How important is trial sample size in neuroimaging experiments?

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Current status of trial sample size in neuroimaging

- Inconvenient parameter when designing an experiment
  - Little attention; chosen for convenience: usually in the range of [10, 40] per condition
  - Implicit assumption: of little importance compared to subject sample size
- Questions
  - Is the lack of attention to trial sample size justifiable?
  - How to quantify the role of trial sample size?
  - How to effectively leverage trial sample size to gain statistical efficiency?
  - How is the trial sample size related to the summary-statistics modeling approach?

Conventional power analysis

- Largely focusing on the number of subjects
  - Tools: fMRIPower; Neurodesign
  - Rarely used; mainly to pacify reviewers
- Difficulties of power analysis
  - Poor practice: effect magnitude usually not reported in literature
  - Not one, but many regions involved
  - Complexity: multiple testing adjustment
- Justifications for Big Data initiatives
  - Small effects
  - Large heterogeneity across subjects
  - Straightforward: more subjects always improve statistical efficiency
  - Only and most cost-effective approach to increase statistical efficiency?

Overview

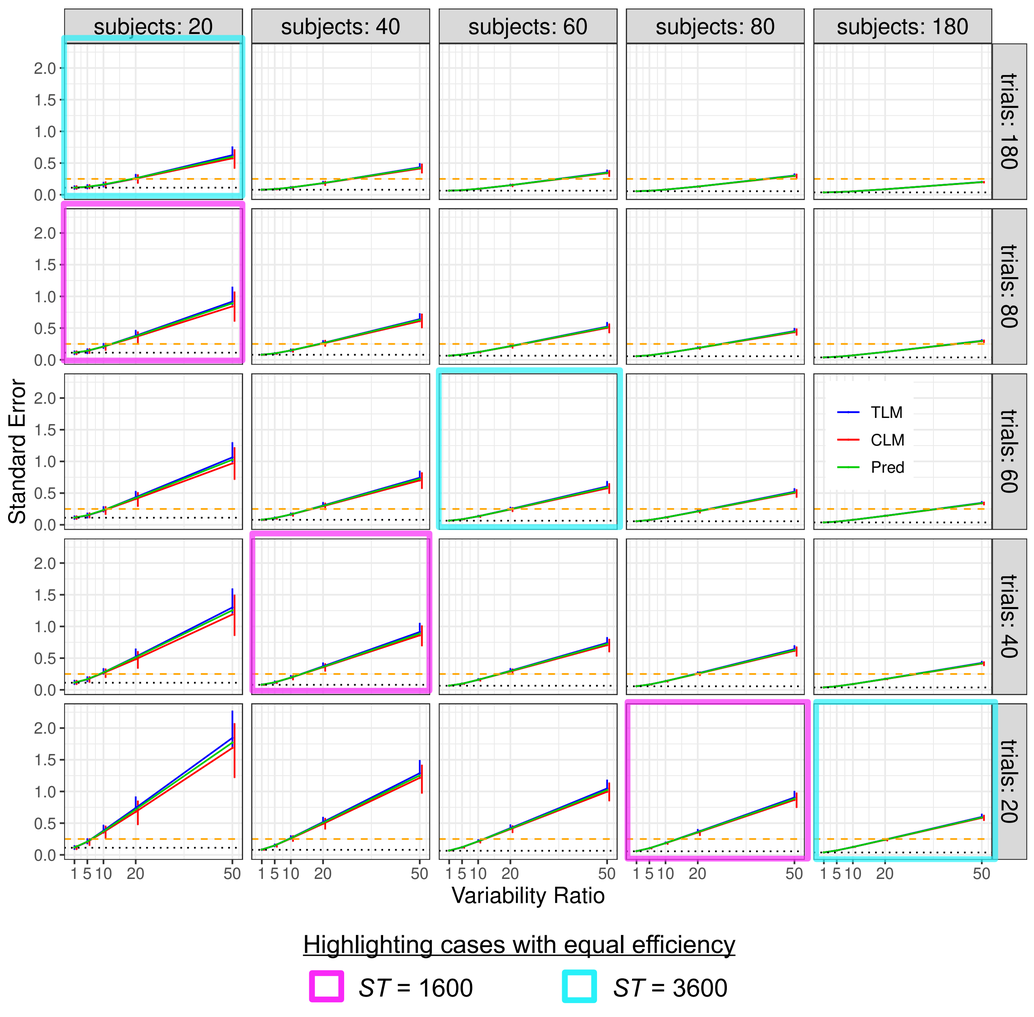
- Adopt a hierarchical model to accurately map the data across multiple levels
- Derive theoretical relationship between trial and subject sample size
- Use simulations to gain insights
- Validate simulation results through an experimental dataset
- Make recommendation for future experimental designs

