

University of Stuttgart
Germany

Mixed-effects models in EEG

Statistically evaluating mixed-effects models for EEG analysis
using large-scale simulations

January 20, 2023

Agenda

Recap



Results



Limitations



Discussion



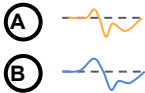
Overview



Number of subjects



Number of items



**Between-subject
variability**



**Modelling
Scheme**

Analysis



**Statistical
Power**



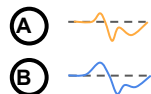
Overview



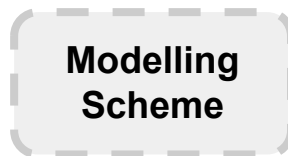
Number of subjects



Number of items



Between-subject
variability



Modelling
Scheme

Analysis



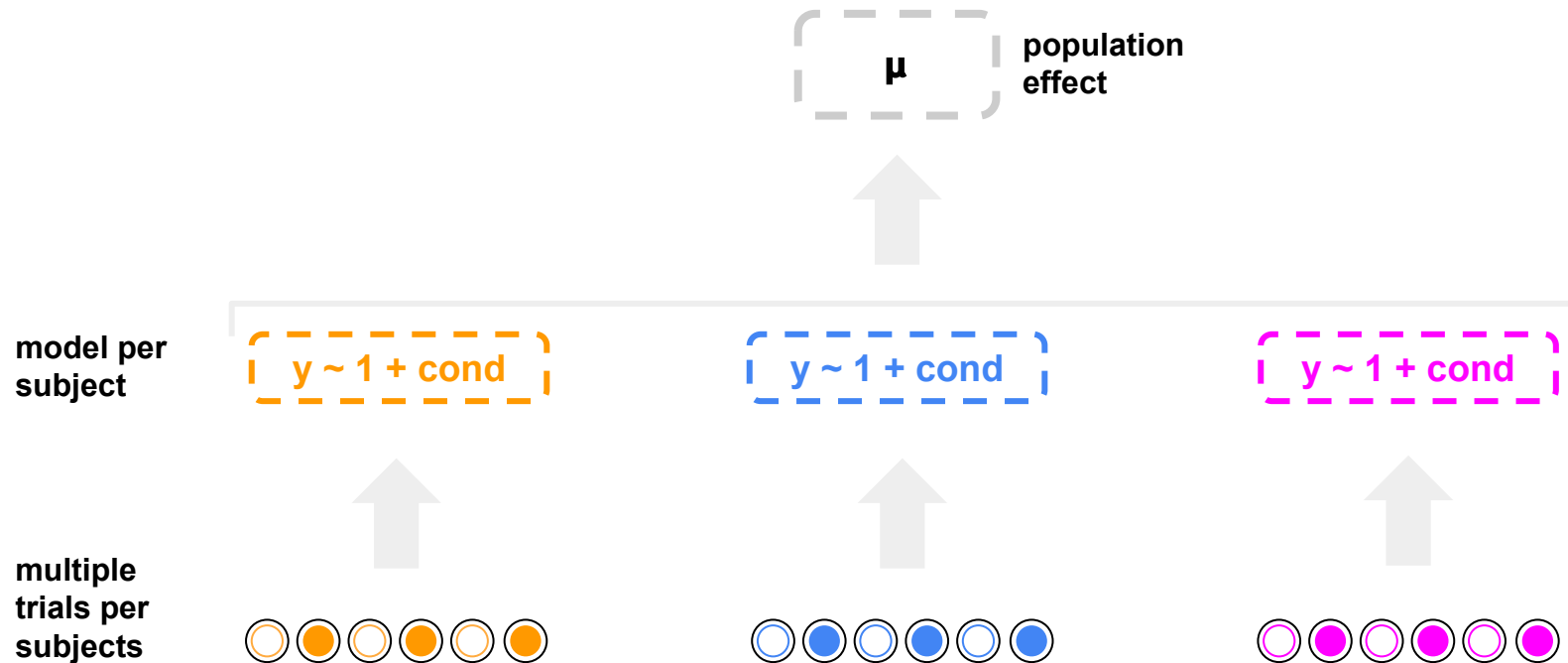
Statistical
Power

Motivation?

