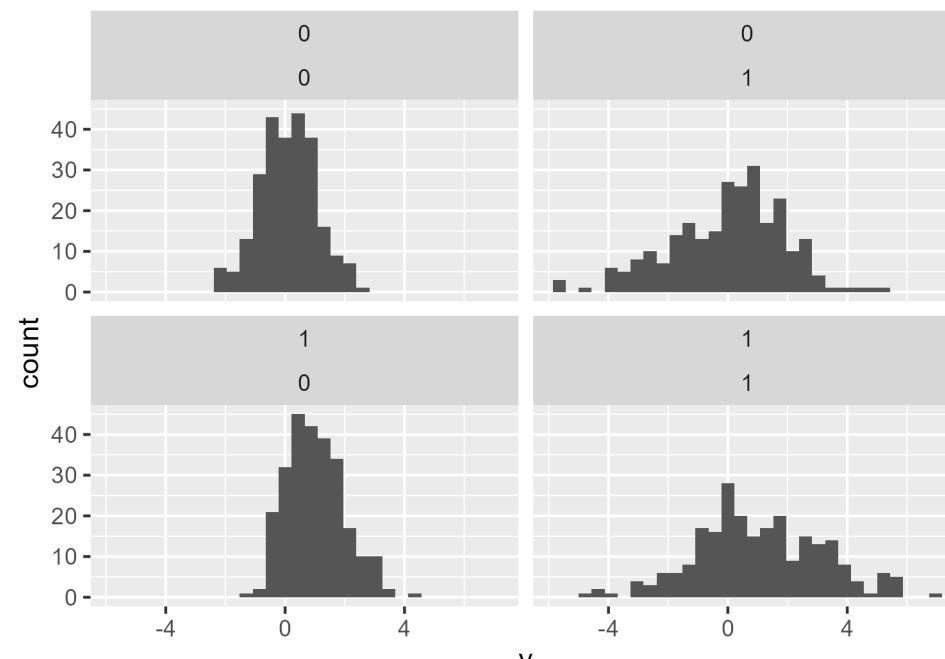
Example: Terminal decline of happiness from SOEP data (Brandmaier, Ram, Wagner, and Gerstorf, 2017)



# A minimal example

# Univariate predictions

Let's simulate some Gaussian data and two dichotomous predictors `pred_mean` and `pred_var` that perfectly predict differences in either location (0 vs 1) or scale (1 vs 2). Also, we throw three uninformative predictors in the mix (binomial distributed) and sample 1,000 cases:



# Run a tree

Specify model in OpenMx (or lavaan):

```
sem <- mxModel("Univariate Gaussian",
  type="RAM",  manifestVars="y",
  [ ... ]
  # variance
  mxPath(from=manifests,arrows=2,free=TRUE,
    values = c(1), labels=c("var_y")),
  # means
  mxPath(from="one",to=manifests, arrows=1,free=TRUE,
    values=c(0), labels=c("mean_y")) )
```

# Run a tree

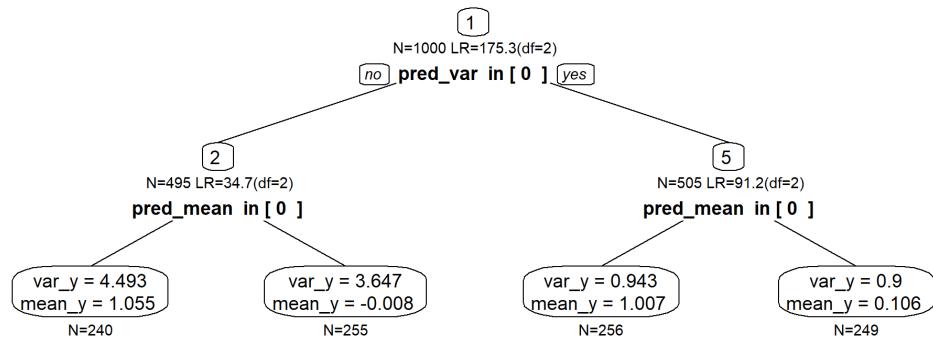
## Run the tree

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sem <- mxModel("Univariate Gaussian",
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  mxPath(from="one", to=manifests, arrows=1, free=TRUE,
    values=c(0), labels=c("mean_y"))

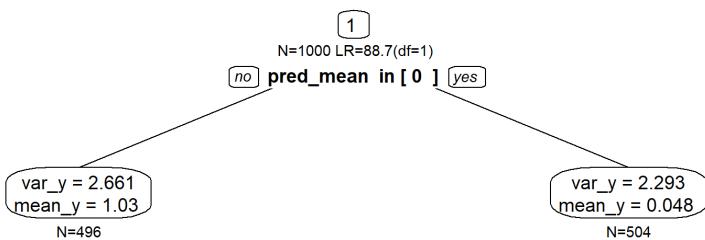
tree <- semtree(sem, simulated_data,
  control=semtree_control(method="score"),
  constraints=semtree.constraints(focus.parameters = "mean_y"))
```

# Tree with and w/o focus

This seems to work...



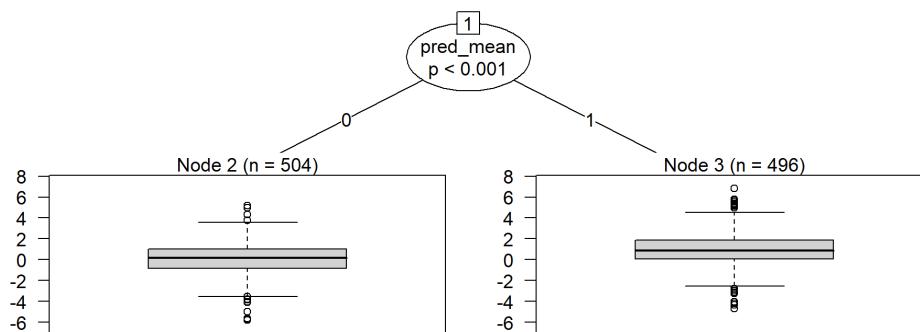
(No focus)



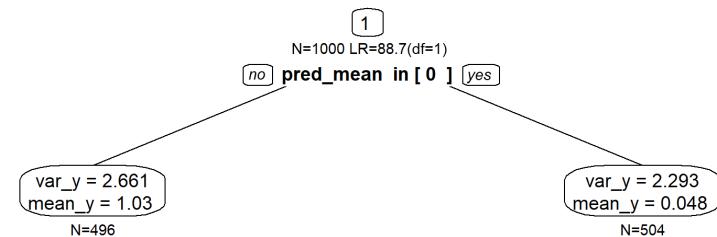
(focus on *mean\_y*)

# To Focus or not to focus

*By the way:* Trees yield identical results in `partykit` and `semtree` (with focus parameter on mean):



made with ❤ by `partykit`



made with ❤ by `semtree`

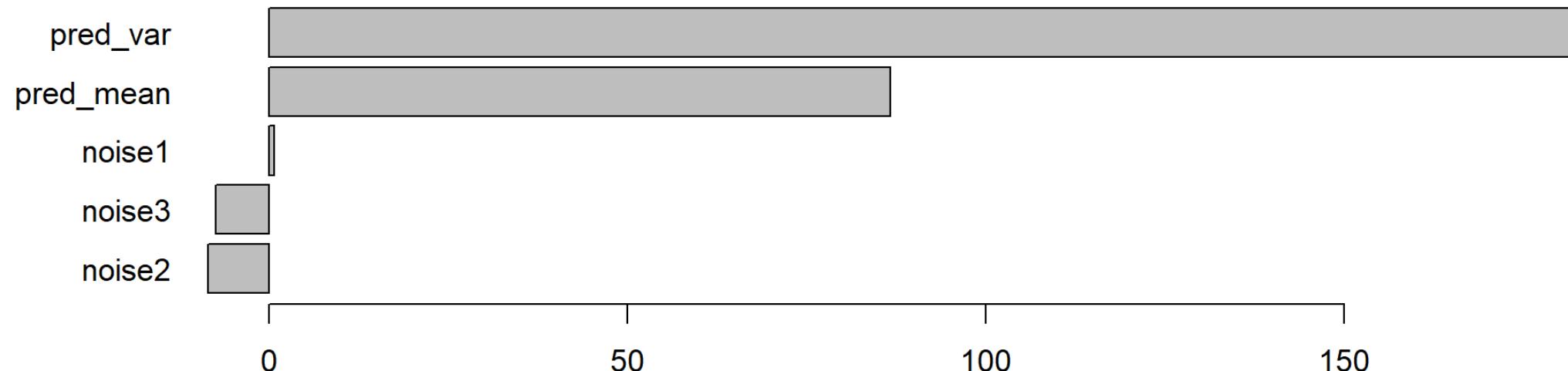
W/o focus: potentially interesting because differences in variances may also be of interest (e.g., meaningful individual differences or reliability differences)

# Run a forest

Run a SEM forest based on a single indicator model with two parameters (mean and variance) again *with focus parameter* and compute variable importance

```
forest <- semforest(sem, simulated_data,  
control=semforest_score_control(num.trees=100),  
constraints=semtree.constraints(focus.parameters = "mean_y"))  
  
vim <- varimp(forest)
```

# (Marginal) Variable importance estimate



This is flawed because the influence of *pred\_var* should be about zero.

