Explicit modeling of the hemodynamic response in linking cognitive computational models to fMRI data

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Introduction

- The linking of computational models of cognition (e.g., the diffusion decision model; DDM) to neuroscientific data (e.g., functional MRI data; fMRI), has been a fruitful approach to constrain theories of both cognition as well as its neural implementation (Schall, 2004; Forstmann et al., 2011; de Hollander et al., in press).

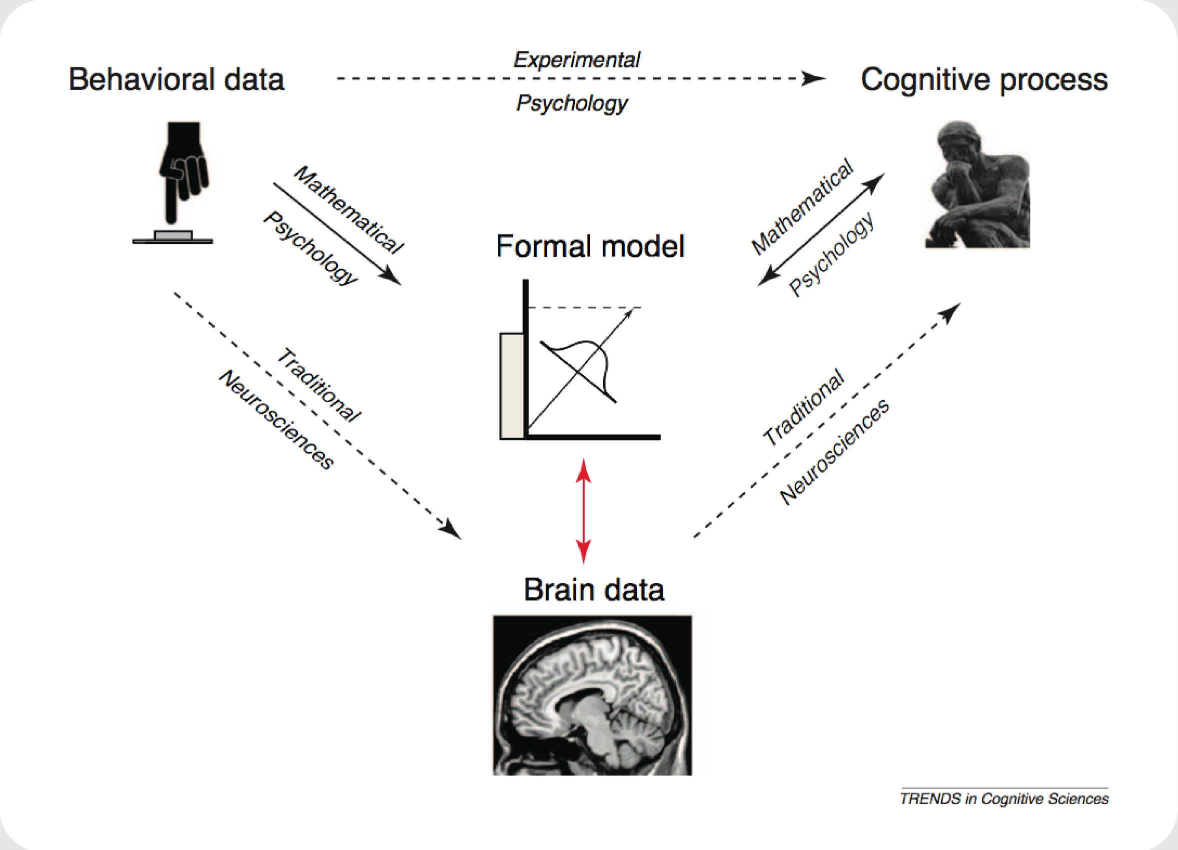

Figure 1: Model-in-the-middle approach (taken from Forstmann et al., 2011).

- A common approach to link computational models to functional MRI data (fMRI) is the *single-trial regression approach*, using the canonical double-gamma hemodynamic response function (HRF).