Theoretical framework

- Data y_{cst}: trial-level effect with c, s and t indexing conditions, subjects and trials
- Model formulation

$$y_{cst} \sim \mathcal{N}(\mu_c + \pi_{cs},\ \sigma_\tau^2);$$
$$\begin{bmatrix}\pi_{1s}\\ \pi_{2s}\end{bmatrix} \sim \mathcal{N}\left(\begin{bmatrix}0\\0\end{bmatrix}, \begin{bmatrix}\sigma_{\pi_1}^2 & \rho\sigma_{\pi_1}\sigma_{\pi_2}\\ \rho\sigma_{\pi_1}\sigma_{\pi_2} & \sigma_{\pi_1}^2\end{bmatrix}\right);\ c = 1, 2;\ \ s = 1, 2, \ldots, S;\ \ t = 1, 2, \ldots, T.$$

- Model parameters
  - μ_c: cth condition effect
  - π_{cs}: sth subject's effect under cth condition
  - $\sigma_{\pi_c}^2$: cross-subject variances under cth condition
  - σ_τ^2: cross-trial variances
  - ρ: correlation between the two conditions
- Variance for effect of interest (contrast between two conditions)
  - $\sigma^2 = 2(1-\rho)\frac{\sigma_\pi^2}{S} + \frac{2\sigma_\tau^2}{ST}$
  - Revealing relationship between the two sample sizes S and T: hyperbolic
  - Variability ratio $R_v = \sigma_\tau/\sigma_\pi$ - indicator for relative magnitude of cross-trial variability



- Insights from simulations
  - Subject sample size always plays a crucial role in statistical efficiency
  - Impact of trial sample size: varying
    - negligible: small cross-trial variability (eg, $R_v \lesssim 1$): implicitly assumed in practice
    - as important as subjects: large cross-trial variability (eg, $R_v \gtrsim 10$): symmetric hyperbola
    - moderate but less impactful than subjects when cross-trial variability is moderate
- Crucial question: what is the typical magnitude of cross-trial variability in real data?

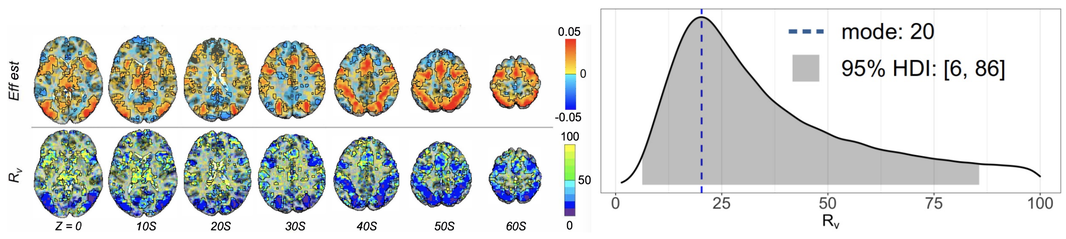
Validation of hyperbolic relationship with experimental dataset