# Problem

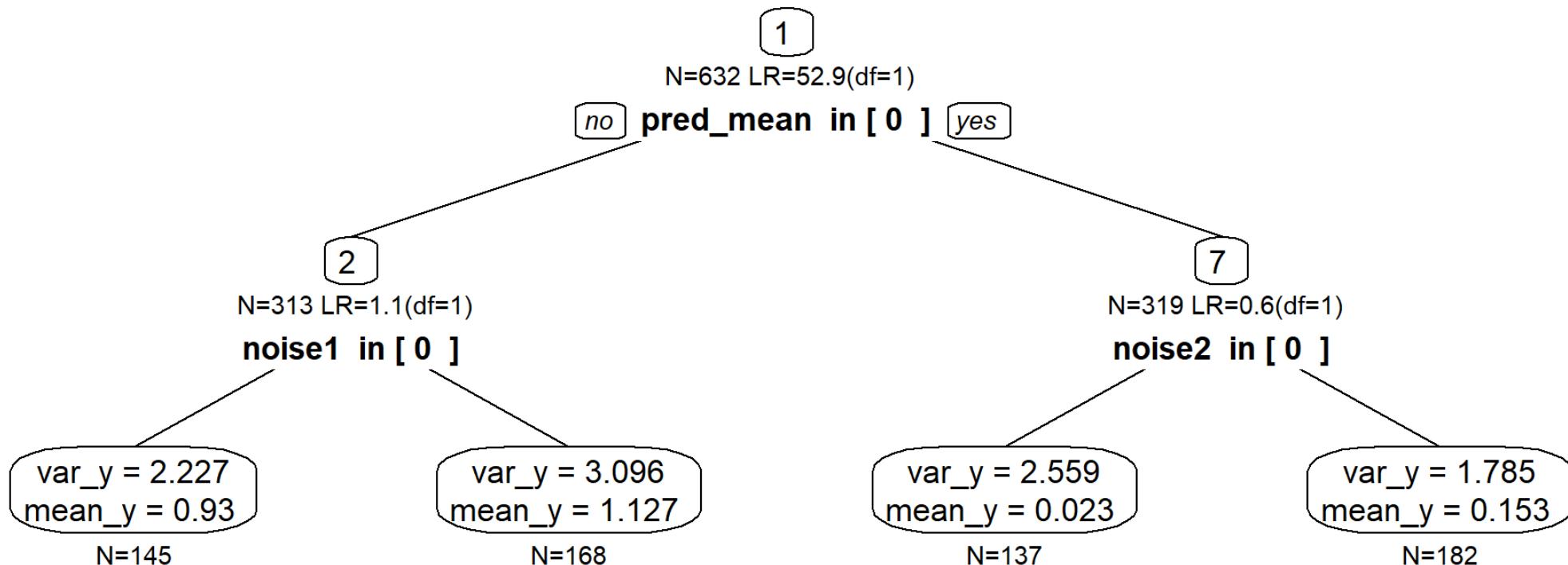
With SEM forest, we grow trees with

- subsampling of predictors (`mtry=2` or  $\sqrt{m}$  or ..)
- no stopping rule ( $\alpha = 1$ ) in order to explore deep conditional effects (~interactions) in the trees

Therefore, the permutation importance estimate will be influenced by differences with respect to all parameters of the model because all predictors will appear in the forest

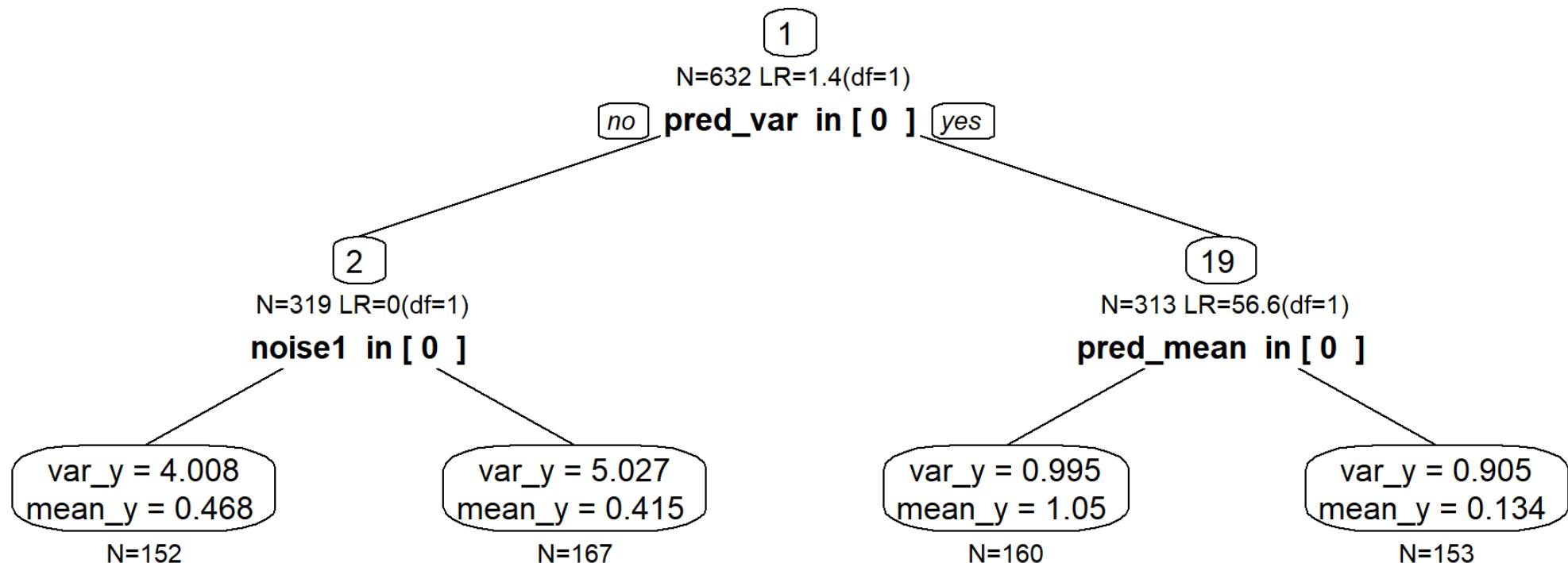
# Inspect first tree

(Pruned) Tree from a forest with focus parameters



# Inspect second tree

Another (pruned) Tree from a forest with focus parameters



# Problem

Problem: This measure of variable importance considers differences w.r.t all parameters of the SEM

Solution: Estimate misfit incurred by only the focus parameters