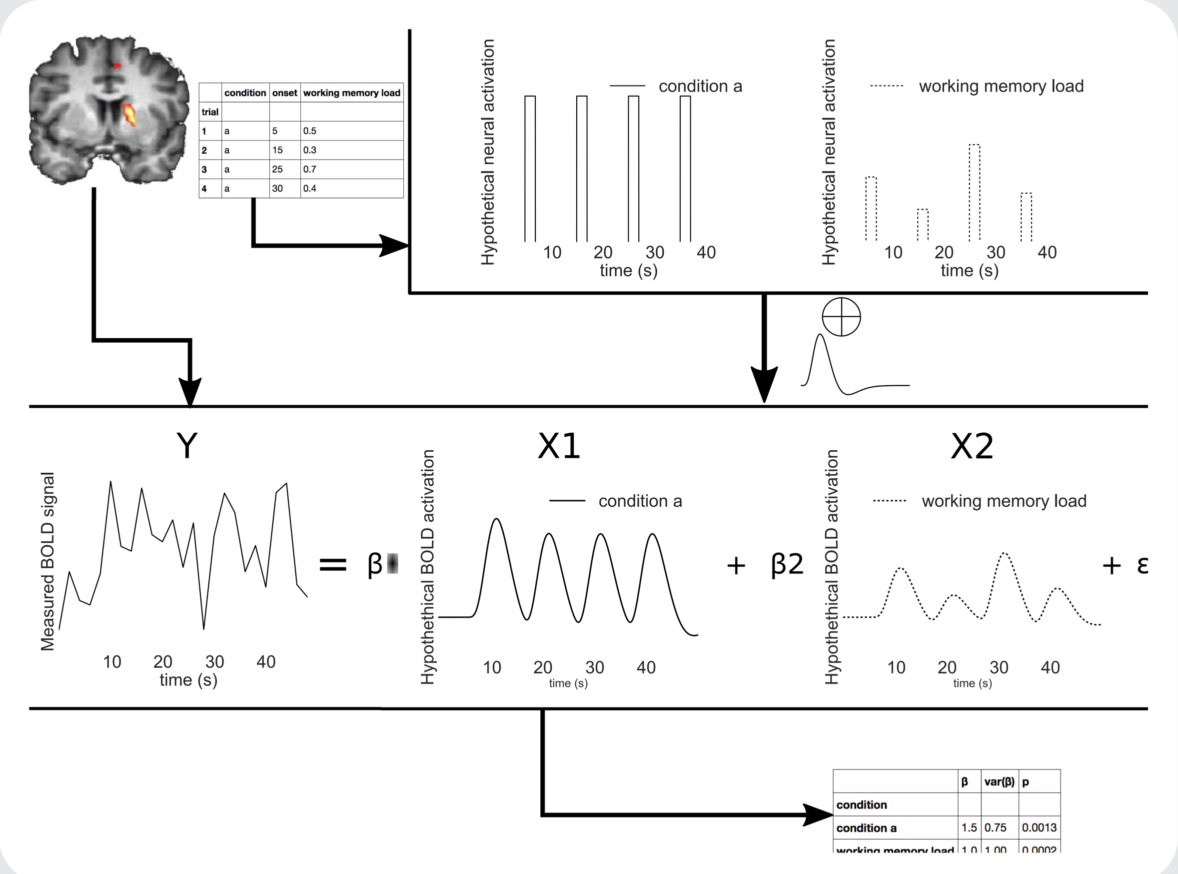

Figure 2: Illustration of the single-trial regression approach.

- The single-trial regression approach entails two crucial assumptions:
  1. The HRF is identical across subjects, brain regions, and conditions.
  2. Variability in cognitive processes only influences the height of the hemodynamic response function (opposed to e.g., dispersion and onset-to-peak).

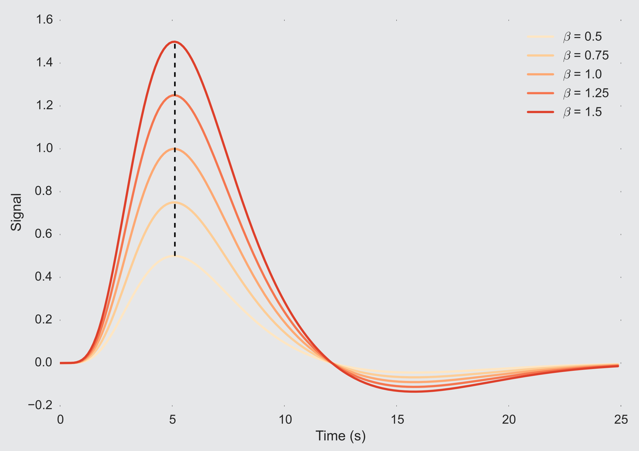

Figure 3: Canonical double-gamma HRF with varying amplitudes.

A more flexible model

- Fits of the canonical HRF to real data can be surprisingly poor.

