Bayesian inference of the SWIFT model: Reading mirrored, scrambled, and normal texts

Maximilian M. Rabe, Johan Chandra, André Krügel, Stefan A. Seelig, & Ralf Engbert

Research Focus Cognitive Sciences, University of Potsdam, Germany

SFB 1287 Limits of Variability in Language
Gefördert durch DFG Deutsche Forschungsgemeinschaft

DOI: 10.17605/OSF.IO/S5JK2

Introduction

SWIFT (Engbert, Nuthmann, Richter, & Kliegl, 2005) is a dynamical cognitive model of eye-movement control in reading. Words within the processing span centered around the current fixation position are processed in parallel via a temporally evolving activation field (see Figure 1).

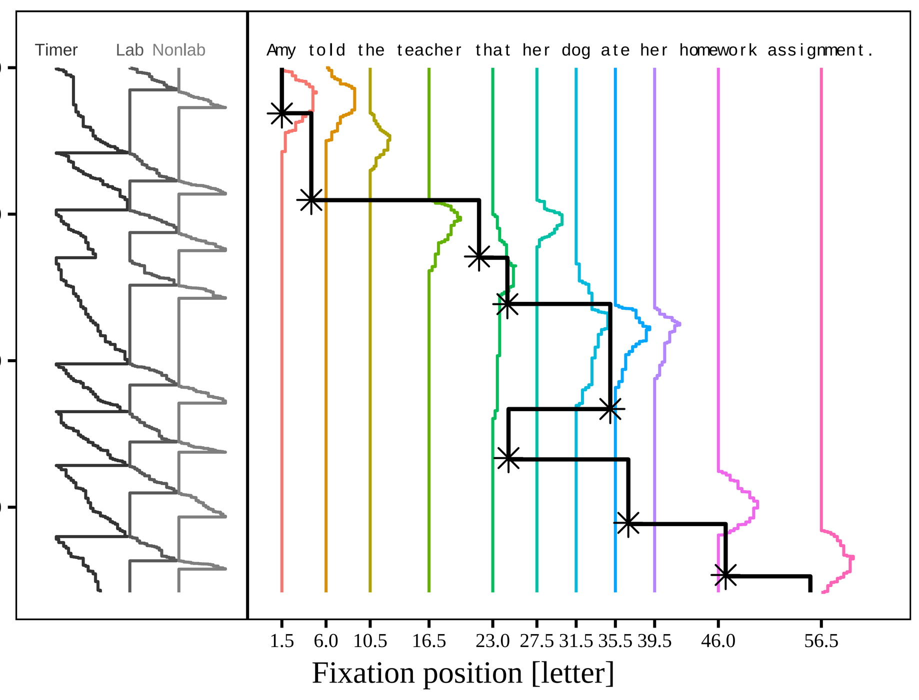

Figure 1. Simulated eye trajectory (solid black line) in the SWIFT model. Thin lines are word activations (colored) and timers (gray) as a function of time. Asterisks mark points in time when a saccade program is executed.

Recently, we implemented SWIFT for Bayesian parameter estimation (Seelig et al., 2019). The model was fitted to a diverse reading dataset in order to evaluate the goodness of fit with various temporal and spatial summary statistics.

For the simulations reported here, we replaced the standard Gaussian saccade error model with Gamma-distributed saccade amplitudes:

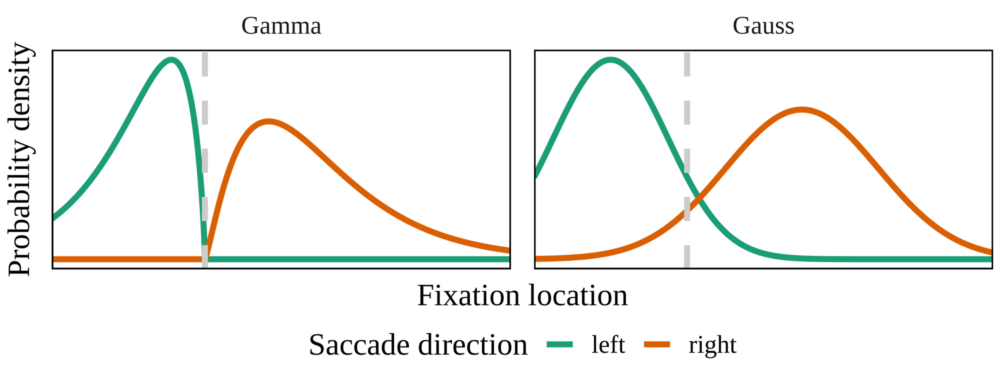

Figure 2. Comparison of saccade amplitude distributions for saccade targets left or right to the current fixation location (dashed gray line).