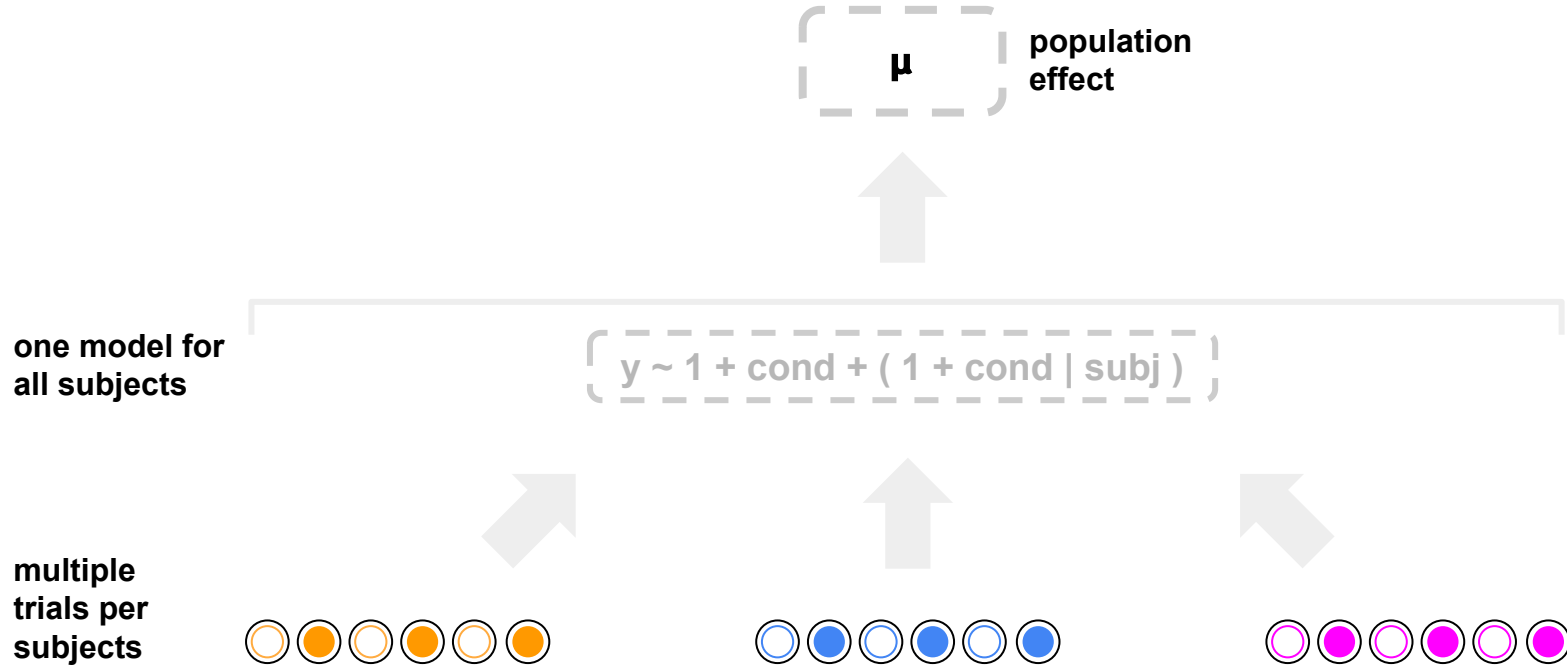
Many neuroscience studies have low statistical power
=> bad reproducibility
=> LMMs better in some cases?



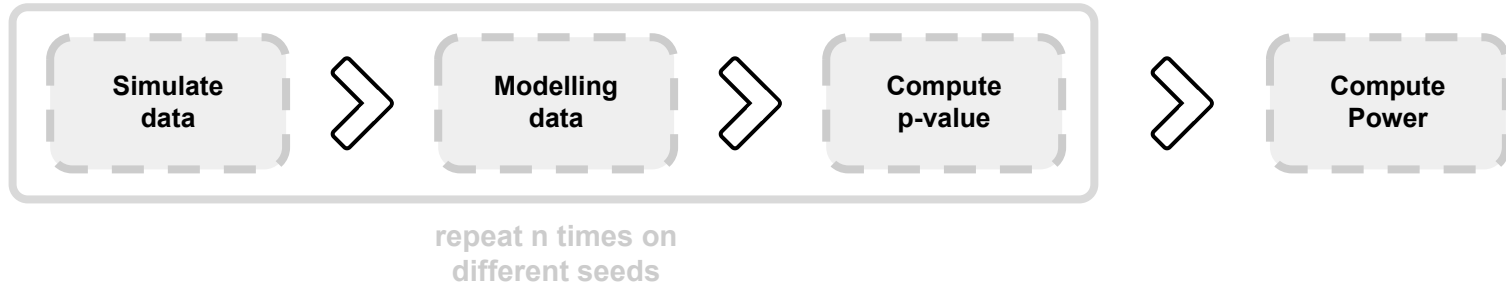
Two-stage approach




Linear mixed model approach





Approach



Simulation Toolbox

 [unfoldtoolbox](#) / [UnfoldSim.jl](#) Public

UnfoldSim

docs **stable** docs **dev**  CI **passing**  codecov unknown

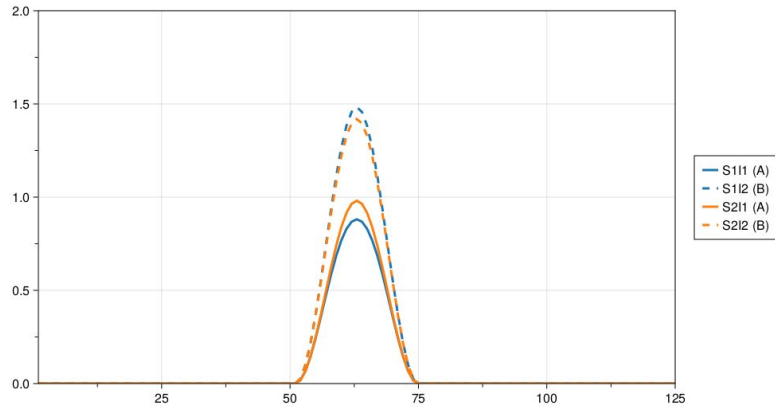
A package to simulate single timeseries model-based ERPs, fMRI activity, pupil dilation etc. If you have one channel, it is a timeseries of (overlapping) event-related activity and some noise - you might have fun here!