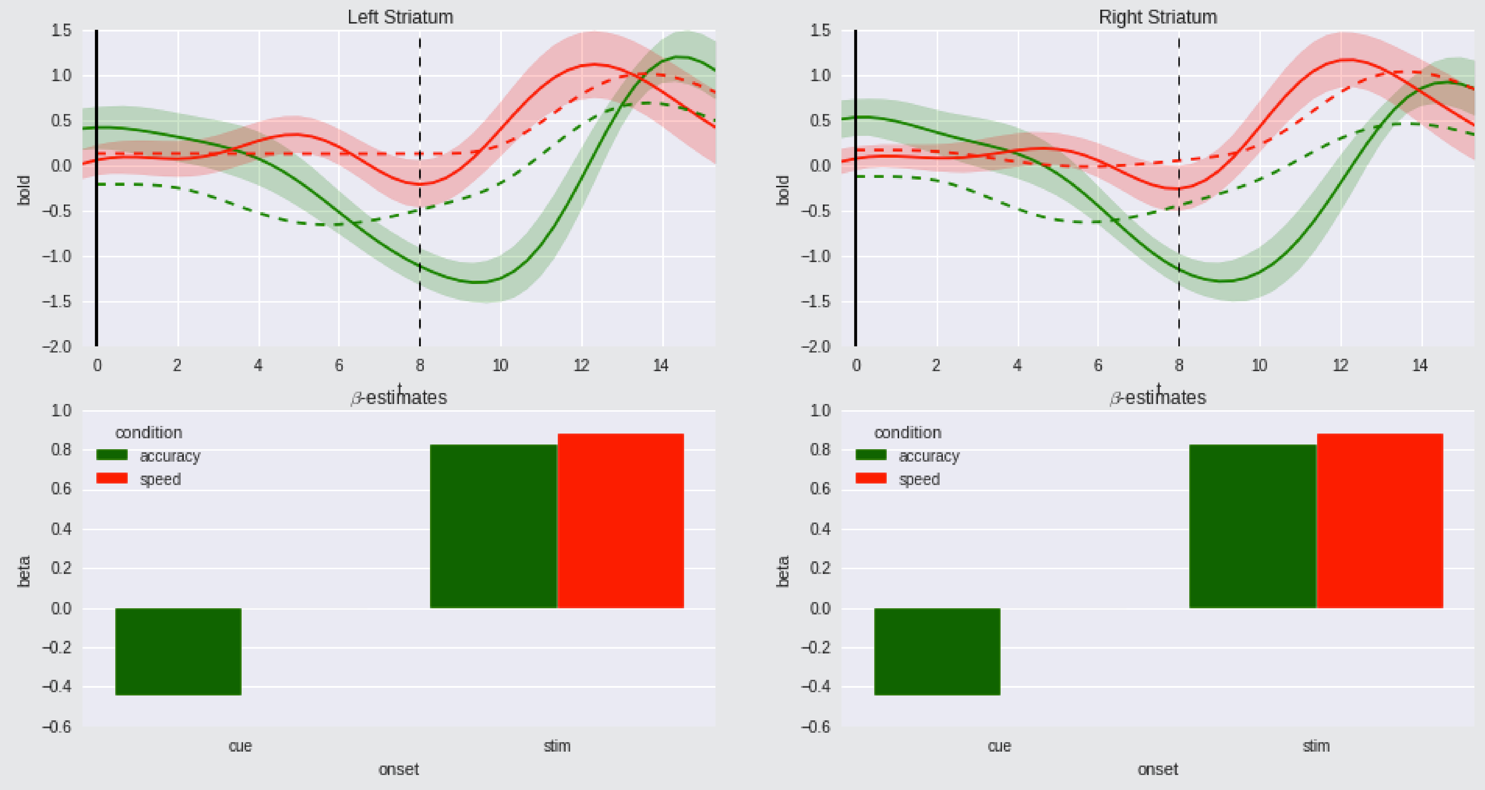

Figure 4: Speed-accuracy experiment (see, Forstmann et al., 2008). Upper panels: Raw BOLD signal derived from the left and right striatum (solid line) and best fit of canonical double-gamma HRF (dotted line). Lower panels: Averaged beta weights for speed and accuracy conditions.

- The canonical double-gamma HRF can be parameterized with more than just the height of the first gamma function, e.g., the time-to-peak or dispersion .