Bayesian parameter estimation

Bayesian model fitting allows us to infer rigorous credibility intervals for model parameters. Additionally, we can determine model parameters for individual participants, which was often precluded in previous methods.

In SWIFT, the likelihood of a fixation f_i is given as the combined spatial and temporal likelihoods, both conditional on all preceding fixations F_{i-1}:

$$P_M(k_i, l_i, T_i | F_{i-1}) = P_{temp}(T_i | F_{i-1}) \cdot P_{spat}(k_i, l_i | T_i, F_{i-1}) \quad (1)$$

Likelihood profiles for selected parameters show that for simulated data, (a) the true parameter values are most likely and (b) model parameters can have different selective influences on spatial and temporal likelihood components:

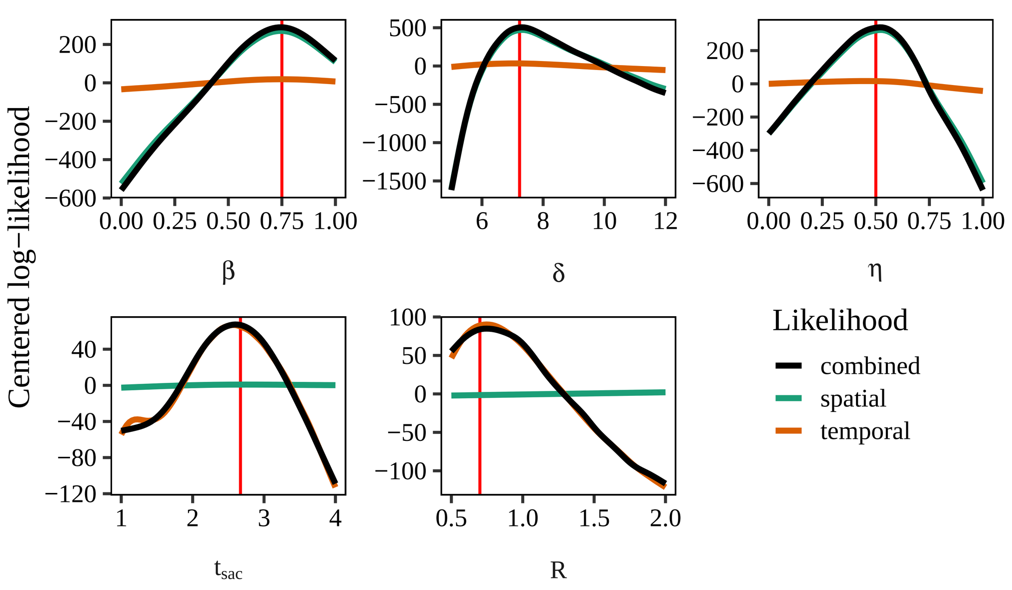

Figure 3. Centered log-likelihood profiles (black) with temporal and spatial components. Each respective likelihood component was centered around its mean. Vertical red lines are true parameter values.

Experimental method

Table 1. Reading conditions

N	Jede	Sprache	der	Welt	besitzt	eine	Grammatik
mL	Jede	Sprache	der	Welt	besitzt	eine	Grammatik
sL	Jdee	Scrahpe	der	Wlet	bsizett	enie	Gmartimak
iW	edeJ	ehcarpS	red	tleW	tztiseb	enie	kitammarG
mW	Jede	Sprache	der	Welt	besitzt	eine	Grammatik

- 36 native German speakers with normal or corrected-to-normal vision
- Normal reading (N) in first lab session
- One of four manipulated reading conditions (see Table 1) in second lab session