Note: Not released yet

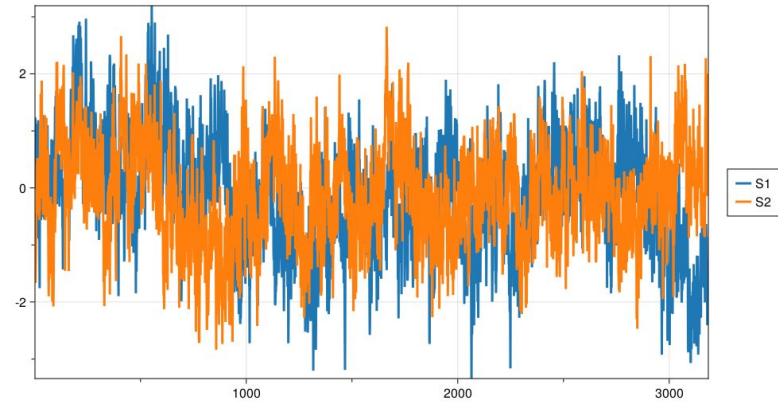


Simulation Toolbox

Simulated ERPs



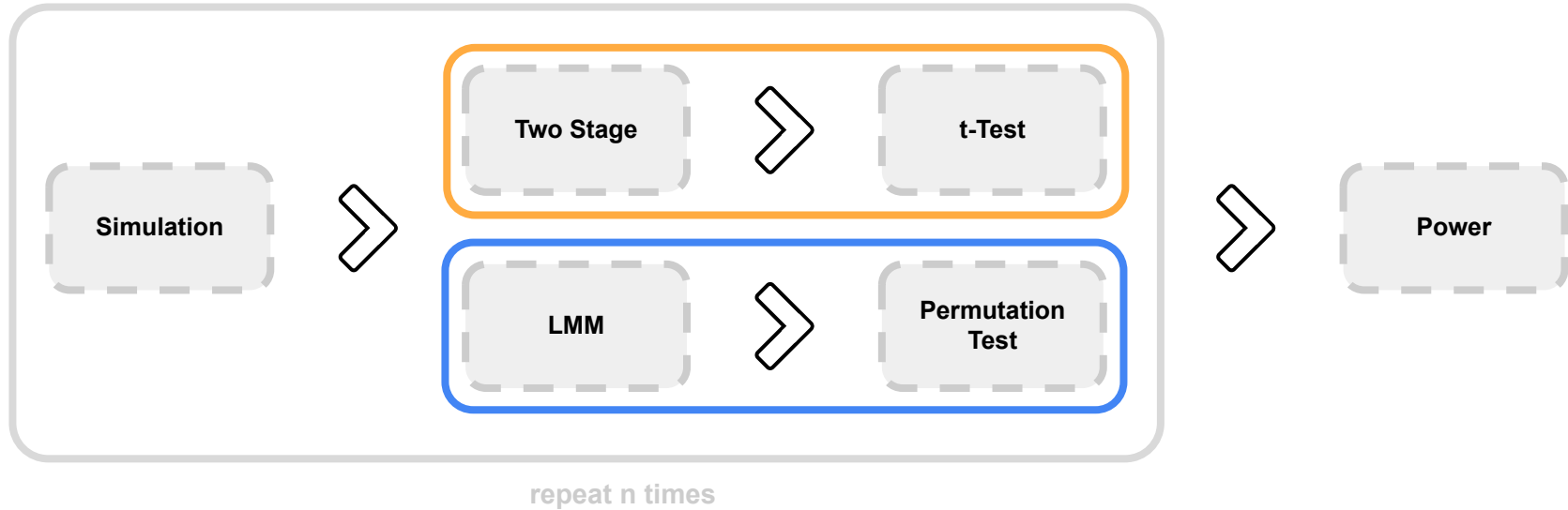
Simulated EEG



Used model notation: $y \sim 1 + \text{cond} + (1 + \text{cond} | \text{subj})$

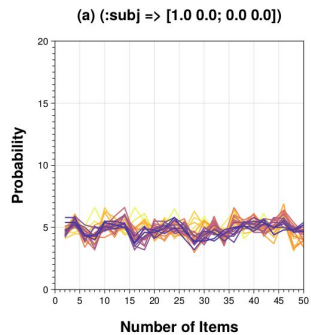


Computing p-values

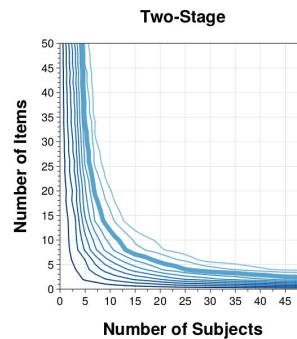


Two-stage vs LMM

Type 1 error



Power contour



two-stage

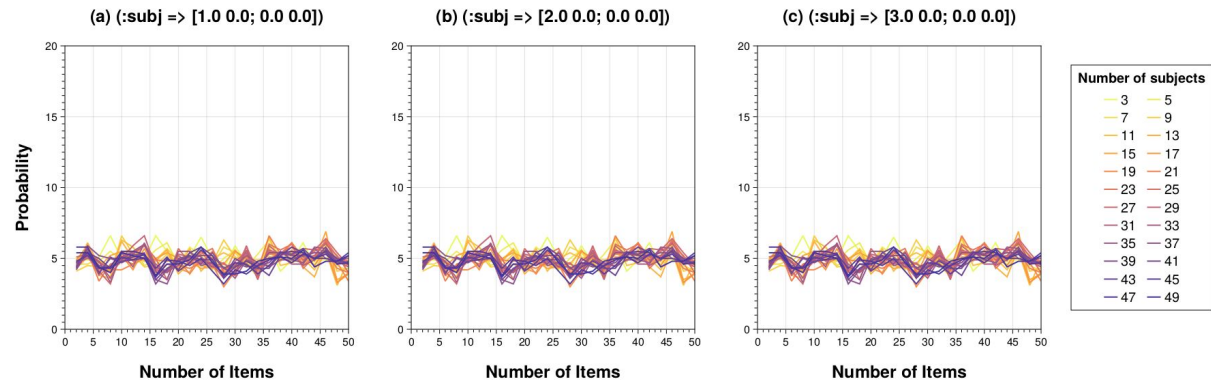
Model

subj int

Varying

Type 1 Error

model = twostage | $\beta = [2.0, 0.0]$ | $\sigma_{\text{res}} = 0.0001$ | noiselevel = 1.0 | noisetype = pink



