Exploring the uni-factorial structure of the general-speed component of response times

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Main argument:

1. Difference scores used to study cognitive control show weak correlations across tasks and poor test-retest reliability.
2. In contrast, across many data sets, the general-speed component of response times in cognitive control tasks has a robust uni-factorial solution.
3. Our goal is to extend the PCA analysis to determine whether univariance is found in the shift, scale, or shape parameters of RT distributions.

1. Cognitive control difference scores

Cognitive control is the ability to ignore irrelevant information and suppress automatic responses. Tasks designed to study it use as dependent measure the difference in the mean response times (RTs) observed between conditions that either require cognitive control or not.

Stroop:

- **Congruent condition:** BLUE RED PURPLE
- **Incongruent condition:** RED PURPLE RED

$$Y_i = \mathrm{RT}_{\mathrm{Incong}} - \mathrm{RT}_{\mathrm{Cong}}$$

Given the large number and variety of tasks used to study cognitive control, one may ask:

Are there robust individual differences in cognitive control?

We re-analyzed the data reported across five different studies where different cognitive control tasks were applied, (see Table 1).

Table 1. A summary of the number of tasks, participants and trials included in the data sets revisited in this project.

No	Tasks	Part	Trials	Cite
1	10	263	144-360	Rey-Mermet et al. (2018)
2	8	522	72-280	Enkavi et al. (2019)
3	3(2)	100	720	Hedge et al. (2018)
4	4	42	640-720	Hedge et al. (2018)
5	3	121	93-194	Von Bastian et al. (2015)
6	3	178	475-760	Whitehead et al. (2018)
7	3	194	516-1187	Whitehead et al. (2018)
8	3	210	568-600	Whitehead et al. (2018)
9	2	38	504	Pratte et al. (2010)

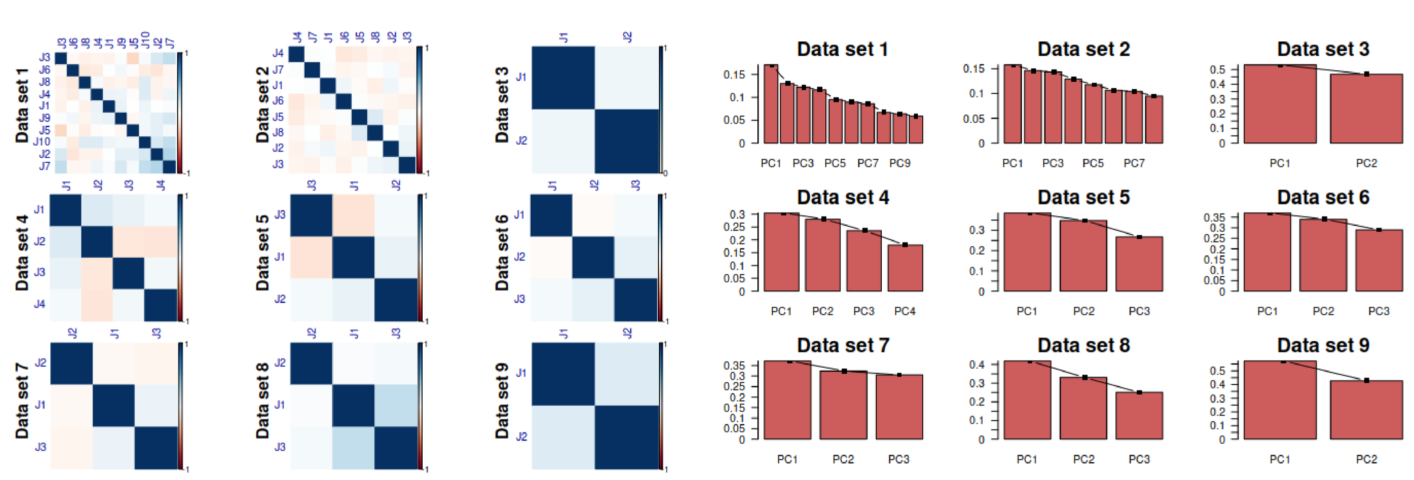

Figure 1. Exploring individual differences in difference scores. Left panel: Correlation matrices of the difference scores across tasks for each of the data sets revisited. Right panel: Scree plots for the difference scores across tasks for each data set.