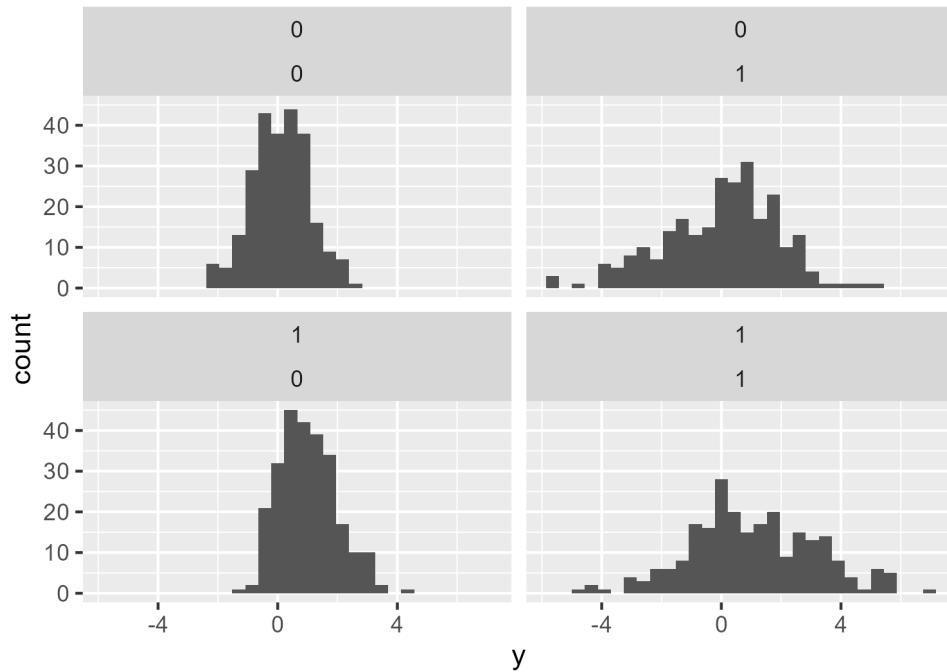
# Algorithm (estimate importance for focus parameters)

Heuristic (💡) Importance Evaluation:

- For each tree, for each observation  $x$ , find leaf model  $M_1$  by traversing the tree and leaf model  $M_2$  by traversing the tree after permuting predictor in question
- Compute -2LL of  $x$  under  $M_1$
- ~~Compute -2LL of  $x$  under  $M_2$~~
- Compute -2LL of  $x$  under  $M_1$  with only focus parameters plugged in from  $M_2$
- Compute -2LL difference

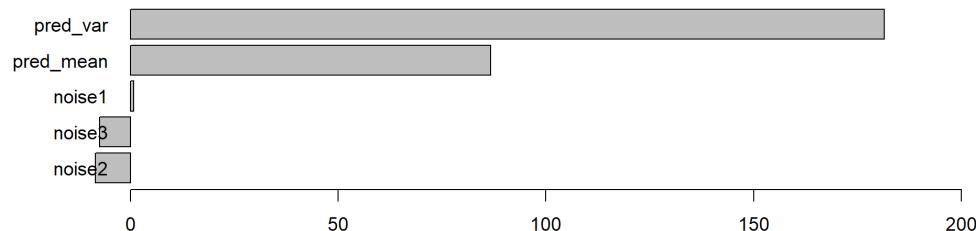
# Back to the simulation

Simulated Data:

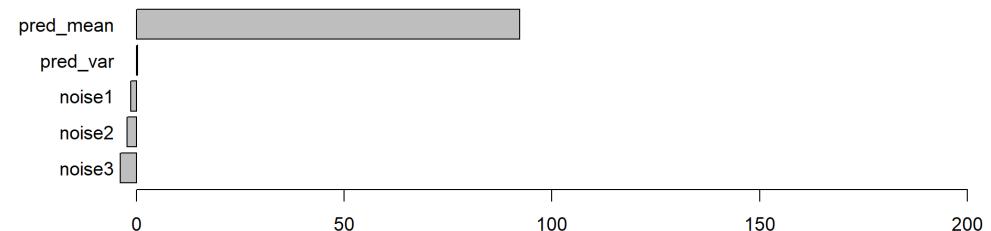


# Importance Estimates

Forest with (score-based) focus parameter on mean:



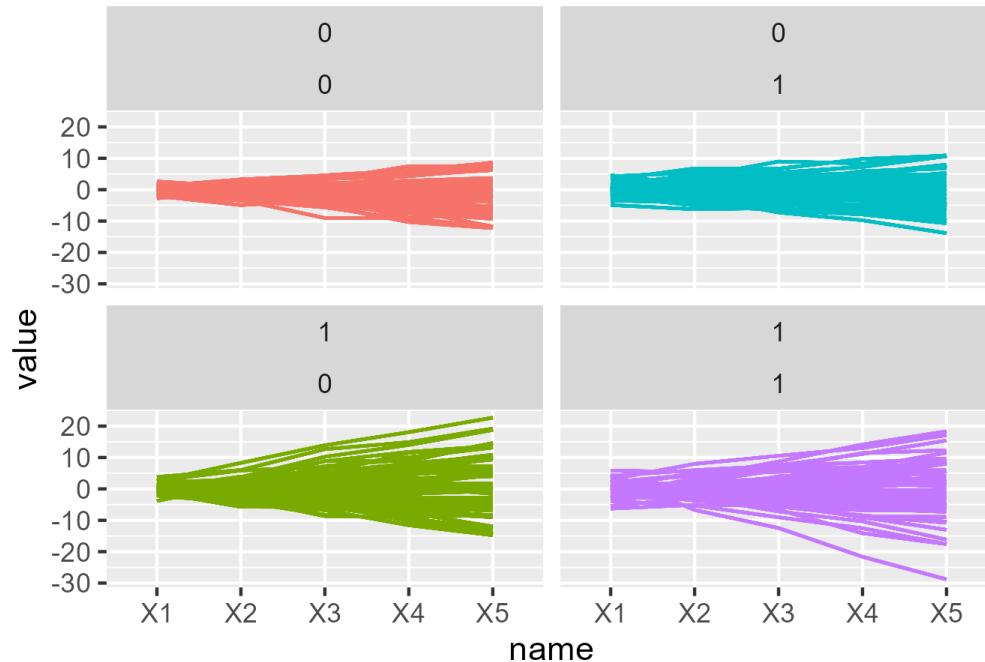
(old scheme)



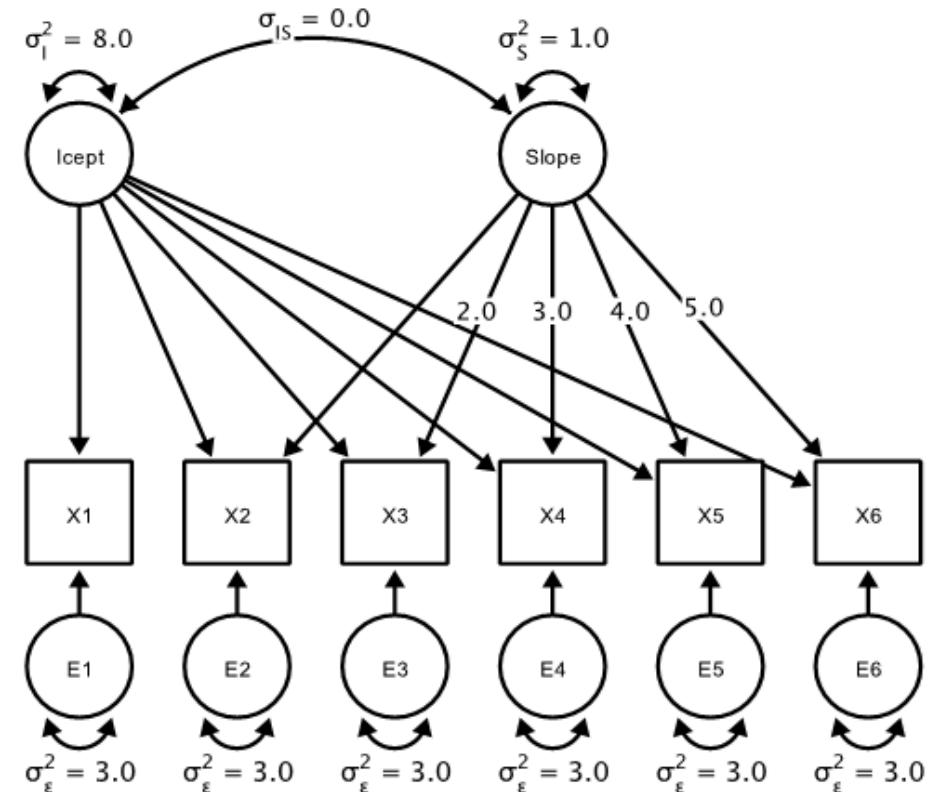