Type 1 Error

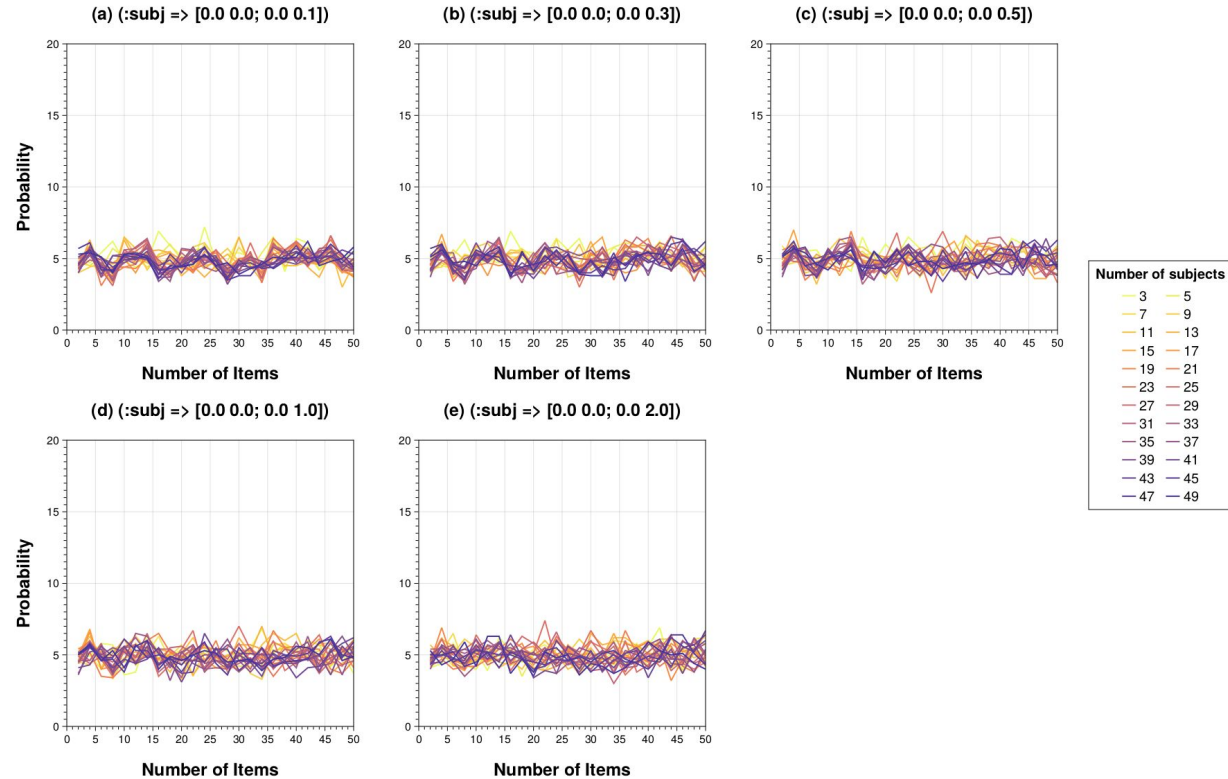
model = twostage | $\beta = [2.0, 0.0]$ | $\sigma_{\text{res}} = 0.0001$ | noiselevel = 1.0 | noisetype = pink

two-stage

Model

subj slope

Varying



Imm

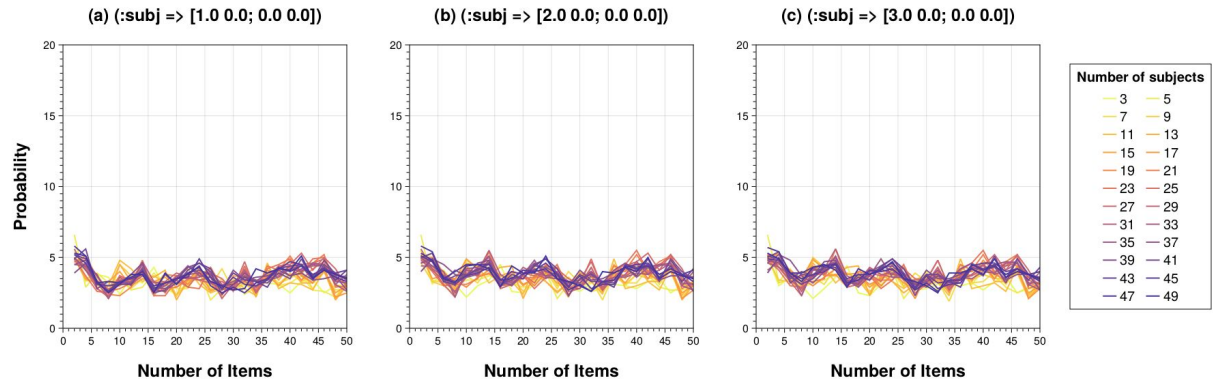
Model

subj int

Varying

Type 1 Error

model = lmmperm | $\beta = [2.0, 0.0]$ | $\sigma_{\text{res}} = 0.0001$ | noiselevel = 1.0 | noisetype = pink