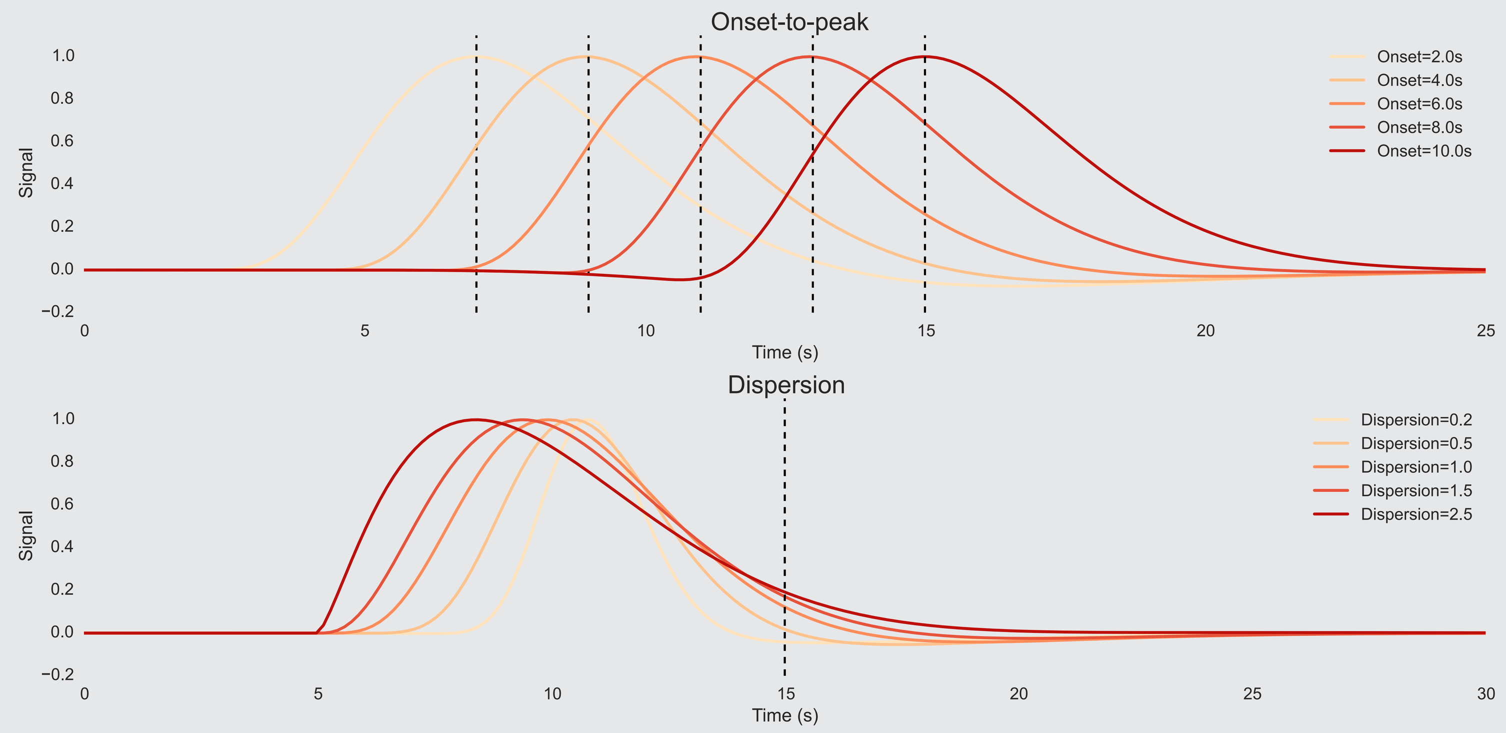

Figure 5: HRFs with different onsets-to-peak and different dispersions.

- We set up a Hierarchical Bayesian Graphical model to estimate the height, onset-to-peak and dispersion of the HRF for different anatomical regions and conditions using Markov Chain Monte Carlo samplig (MCMC). The Baysian Graphical model allows to:
  1. Use priors to inform parameter estimation (Kruschke, 2011).
  2. Learn about the uncertainty of estimates by using the dispersion and covariance of the posteriors (Gelman et al., 2014).
  3. Systematically compare different models (Vandekerckhove et al., 2015).
- By combining the likelihood of a cognitive model with this HRF-model we can use either regression (Wiecki et al., 2013) or covariance estimation (Turner et al., 2013) to test whether specific aspects of the HRF are related to specific latent cognitive variables.