(new scheme)

# Some more examples

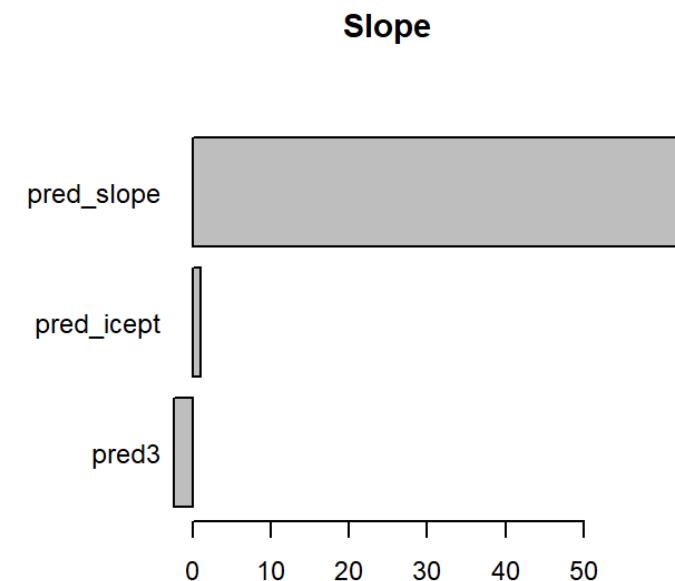
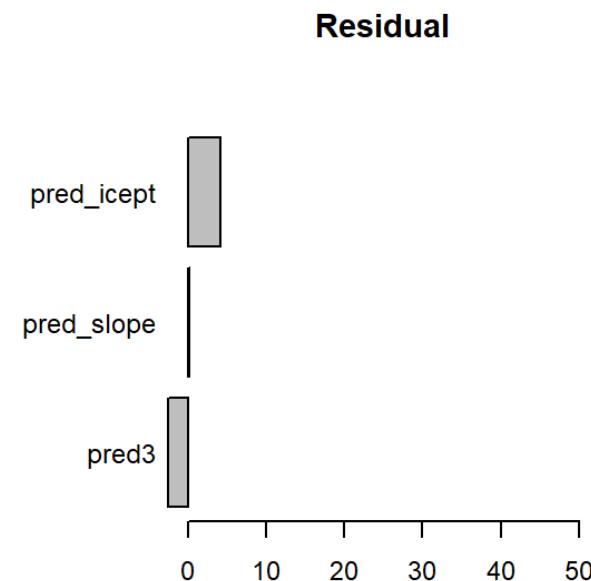
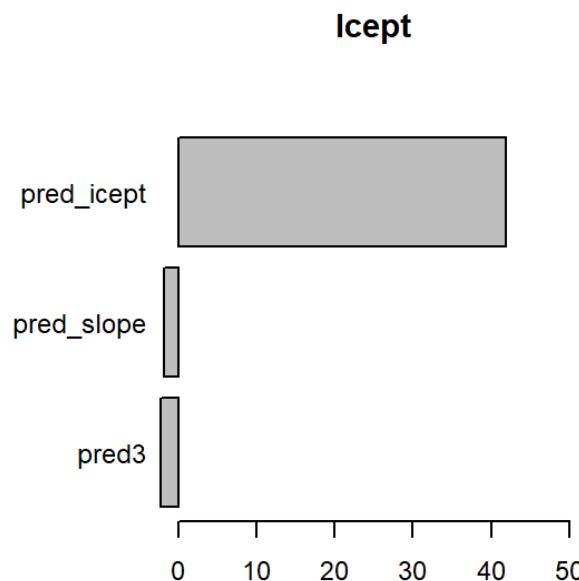
# Back to Latent Growth Curve Models



Differences in intercept variance (2,5; cols) or slope variance (2;5, rows),  $n = 200$  per group



# Back to Latent Growth Curve Models

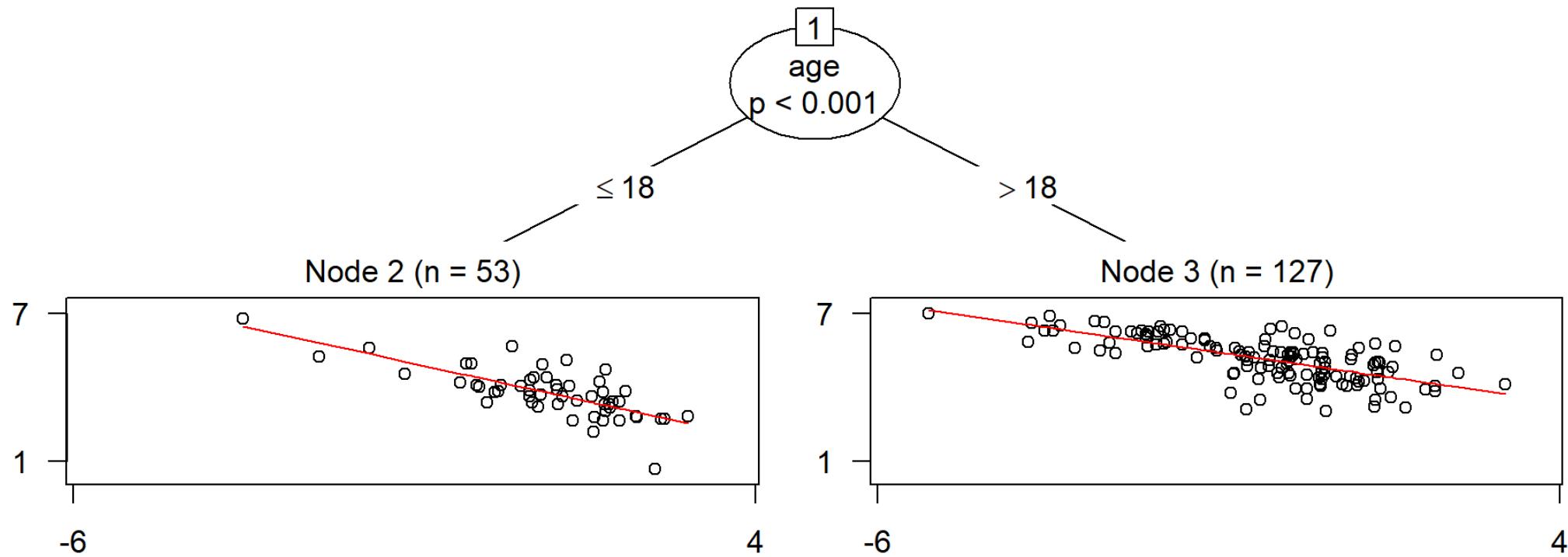


# Journal Pricing

- The model to be partitioned is a linear regression for the number of library subscriptions by price per citation in log-log specification (i.e., with  $k = 2$  coefficients) Zeileis, Hothorn, and Hornik (2008)
- Predictors: the raw price and number of citations, the age of the journal, number of characters and a factor indicating whether the journal is associated with a society or not.