Results

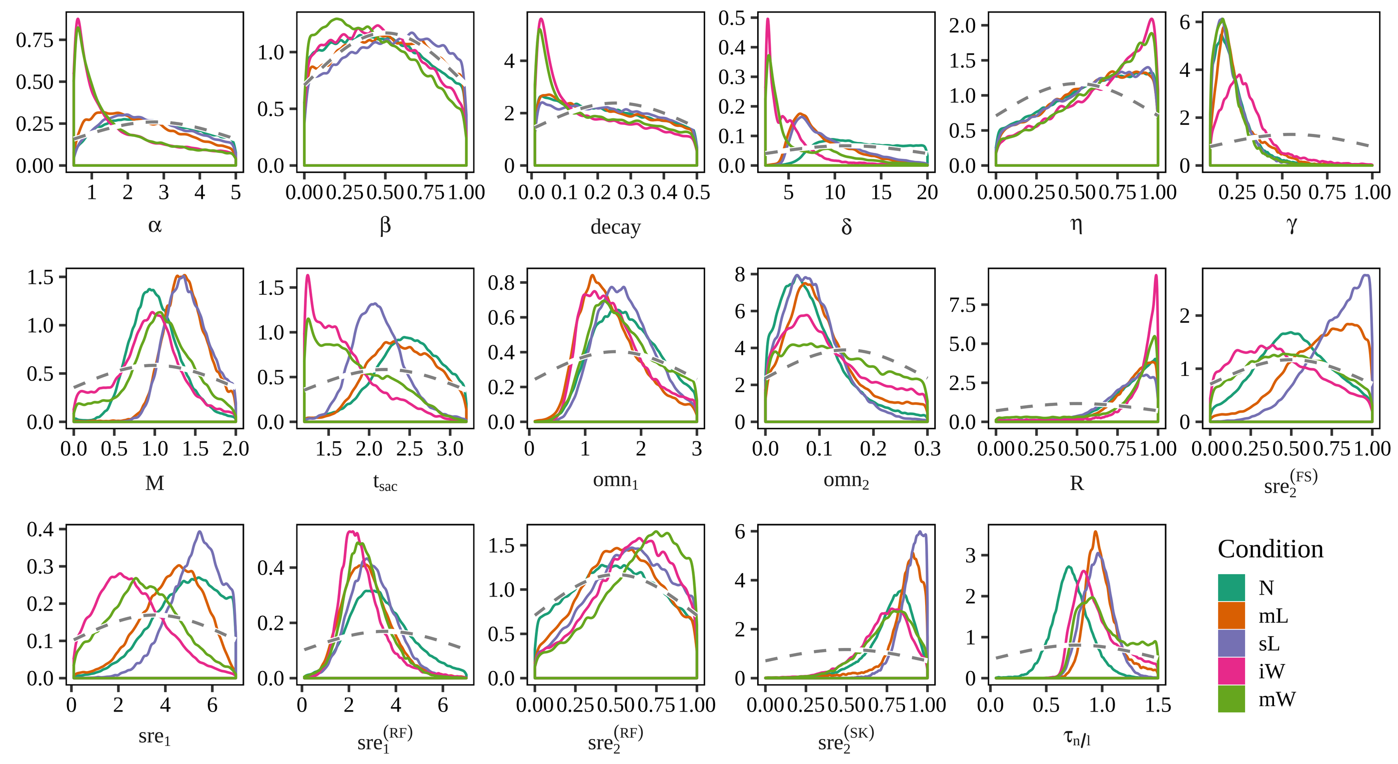

Figure 4. Posterior parameter distributions. Each color represents the aggregated sampled posteriors across all subjects in that condition. Priors (gray dashed lines) are truncated normal with support on 1 SD around the mean and were identical across subjects and conditions.