2. General-speed has a unifactorial structure

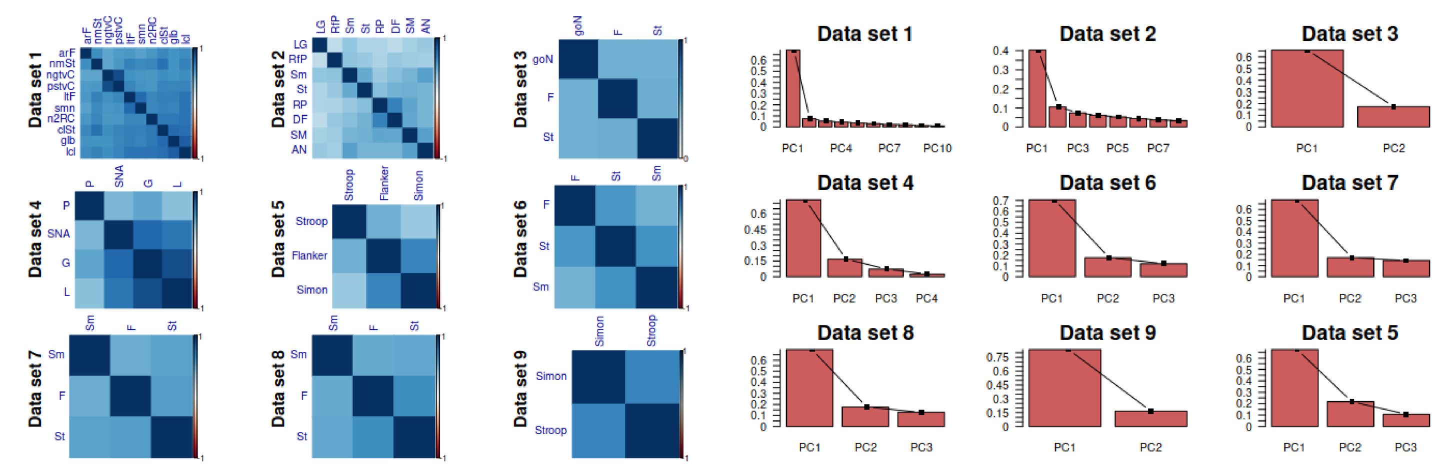

Figure 2. Exploring individual differences in general-speed. Left panel: Correlation matrices of the mean simple-RT across tasks for each of the data sets revisited. Right panel: Scree plots for the mean simple-RT across tasks for each data set.

3. Fitting an Ex-Gaussian distribution

The RT observed on any trial k for every participant i doing task j is modeled as a draw from an ExGaussian distribution, so that:

$$Y_{ijk} \sim \text{Normal}(\mu_{ij} + \tau_{ijk}, \sigma^2_{ij})$$
$$\tau_{ijk} \sim \text{Exp}\left(\frac{1}{\nu_{ij}}\right)$$

We applied this model to a subset of 7 tasks and 100 participants from a larger data set [1].

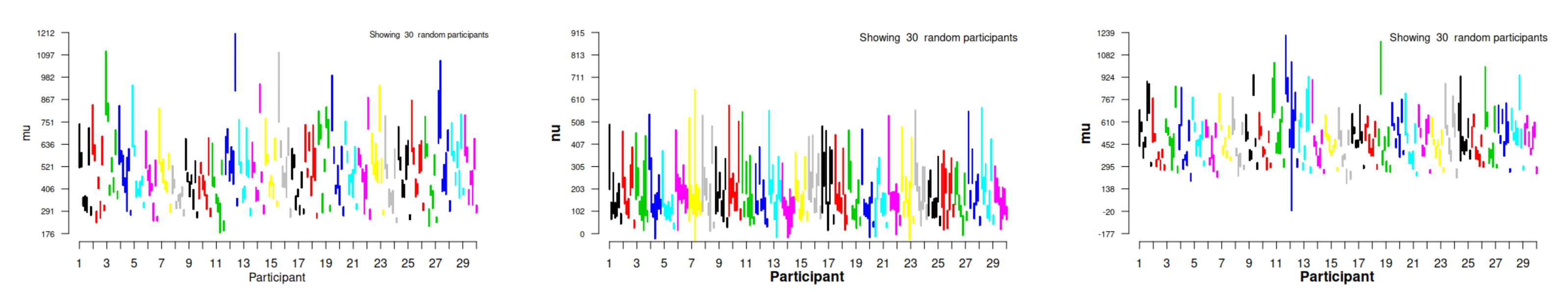

Figure 3. Individual posterior samples for μ_{ij} (left), ν_{ij} (center) and σ_{ij} (right). On all panels, change of colors separate participants, with a same-color line per task. We only show results for 30 random participants.