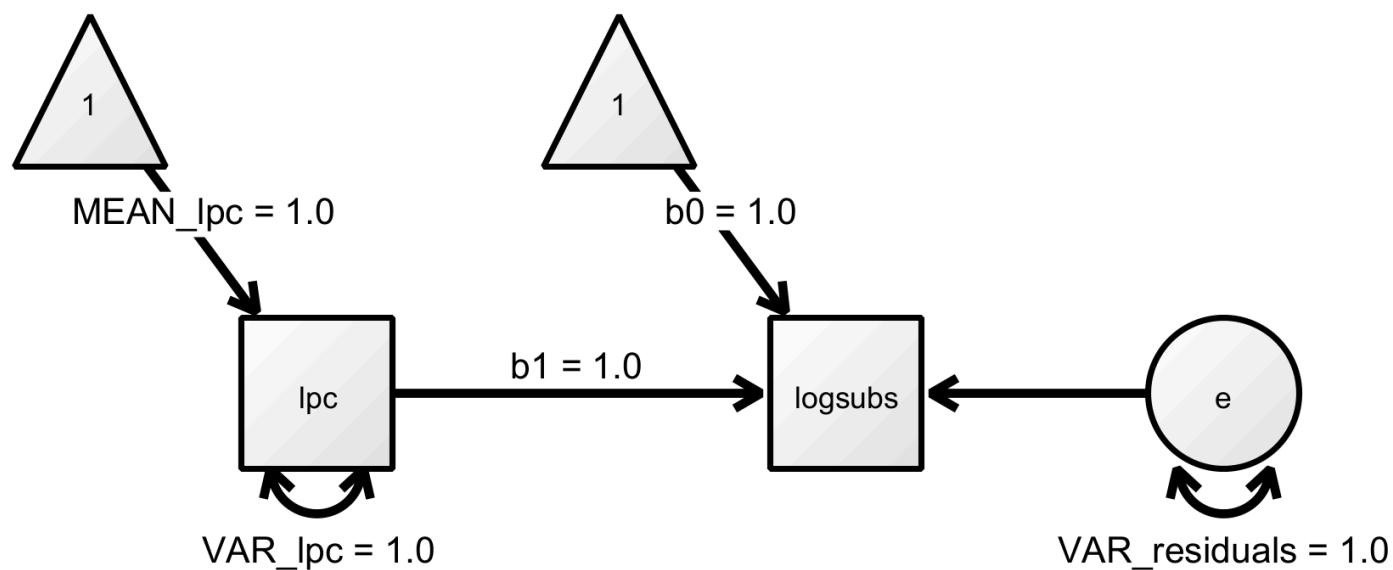
```
library(partykit)
j_tree <- partykit::lmtree(logsubs ~ lpc | price + citations +
                           + age + chars + society, data = Journals)
```

# Journal Pricing



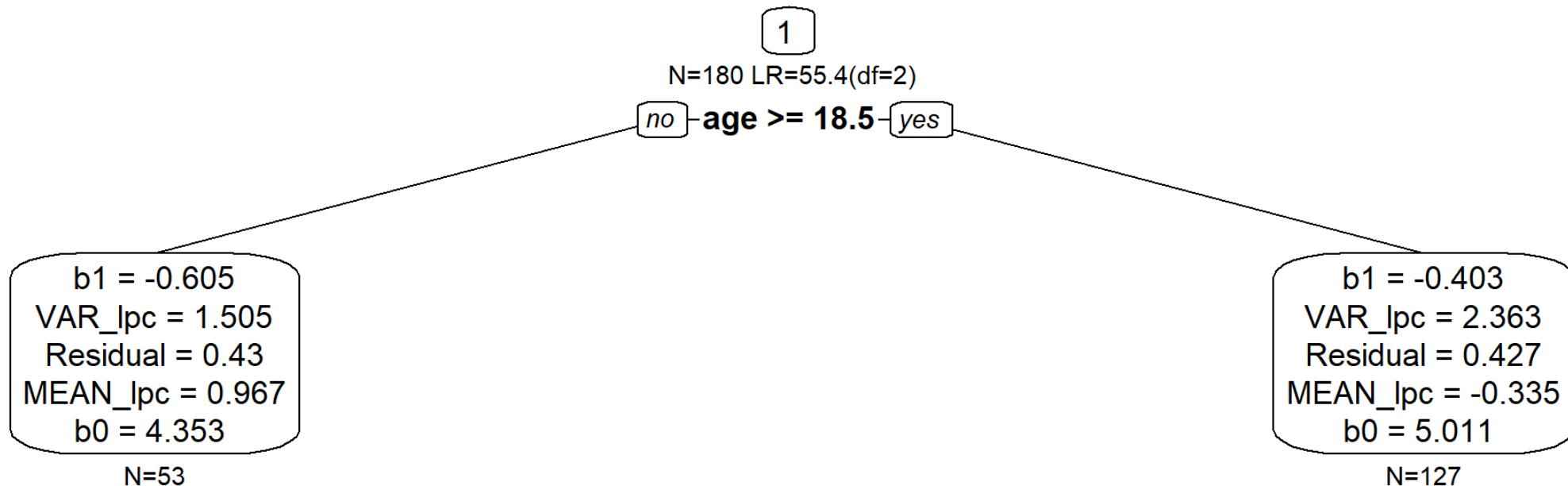
(Subscriptions per price-by-citation in log-scale)

# Regression SEM Tree



# SEM Tree with focus parameter

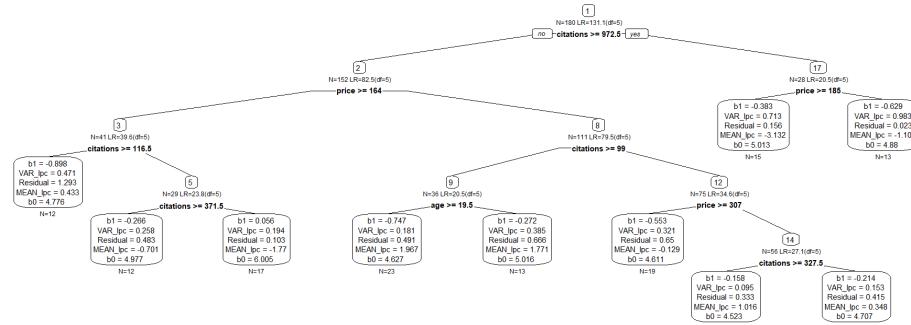
Focus parameter on regression coefficient and constant:



Identical result: somewhat shallower slope for older journals

# Tree w/o focus parameter

- If we run the tree without focus parameter, all parameters become potentially relevant
- Splits could be because of differences in intercept, differences in residual variance, or differences in predictor variance



# Parameter Estimates of Trees

Here, we find differences w.r.t. all parameters (e.g., predictor mean and variance  $MEAN\_lpc$  and  $VAR\_lpc$ ) and also a large range of regression coefficients  $b_1$  ranging from -0.9 to 0.06.