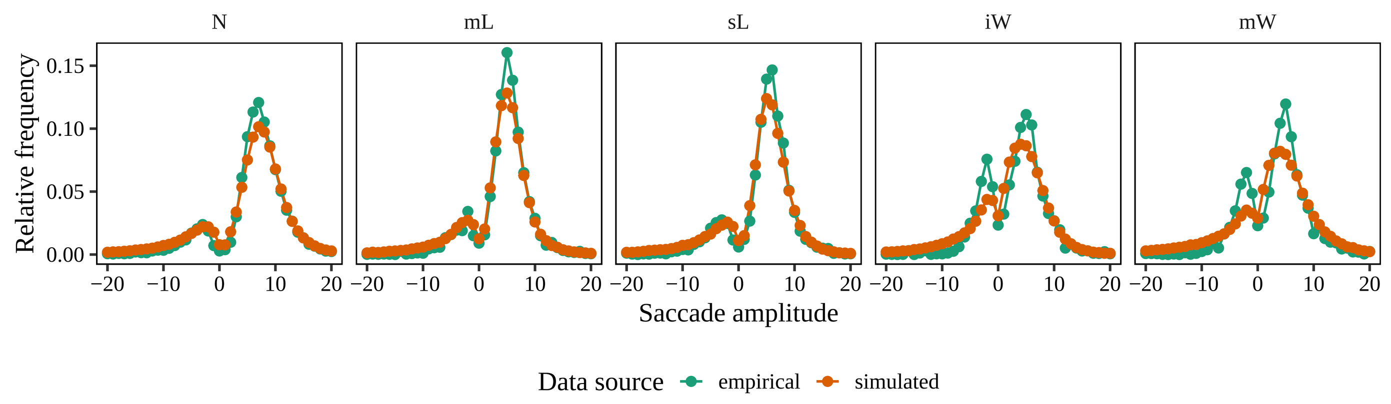

Figure 5. Empirical and simulated saccade amplitudes aggregated across all participants in each experimental condition, including the baseline condition (N).