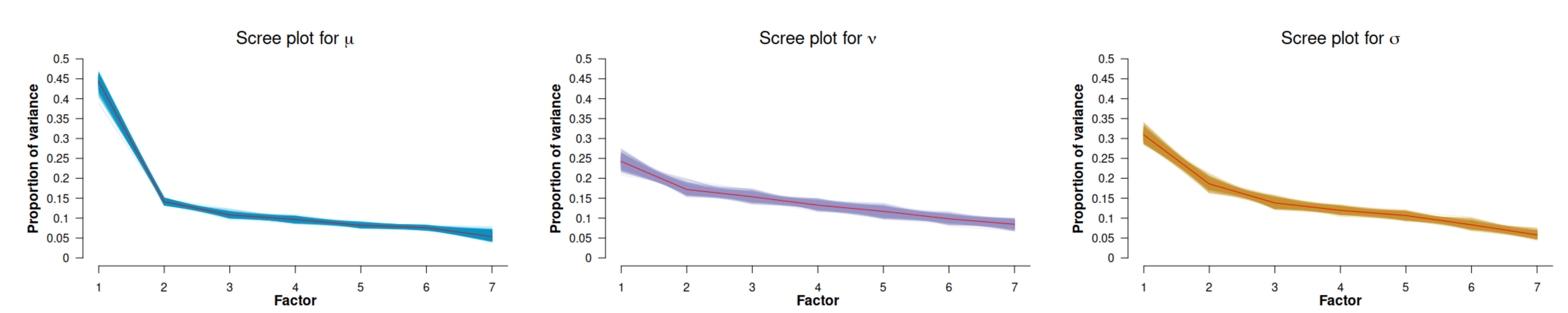

Figure 4. We conducted an iterative PCA revision for $n = 1000$ random posterior samples. The three panels present the overlapping Screeplots obtained across each iteration (left: μ_{ij}, center: ν_{ij} and right: σ_{ij}). The thin lines correspond to the average result.

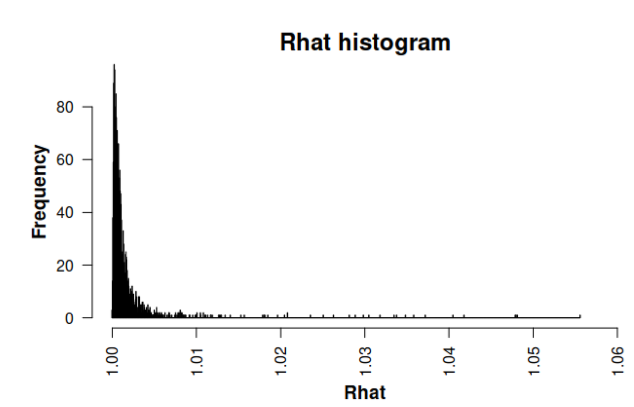

Figure 5. Distribution of Rhats computed across chains while sampling the hereby mentioned model.

These are preliminary results

Future/Current steps: Cognitive Latent Variable Modeling

We're working on a Cognitive Latent Variable Model where either μ_{ij}, ν_{ij} or σ_{ij}, all parameters of a participant-by-task ExGaussian distribution, is assumed to have a factorial composition. So that:

$$y_{ijk} \sim \text{Normal}(\mu_{ij} + \tau_{ijk}, \sigma^2_{ij})$$
$$\tau_{ijk} \sim \text{Exp}\left(\frac{1}{\nu_{ij}}\right)$$

$$\mu_{ij} \text{ or } \sigma_{ijk} \text{ or } \nu_{ijk} = \lambda_0 + (\phi_{1i} \times \lambda_{1j}) + \cdots + (\phi_{Fi} \times \lambda_{Fj})$$

where λ_0 is the Intercept, ϕ_{1i} represents the first factor score for participant i weighted by λ_{1j} that captures the weight of task j on this first factor.

$$\mu_{[I\times J]} \text{ or } \nu_{[I\times J]} \text{ or } \sigma_{[I\times J]} = \Phi_{[I\times F]}\Lambda_{[F\times J]}$$

In order to guarantee that the model is identified, we enforce the following restrictions:

1. All elements of Φ are assumed to be normally distributed (i.e. they vary freely).
2. The Λ matrix is sparse, with only a few non-zero elements, some of which will be fixed to 1.

Acknowledgements

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Data sets were collected from:

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