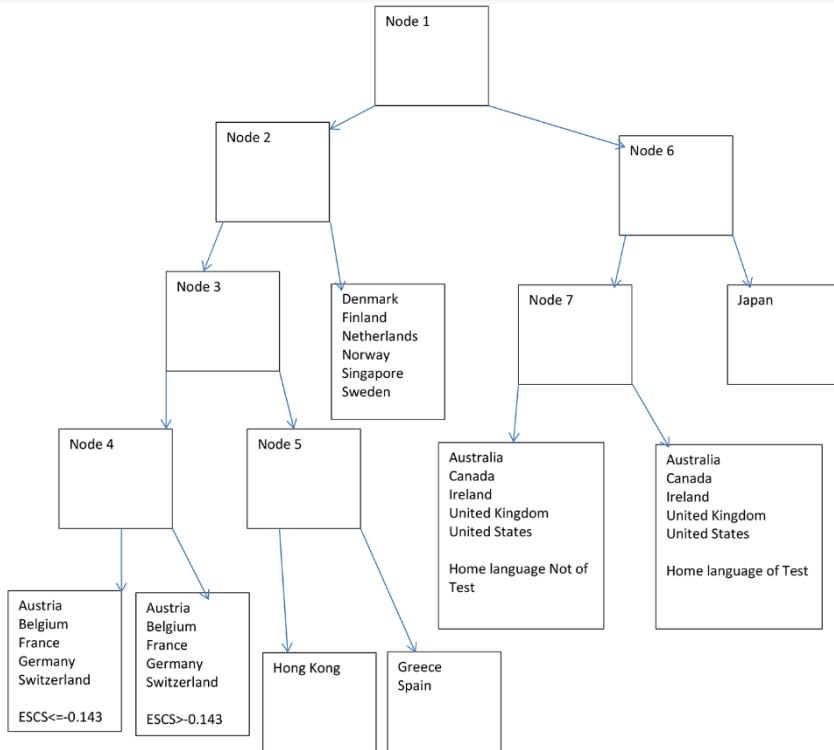
	Leaf #1	Leaf #2	Leaf #3	Leaf #4	Leaf #5	Leaf #6	Leaf #7	Leaf #8	Leaf #9	Leaf #10
b1	-0.90	-0.27	0.06	-0.75	-0.27	-0.55	-0.16	-0.21	-0.38	-0.63
VAR_lpc	0.47	0.26	0.19	0.18	0.38	0.32	0.09	0.15	0.71	0.98
Residual	1.29	0.48	0.10	0.49	0.67	0.65	0.33	0.41	0.16	0.02
MEAN_lpc	0.43	-0.70	-1.77	1.97	1.77	-0.13	1.02	0.35	-3.13	-1.10
b0	4.78	4.98	6.00	4.63	5.02	4.61	4.52	4.71	5.01	4.88

# Measurement Invariance

# Measurement Invariance Testing

- "Lack of evidence of measurement invariance equivocates conclusions and casts doubt on theory in the behavioral sciences" (Horn and McArdle, 1992)
- Measurement Invariance is usually based on multigroup SEM/CFA (Marsh, Morin, Parker, and Kaur, 2014)
- SEM Trees were suggested as a tool for measurement invariance testing, that is, to explore differential item functioning (Finch, 2017; Sterner and Goretzko, 2023), that is to find moderators of factor loadings
- CFA partitioning can even be used without any groups at all (Merkle and Zeileis, 2013)
- As an example, Finch (2017) looked at a *attitudes towards reading items* questionnaire

# Measurement Invariance



SEMtree does not isolate specific differences among model parameters, but rather identifies differences in whole patterns of model parameters - (Finch, 2017)

# BFI

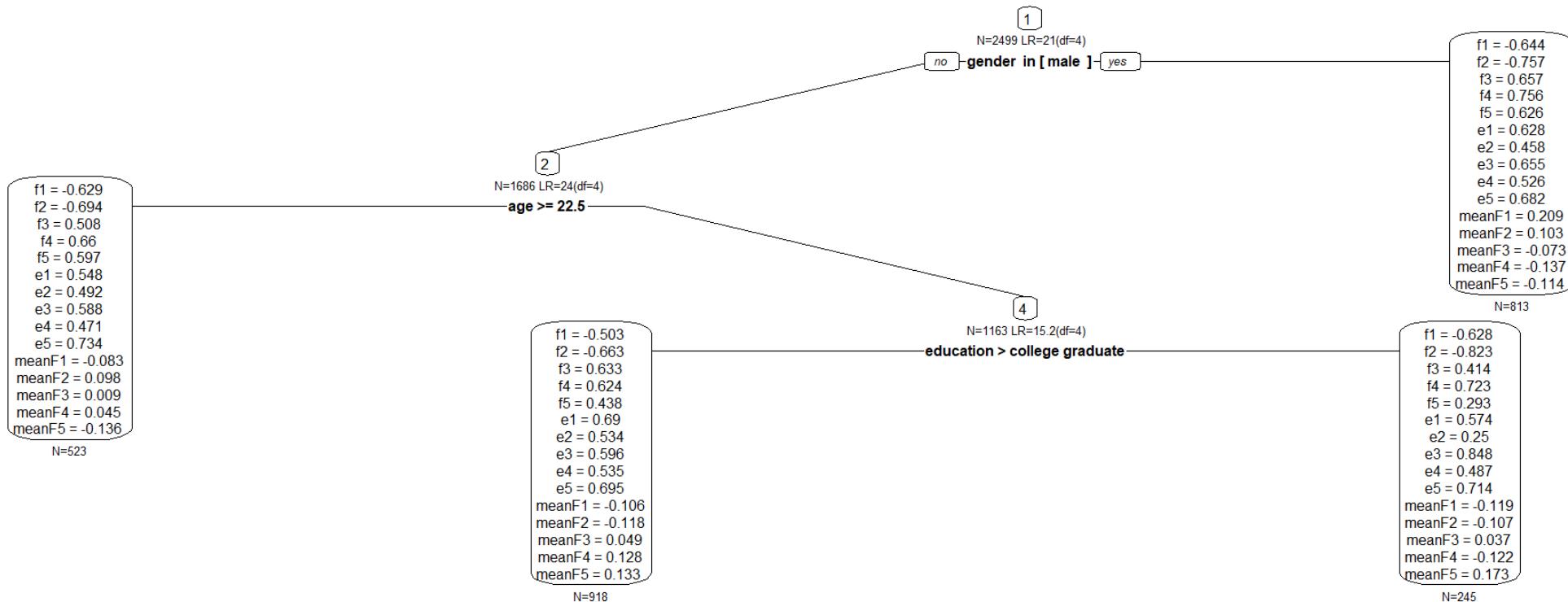
As an example:

- International Personality Item Pool `bfi` from `psych` package
- $n = 2,800$
- 25 personality self report items (representing 5 OCEAN factors)
- Three demographic variables as predictors: age (metric), education (ordinal), sex (nominal)

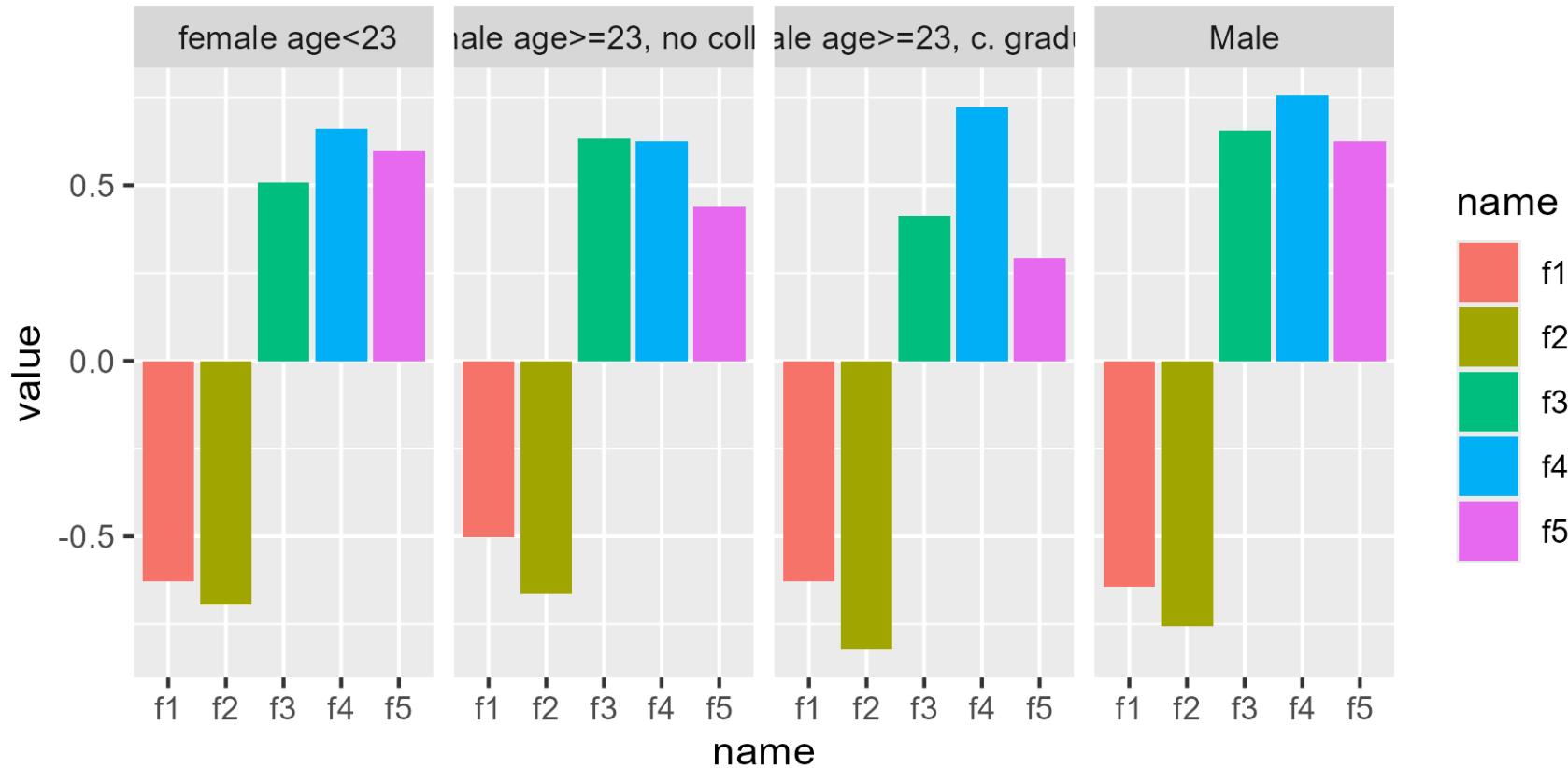
# BFI

- Specify a CFA of five indicators for the construct *extraversion*: "don't talk a lot", "find it difficult to approach others", "Know how to captivate propl", "Make friends easily", "Take charge"