Type 1 Error

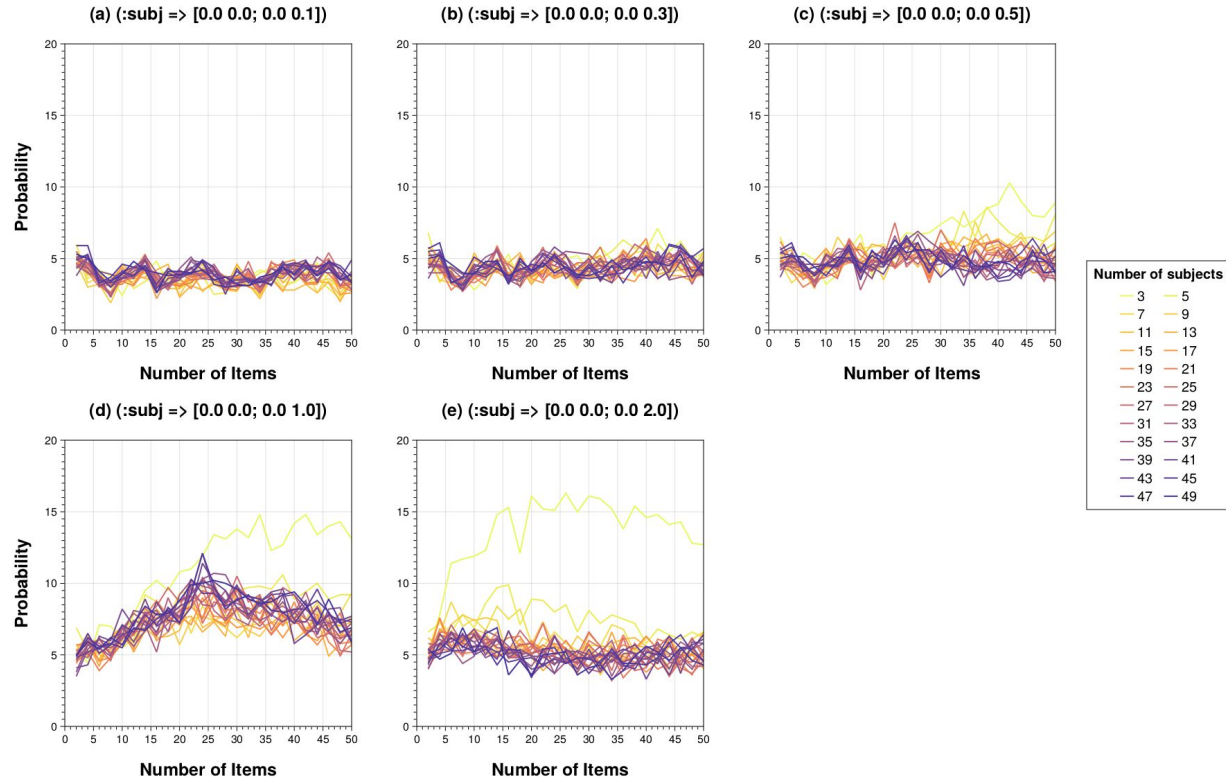
model = lmmperm | $\beta = [2.0, 0.0]$ | $\sigma_{\text{res}} = 0.0001$ | noiselevel = 1.0 | noisetype = pink

Imm

Model

subj slope

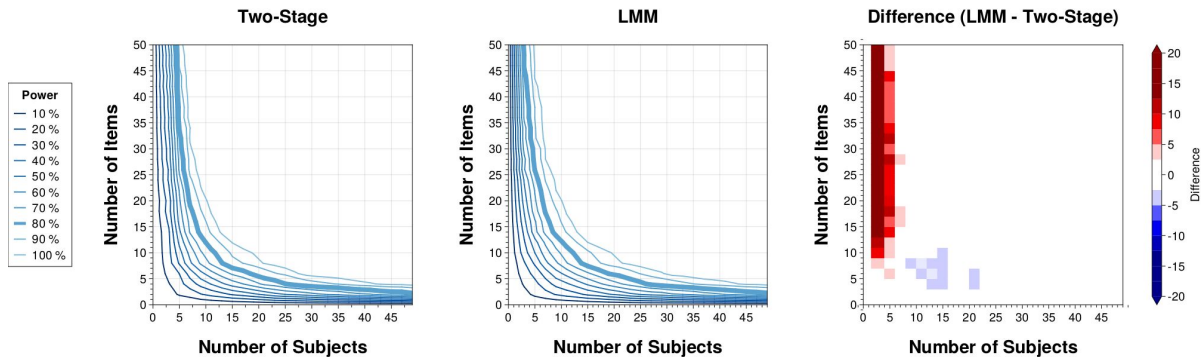
Varying



Varying subject intercept variance

Power (Two-Stage vs. LMM)

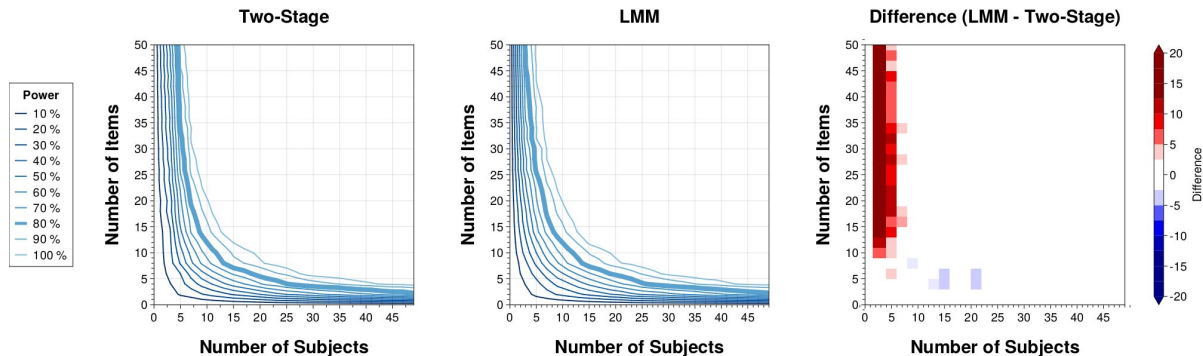
$\beta = [2.0, 0.5]$ | $\sigma_{\text{ranef}} = (\text{;subj} => [1.0 \ 0.0; 0.0 \ 0.0])$
noiselevel = 1.0 | noisetype = pink | $\sigma_{\text{res}} = 0.0001$