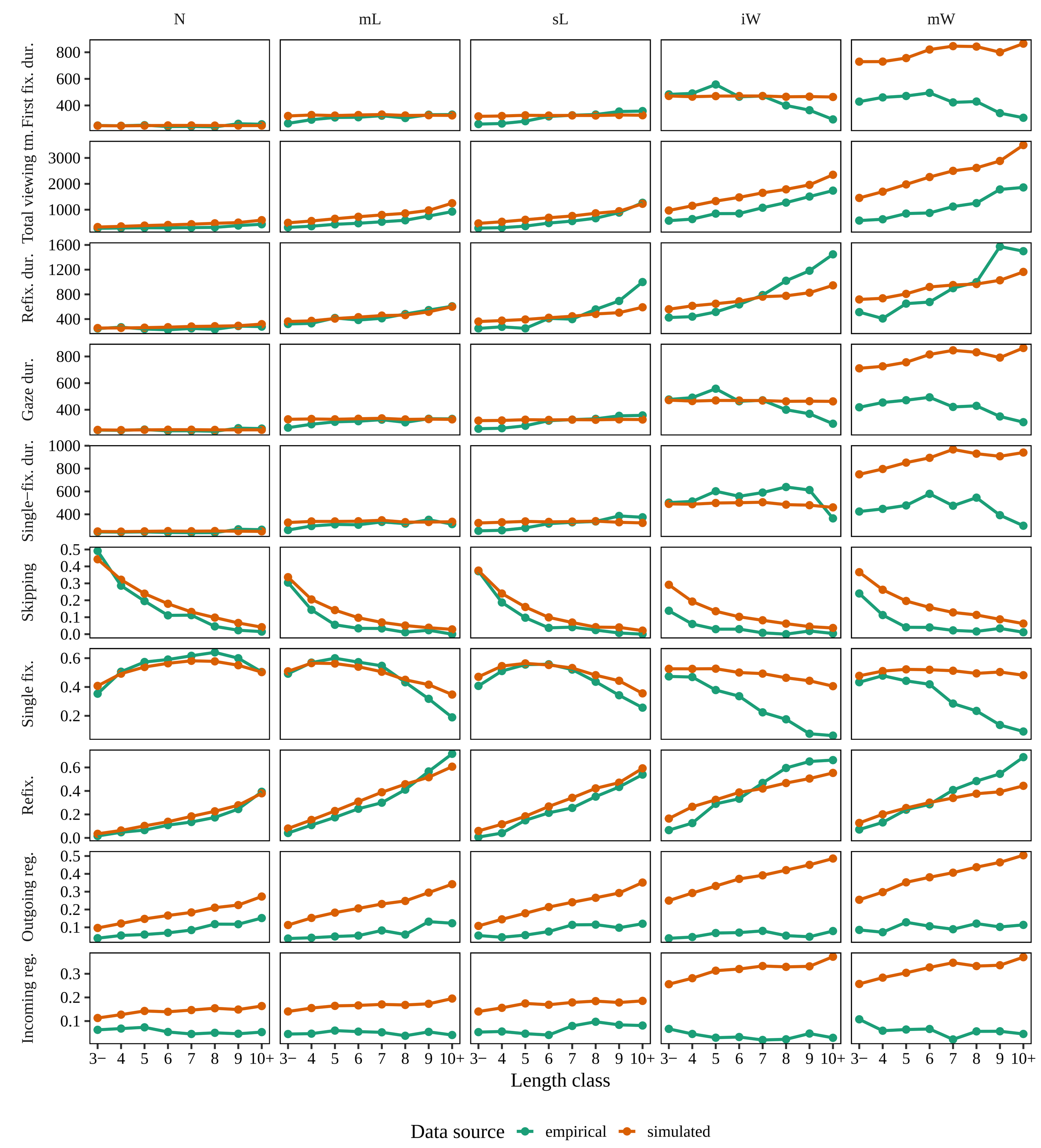

Figure 6. Empirical and simulated temporal (1–5) and spatial (6–10) summary statistics for different experimental conditions, aggregated across subjects, as a function of word length.

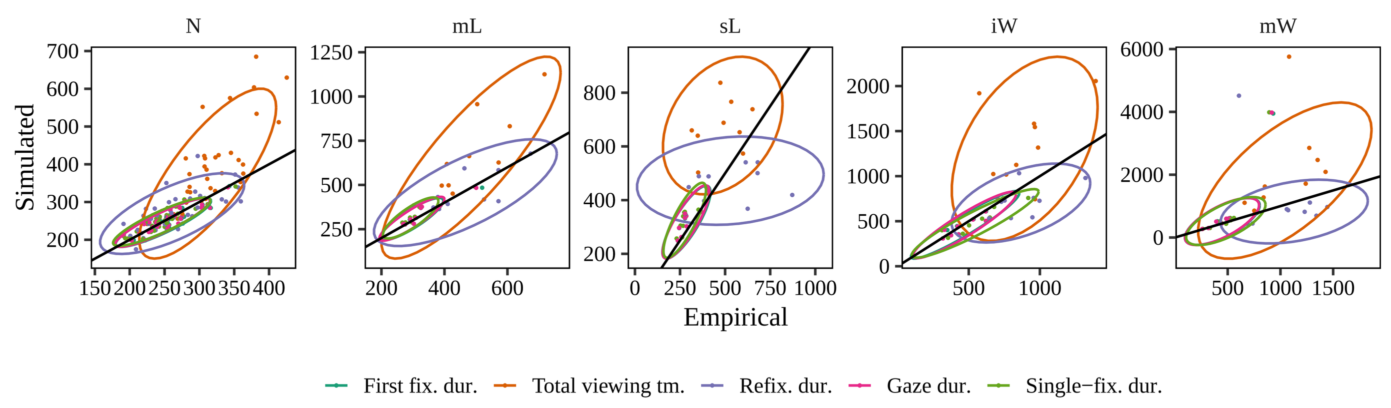

Figure 7. Correlation between empirical and simulated temporal summary statistics. Each participant is represented by one dot in each color in the respective experimental condition (panel).