- Anchor item: "don't talk a lot"
- choose only factor loadings and residuals as focus parameters (but not intercepts or latent mean/variance)
- Predictors: age, sex, and education

# BFI Tree



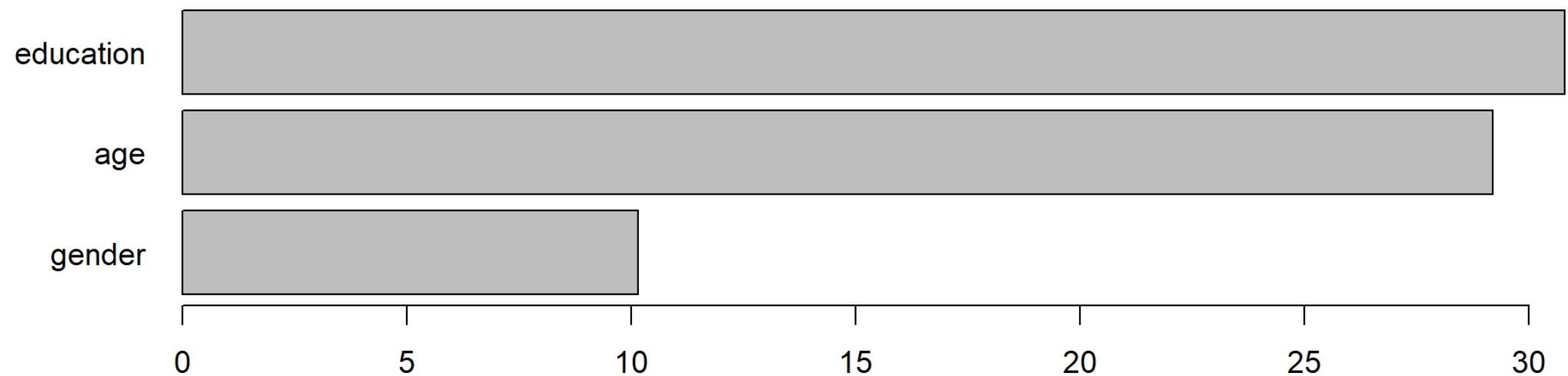
# BFI Loadings



(f3: Know how to captivate people and f5: Take charge - professional skills vs personality?)

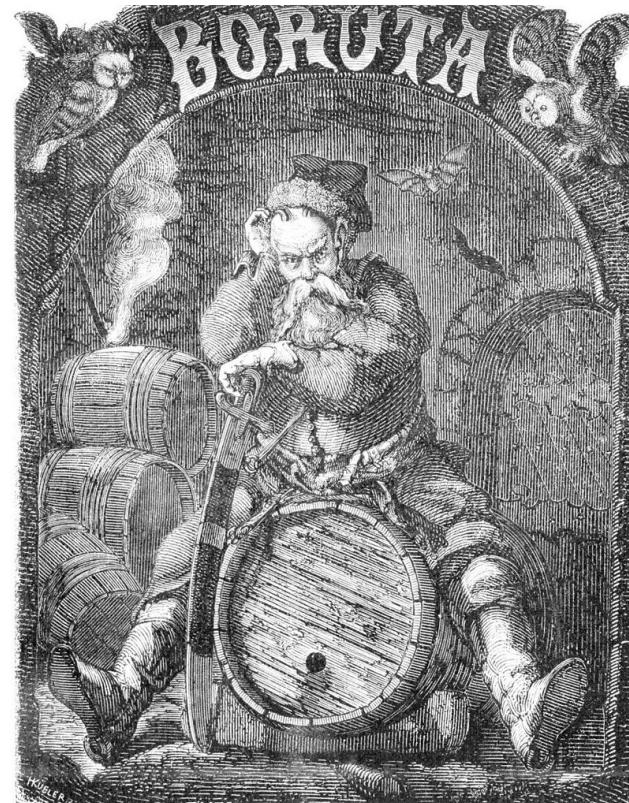
# BFI Forest

Permutation variable importance with focus parameters loadings:



# Outlook I

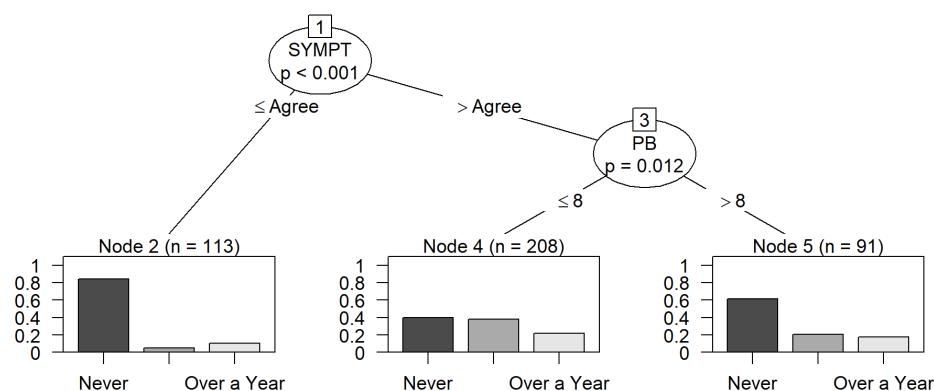
- Adapt BORUTA (Kursa and Rudnicki, 2010a) to SEM Tree (with Priyanka Paul & Timothy Brick, PennState)
- BORUTA is a heuristic to determine a cut-off between important and not-important variables



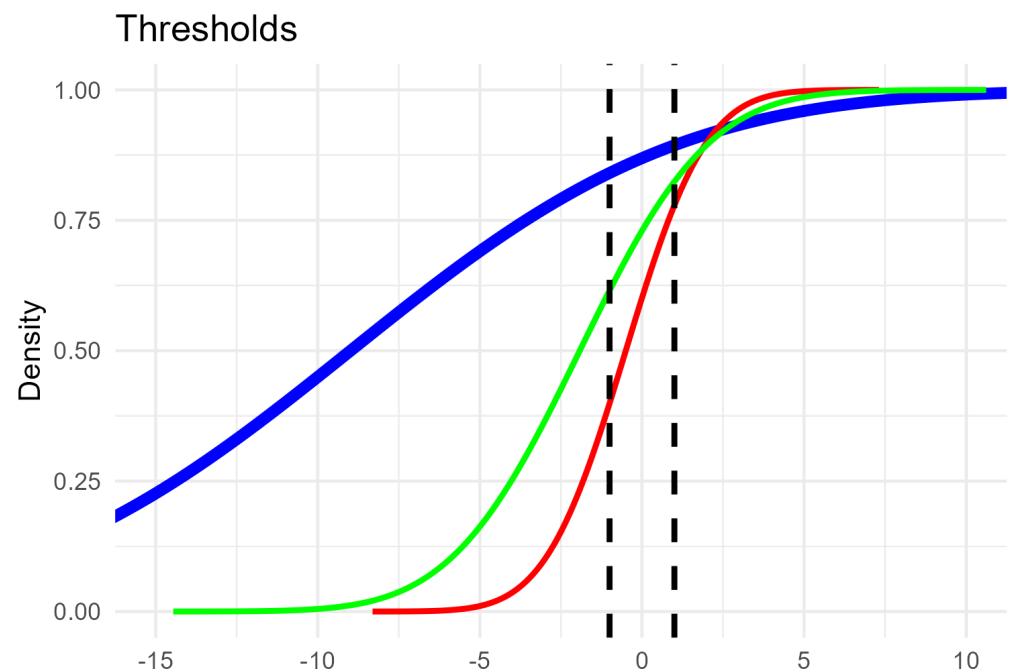
A spirit or devil from slavic mythology, image from Wikipedia/Public

# Outlook II

(Joint) Ordinal models using threshold models (example: mammography screening experience and opinions from (Hothorn, Hornik, and Zeileis, 2006) with  $n = 412$ )



- SYMPT: You do not need a mamogram unless you develop symptoms
- PB: Perceived benefit (low value = strong)



# Summary

- SEM Trees and Forests are a form of model-based recursive partitioning
- They can be implemented either via the `semtree` package or via `partykit` (<https://www.zeileis.org/news/lavaantree/>)
- Offer a way to explore theory-driven SEM with variable importance and partial dependence plots
- Focus parameters may be important when exploring the importance of predictors for subsets of parameters (e.g., individual differences vs means, or intercept vs slopes in growth models)
- If you have a theory, test the theory first, then explore!