Varying subject intercept variance

Power (Two-Stage vs. LMM)

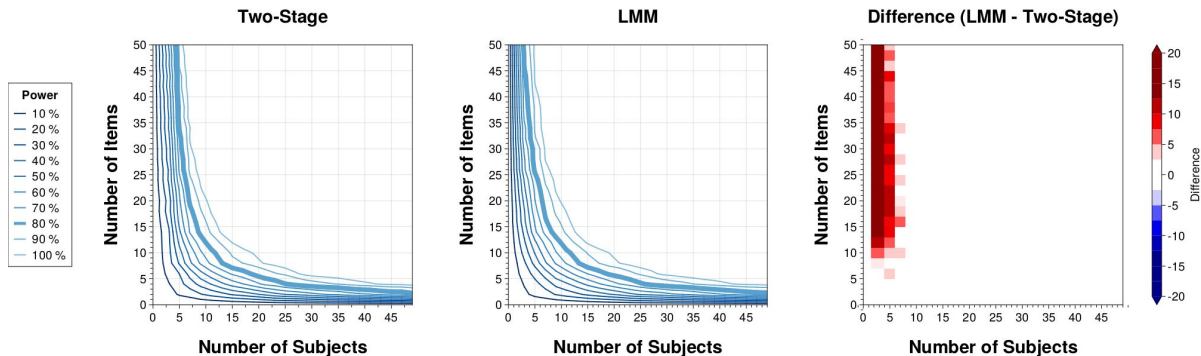
$\beta = [2.0, 0.5]$ | $\sigma_{\text{ranef}} = (\text{;subj} => [2.0 \ 0.0; 0.0 \ 0.0])$
noiselevel = 1.0 | noisetype = pink | $\sigma_{\text{res}} = 0.0001$



Varying subject intercept variance

Power (Two-Stage vs. LMM)

$\beta = [2.0, 0.5]$ | $\sigma_{\text{ranef}} = (\text{;subj} => [3.0 \ 0.0; 0.0 \ 0.0])$
noiselevel = 1.0 | noisetype = pink | $\sigma_{\text{res}} = 0.0001$



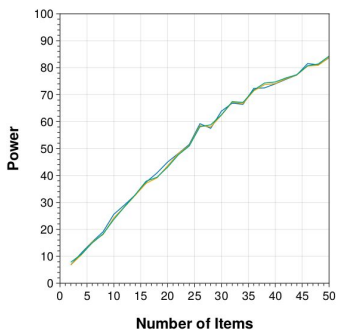
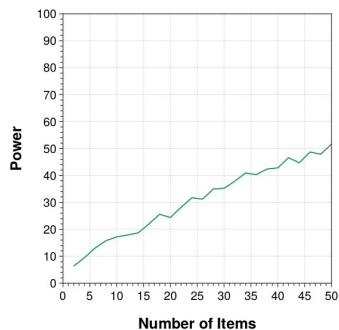
Varying subject intercept variance

Power (Two-Stage vs. LMM)

nsubj = 3 | $\beta = [2.0, 0.5]$ | $\sigma_{\text{res}} = 0.0001$
noiselevel = 1.0 | noisetype = pink

Two-Stage

LMM



σ_{ranef}

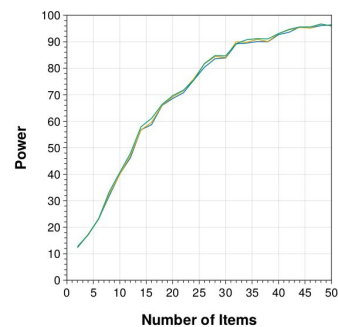
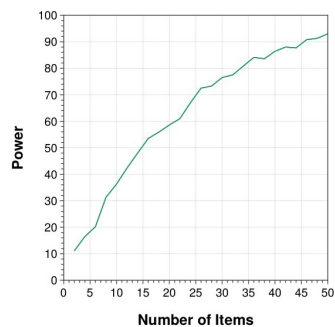
- (subj => [1.0 0.0; 0.0 0.0])
- (subj => [2.0 0.0; 0.0 0.0])
- (subj => [3.0 0.0; 0.0 0.0])

Power (Two-Stage vs. LMM)

nsubj = 5 | $\beta = [2.0, 0.5]$ | $\sigma_{\text{res}} = 0.0001$
noiselevel = 1.0 | noisetype = pink

Two-Stage

LMM



σ_{ranef}

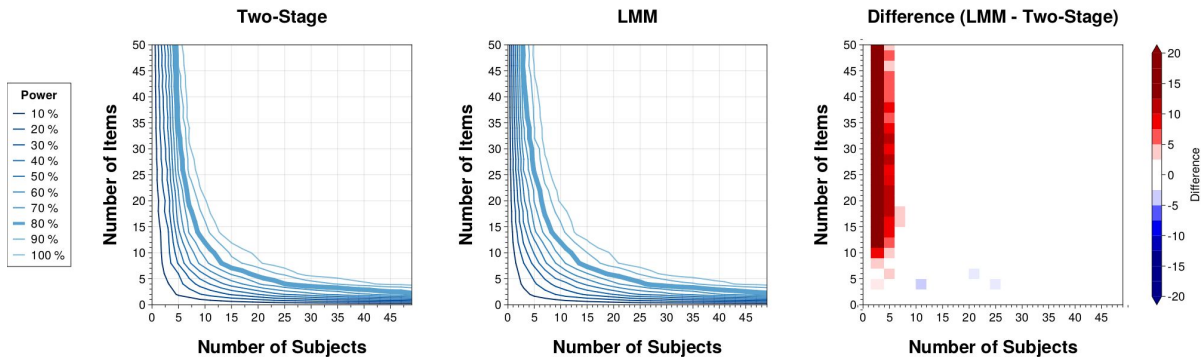
- (subj => [1.0 0.0; 0.0 0.0])
- (subj => [2.0 0.0; 0.0 0.0])
- (subj => [3.0 0.0; 0.0 0.0])