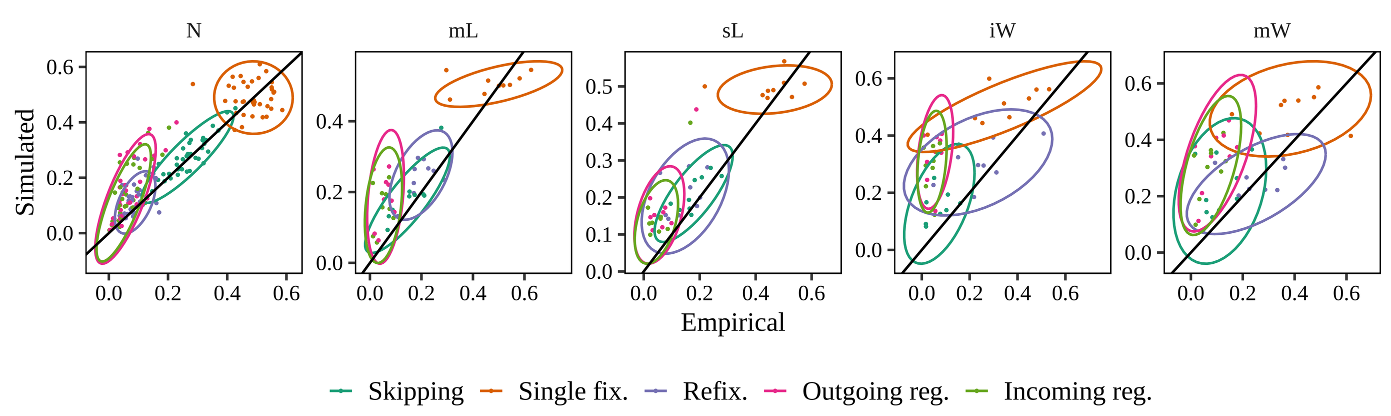

Figure 8. Correlation between empirical and simulated spatial summary statistics. Each participant is represented by one dot in each color in the respective experimental condition (panel).

Computational modelling

- 17 free parameters (see Figure 4)
- 72 datasets (36 subjects × 2 sessions)
- 5 chains/dataset × 20,000 iterations/chain
- DREAMzs sampling algorithm (Vrugt et al., 2009)
- Modified version of PyDREAM (Shockley, 2019), enabling evaluation of the pseudo-marginal likelihood
- SWIFT was fitted to 70% of the data, posterior predictive checks (Figures 5–8) for the remaining 30%