# Thank You

- Slides: <https://github.com/brandmaier/focus-talk-dagstat2025>
- Package on CRAN: [semtree](#)

Contact:

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on Bluesky or

<https://www.brandmaier.de>



# Reproducibility + Exploratory Methods

# Why should we work reproducibly?

Many good reasons like:

- Transparency
- Trustworthiness
- Replication
- Cumulative science

Transparency and accessibility are central scientific values, and open, reproducible projects will increase the efficiency and veracity of knowledge accumulation .

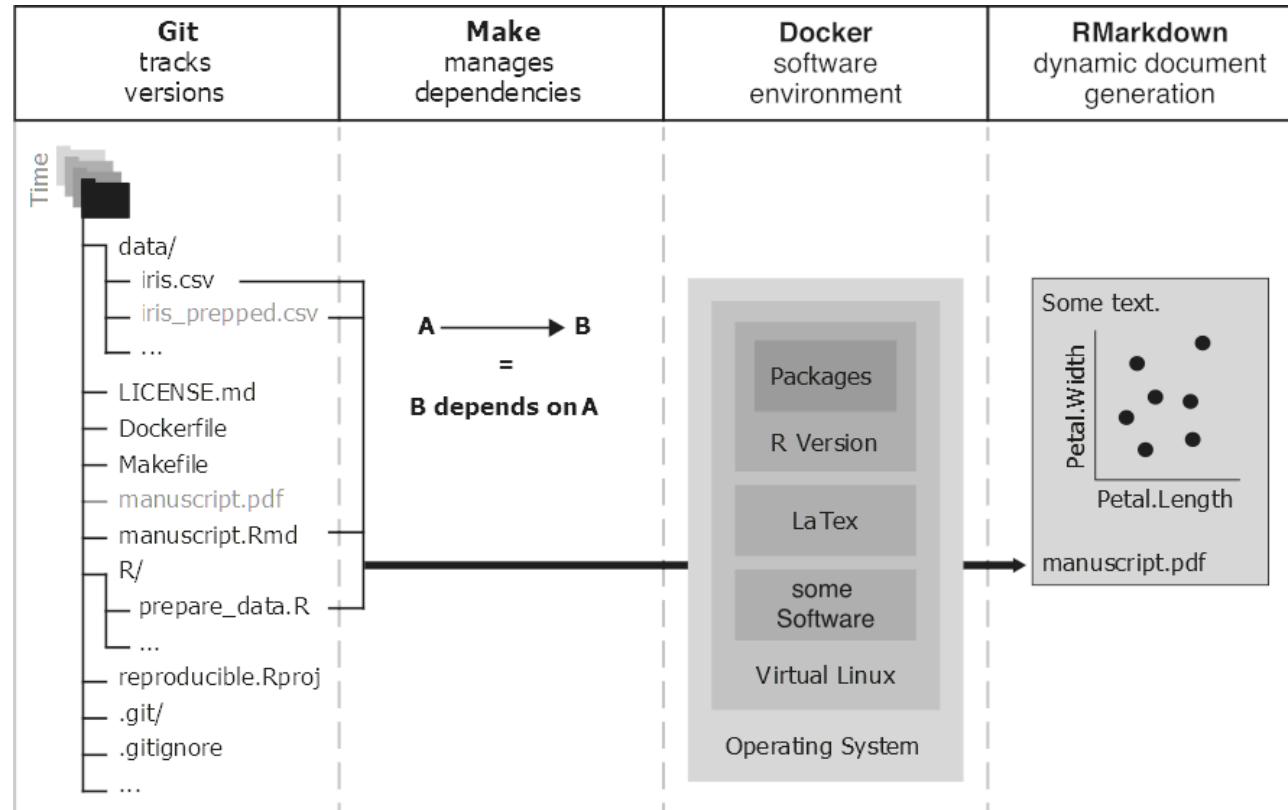
**Your closest collaborator is you six months ago, but you don't reply to emails.**

From Karl Broman's lecture on reproducibility, paraphrasing Mark Holden

# Sources of Failure to Reproduce Results

1. **Multiple versions of scripts/data** (e.g., dataset has changed over, i.e., was further cleaned or extended)
2. **Multiple scripts** in a pipeline; unclear which scripts should be executed in which order
3. **Copy&paste errors** (e.g., inconsistency between reported result and reproduced result)
4. Broken **software dependencies** (e.g., analysis broken after update, missing package, just comes out differently on a different computer )

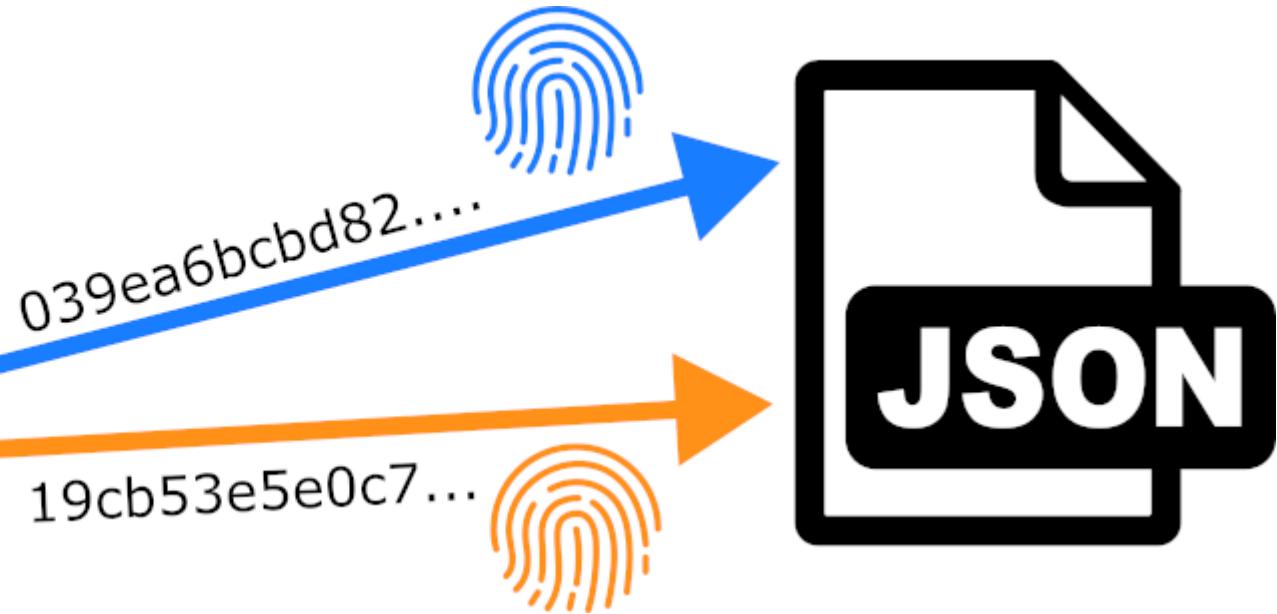
# Four Elements of Reproducibility



from Peikert and Brandmaier (2020) and `repro` package

# reproducibleRchunks

```
14  
15 - ## Some Computation  
16  
17 Here is a computation:  
18  
19 - {reproducibleR addition}  
20 my_sum <- x + 1  
21  
22
```



(now on CRAN: [reproducibleRchunks](#))

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