Preliminary results

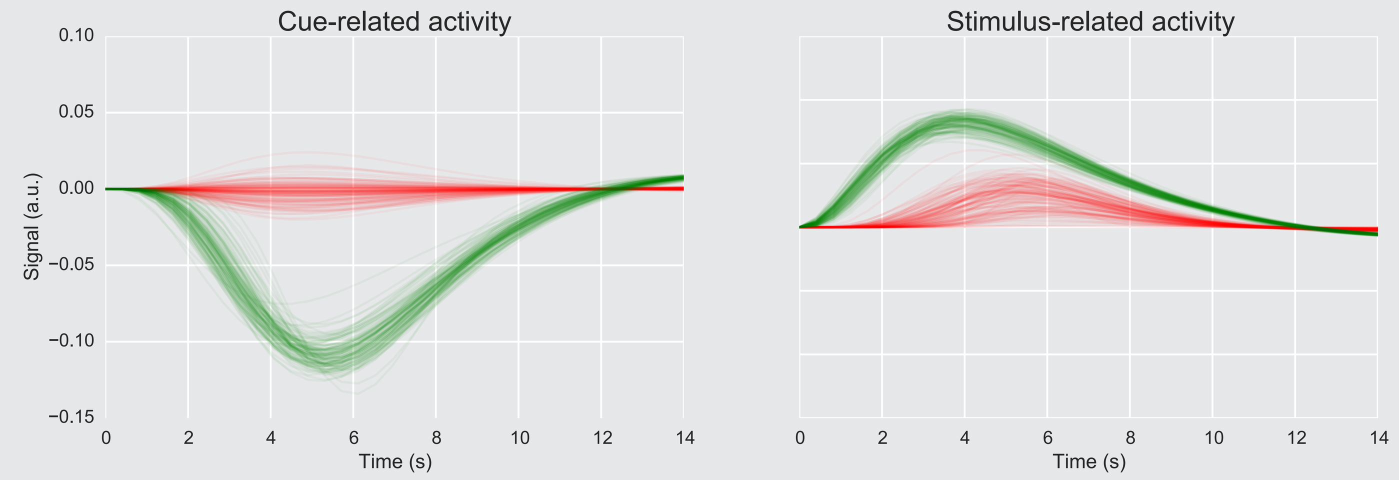

Figure 6: Posterior predictive plot of cue- and stimulus-locked HRFs for the speed- and accuracy-stressed condition.