Data information

- 42 subjects
- Eriksen Flanker task with two trial types: congruent and incongruent
- 8 runs, ~380 trials per condition per subject (350 ± 36 incongruent, 412 ± 19 congruent trials)
- 4 trial sample sizes
  - 12.5%: ≈ 48 trials from the first run
  - 25%: ≈ 95 trials from two runs
  - 50%: ≈ 190 trials from four runs
  - 100%: ≈ 380 trials from full dataset
- 2 modeling approaches
  - Hierarchical framework with trial-level modeling (TLM)
  - Conventional summary statistics approach through condition-level modeling (CLM)
- Questions to be addressed
  - Relative importance of trial sample size compared to subjects
  - Relative magnitude of cross-trial variability: variability ratio R_v
  - Performance of conventional summary statistics approach

Cross-trial variability R_v

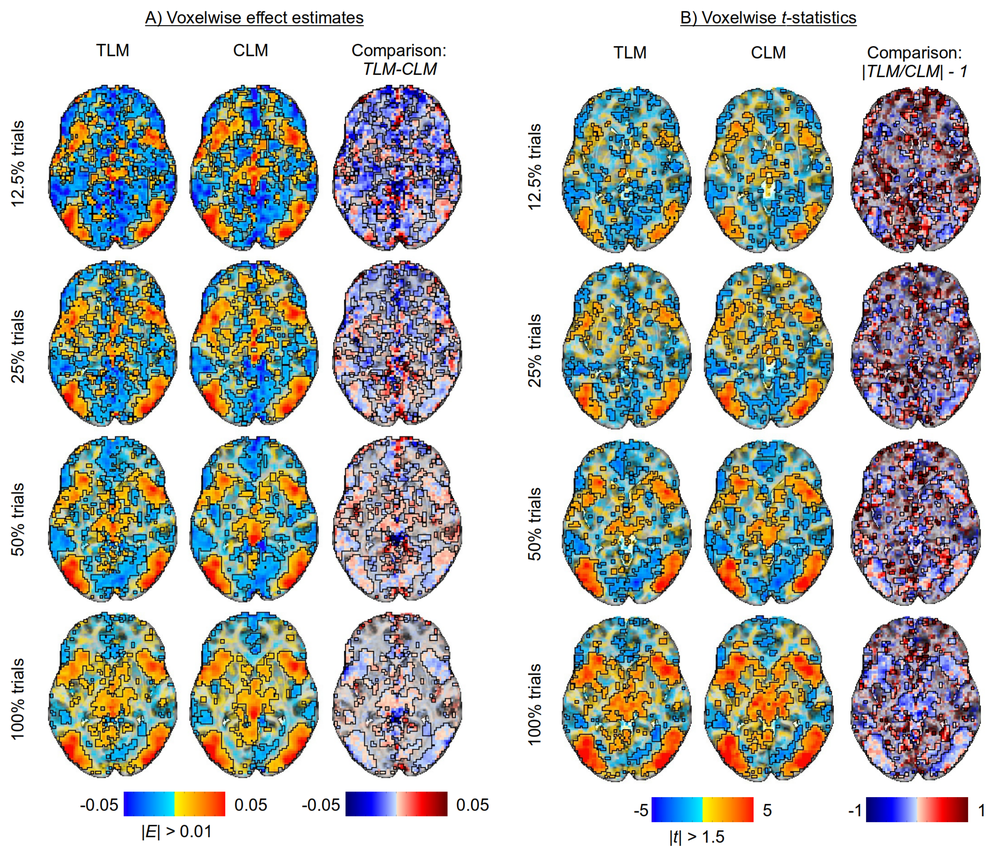
- Typical range of cross-trial variability: $R_v > 5$



Impact of trial sample size

- Hyperbolically symmetric: With moderate to large R_v, trials almost as important as subjects
- More cost-effective to increase both trials and subjects
- TLM vs CLM: quite similar statistical results in most regions

Revelations from experimental data



Conclusions

- Trial sample size: nearly similar impact as subject sample size on statistical efficiency
- More effectively to increase both trials and subjects simultaneously
- Trials can be leveraged alongside subjects to improve cost-effectiveness
- Trial-level modeling is preferred especially when trial sample size is small

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References

Chen et al, 2022. Hyperbolic trade-off: The importance of balancing trial and subject sample sizes in neuroimaging. NeuroImage 247, 118786.