Parameter estimates

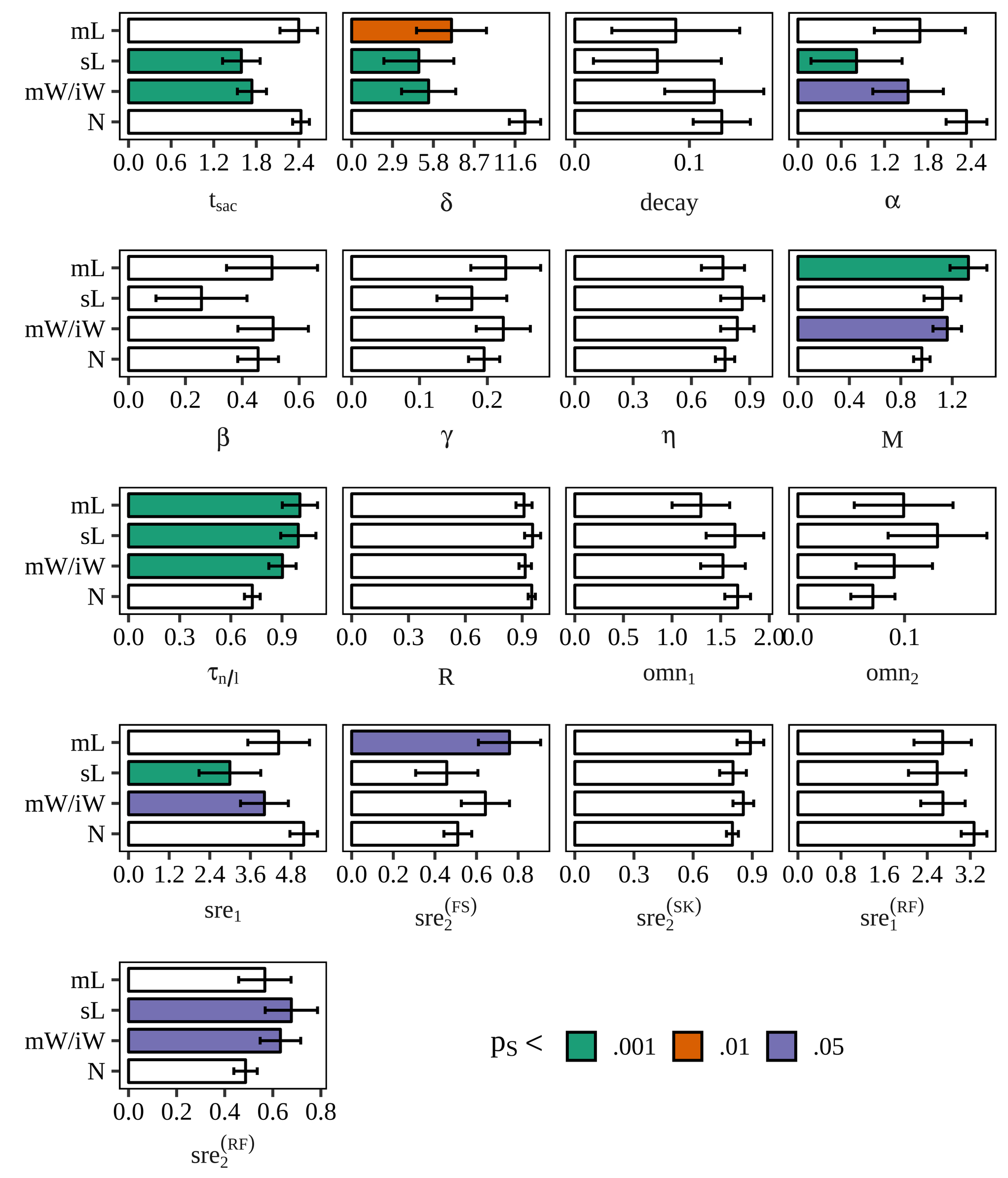

Figure 9. Linear regression coefficient estimates of model parameter estimates between experimental conditions. Error bars are 95% confidence intervals around the estimated means. The baseline is tested against zero, while conditions are tested against the baseline. p-values are corrected for independent multiple testing according to Šidák (1967) with $p_S = 1 - (1 - p)^{17}$.

Compared to the baseline condition, significantly different parameters in the manipulated reading conditions indicate...

- Slower overall processing (α) in iW/mW and sL conditions
- Smaller processing span (δ)
- Shorter saccade intervals (t_{sac}) in iW/mW and sL
- Longer labile and non-labile processing stage ($\tau_{n/l}$)
- Longer corrective fixations after mislocation (M) in iW/mW and mL conditions
- Shorter optimal saccade amplitude (SRE intercept sre_1) in iW/mW and sL conditions
- Less targeted saccades (higher SRE slope $sre_2^{(.)}$) for forward fixations in mL and for refixations in iW/mW and sL conditions

Summary

- SWIFT was successfully fitted to empirical data collected under different reading conditions
- Goodness of fit was ensured by comparing empirical and simulated summary statistics
- Subject-level parameters can reliably predict characteristics of reading patterns in unseen trials
- Differences in subject-level parameters could explain why and how differences in reading behavior arise

References

Engbert, R., Nuthmann, A., Richter, E. M., & Kliegl, R. (2005). SWIFT: A dynamical model of saccade generation during reading. *Psychological Review*, *112*(4), 777–813. doi: 10.1037/0033-295X.112.4.777

Seelig, S. A., Rabe, M. M., Malem-Shinitski, N., Risse, S., Reich, S., & Engbert, R. (2019). Bayesian parameter estimation for the SWIFT model of eye-movement control during reading. *Journal of Mathematical Psychology*. (Manuscript under review)

Shockley, E. (2019). *PyDREAM*. Retrieved from `https://github.com/LoLab-VU/PyDREAM`

Šidák, Z. (1967). Rectangular confidence regions for the means of multivariate normal distributions. *Journal of the American Statistical Association*, *62*, 626–633. doi: 10.1080/01621459.1967.10482935

Vrugt, J. A., ter Braak, C., Diks, C., Robinson, B. A., Hyman, J. M., & Higdon, D. (2009, jan). Accelerating markov chain monte carlo simulation by differential evolution with self-adaptive randomized subspace sampling. *International Journal of Nonlinear Sciences and Numerical Simulation*, *10*(3). doi: 10.1515/ijnsns.2009.10.3.273

Acknowledgements

This work was funded by the Deutsche Forschungsgemeinschaft (DFG, German Research Foundation) – Project no. 317633480 – SFB 1287, project B03. We acknowledge the North-German Supercomputing Alliance (HLRN) for providing high-performance computing resources that have contributed to the research results reported in this paper.