Varying subject slope variance

Power (Two-Stage vs. LMM)

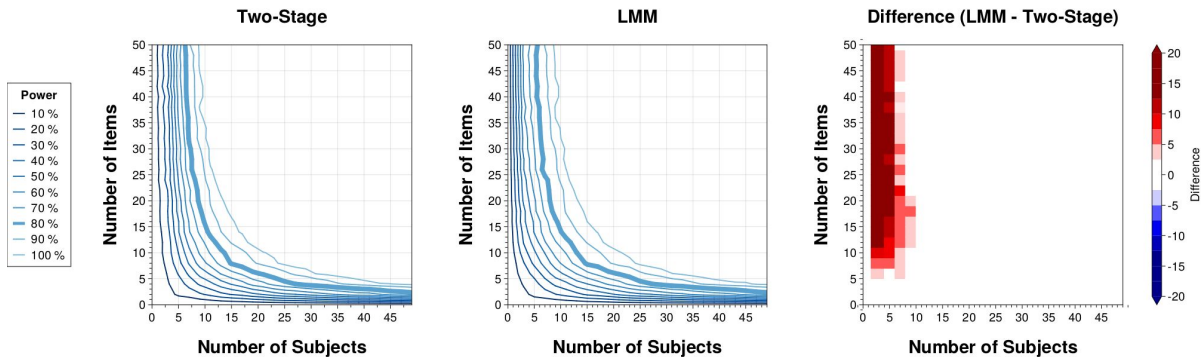
$\beta = [2.0, 0.5]$ | $\sigma_{\text{ranef}} = (\text{;subj} => [0.0 \ 0.0; 0.0 \ 0.0])$
noiselevel = 1.0 | noisetype = pink | $\sigma_{\text{res}} = 0.0001$



Varying subject slope variance

Power (Two-Stage vs. LMM)

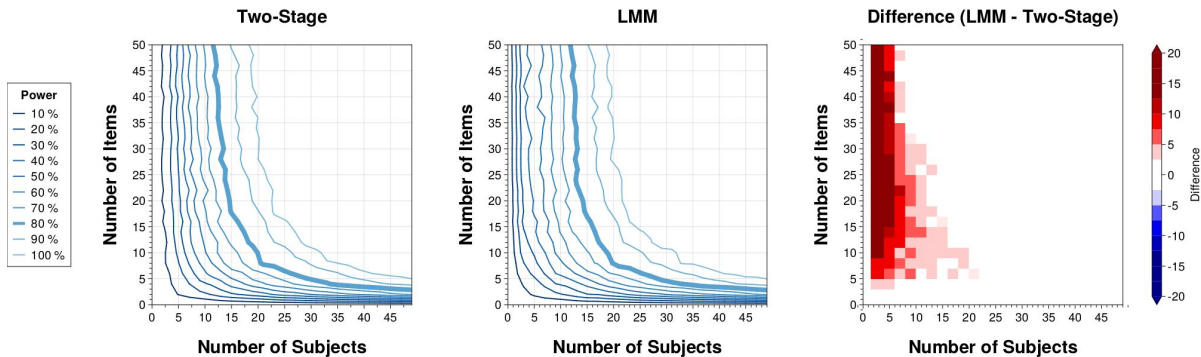
$\beta = [2.0, 0.5]$ | $\sigma_{\text{ranef}} = (\text{;subj} => [0.0 \ 0.0; 0.0 \ 0.5])$
noiselevel = 1.0 | noisetype = pink | $\sigma_{\text{res}} = 0.0001$



Varying subject slope variance

Power (Two-Stage vs. LMM)

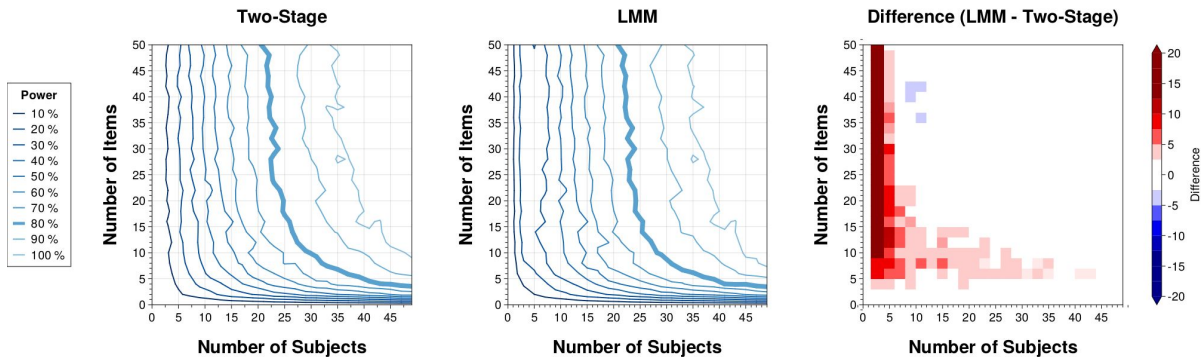
$\beta = [2.0, 0.5]$ | $\sigma_{\text{ranef}} = (\text{;subj} => [0.0 \ 0.0; 0.0 \ 1.0])$
noiselevel = 1.0 | noisetype = pink | $\sigma_{\text{res}} = 0.0001$