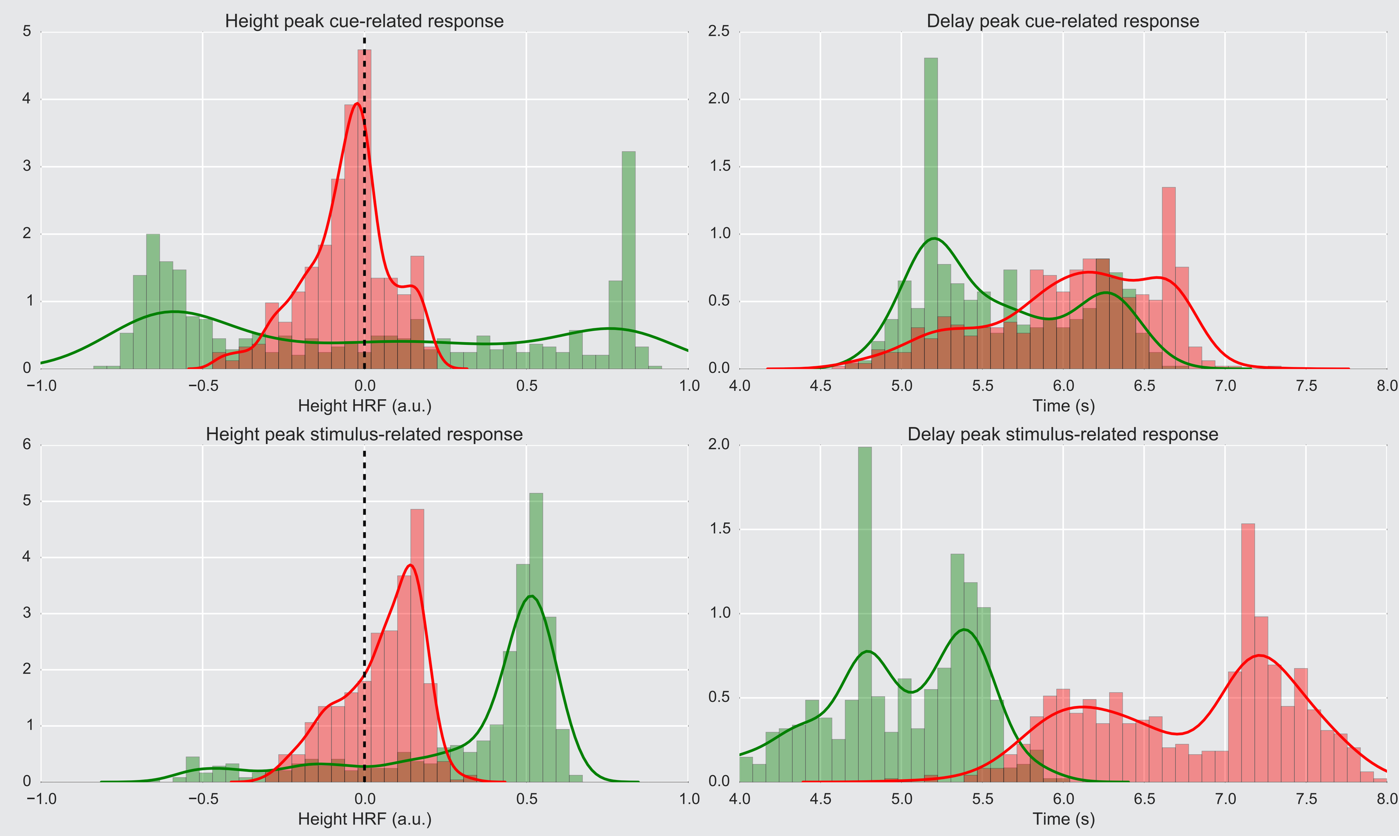

Figure 7: Posterior distributions of HRF parameters for cue- and stimulus-locked HRFs for the speed- and accuracy-stressed condition.

Open questions

- Can the modulation of specific aspects of the HRF be interpreted in specific ways? For example:
  - Can the onset-to-peak parameter be interpreted as a proxy to when a cognitive process commenced?
- Are current cognitive models suitable for direct comparison to fMRI data? For example:
  - Is it sensible to map "drift rate areas"? (O'Reilly & Mars, 2011)
  - Can the extended HRF models predict behavior better than traditional models?

References

de Hollander, G., Forstmann, B. U., & Brown, S. D. (in press). Different ways of linking behavioral and neural data via computational cognitive models. *Biological Psychiatry: Cognitive Neuroscience and Neuroimaging*.

Forstmann, B. U., Dutilh, G., Brown, S., Neumann, J., Von Cramon, D. Y., Ridderinkhof, K. R., & Wagenmakers, E.-J. (2008). Striatum and pre-SMA facilitate decision-making under time pressure. *Proceedings of the National Academy of Sciences*, *105*(45), 17538–17542.

Forstmann, B. U., Wagenmakers, E.-J., Eichele, T., Brown, S., & Serences, J. T. (2011, June). Reciprocal relations between cognitive neuroscience and formal cognitive models: opposites attract? *Trends in Cognitive Sciences*, *15*(6), 272–279.

Gelman, A., Carlin, J. B., Stern, H. S., & Rubin, D. B. (2014). *Bayesian data analysis* (Vol. 2). Taylor & Francis.

Kruschke, J. K. (2011). *Doing Bayesian Data Analysis: A Tutorial with R and BUGS*. Barlington: Academic Press.

O'Reilly, J. X., & Mars, R. B. (2011, October). Computational neuroimaging: localising Greek letters? Comment on Forstmann et al. *Trends in Cognitive Sciences*, *15*(10), 450.

Schall, J. D. (2004, February). On Building a Bridge Between Brain and Behavior. *Annual Review of Psychology*, *55*(1), 23–50.

Turner, B. M., Forstmann, B. U., Wagenmakers, E.-J., Brown, S. D., Sederberg, P. B., & Steyvers, M. (2013, May). A Bayesian framework for simultaneously modeling neural and behavioral data. *NeuroImage*, *72*, 193–206.

Vandekerckhove, J., Matzke, D., & Wagenmakers, E.-J. (2015). Model Comparison and the Principle of Parsimony . In *The oxford handbook of computational and mathematical psychology* (p. 300). Oxford University Press.

Wiecki, T. V., Sofer, I., & Frank, M. J. (2013). HDDM: Hierarchical Bayesian estimation of the Drift-Diffusion Model in Python. *Frontiers in neuroinformatics*, *7*, 14.