Varying subject slope variance

Power (Two-Stage vs. LMM)

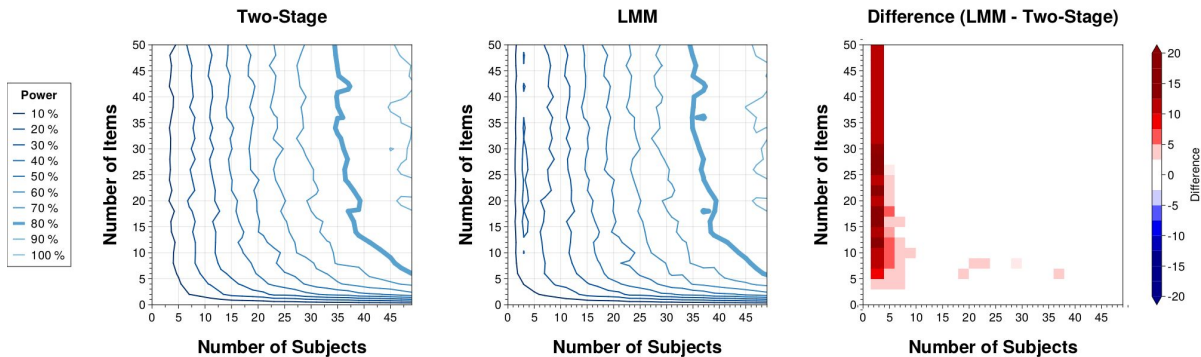
$\beta = [2.0, 0.5]$ | $\sigma_{\text{ranef}} = (\text{;subj} => [0.0 \ 0.0; 0.0 \ 1.5])$
noiselevel = 1.0 | noisetype = pink | $\sigma_{\text{res}} = 0.0001$



Varying subject slope variance

Power (Two-Stage vs. LMM)

$\beta = [2.0, 0.5]$ | $\sigma_{\text{ranef}} = (\text{;subj} => [0.0 \ 0.0; 0.0 \ 2.0])$
noiselevel = 1.0 | noisetype = pink | $\sigma_{\text{res}} = 0.0001$



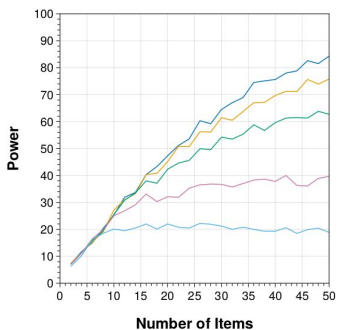
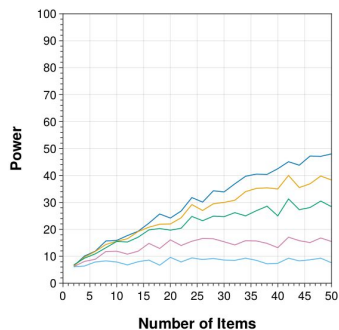
Varying subject slope variance

Power (Two-Stage vs. LMM)

nsubj = 3 | $\beta = [2.0, 0.5]$ | $\sigma_{\text{res}} = 0.0001$
noiselevel = 1.0 | noisetype = pink

Two-Stage

LMM



σ_{aneff}

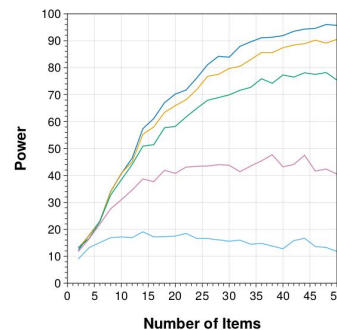
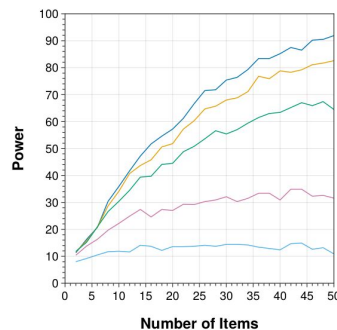
- (:subj => [0.0 0.0; 0.0 0.1])
- (:subj => [0.0 0.0; 0.0 0.3])
- (:subj => [0.0 0.0; 0.0 0.5])
- (:subj => [0.0 0.0; 0.0 1.0])
- (:subj => [0.0 0.0; 0.0 2.0])

Power (Two-Stage vs. LMM)

nsubj = 5 | $\beta = [2.0, 0.5]$ | $\sigma_{\text{res}} = 0.0001$
noiselevel = 1.0 | noisetype = pink

Two-Stage

LMM



σ_{aneff}

- (:subj => [0.0 0.0; 0.0 0.1])
- (:subj => [0.0 0.0; 0.0 0.3])
- (:subj => [0.0 0.0; 0.0 0.5])
- (:subj => [0.0 0.0; 0.0 1.0])
- (:subj => [0.0 0.0; 0.0 2.0])



Limitations

Simulated data

**Small parameter
space**

**Increased type 1
error for LMMs**



Conclusion



Observed results did NOT show an advantage of the LMMs over the two-stage approach



Different scenarios / parameters need to be investigated for a more founded conclusion



UnfoldSim.jl good starting point for further investigation



Discussion

References

Phillip Alday, Douglas Bates, Lisa DeBruine, PhD José Bayoán Santiago Calderón, and Lisa Schwetlick. Repsychling/mixedmodelssim.jl: v0.2.6, October 2021. URL <https://doi.org/10.5281/zenodo.5543934>.

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