SFB 1287 Limits of Variability in Language
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# Parameter inference and model comparison in dynamical cognitive models: SWIFT (SFB 1287 B03)

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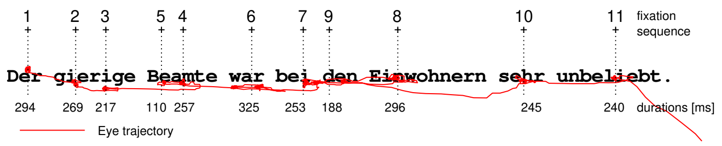



Figure 1. Eye movements generally consist of longer periods of relative rest (**fixations**, 150-300 ms) where visually available information is gathered, alternating with short periods of very fast ballistic movements (**saccades**, 10-20 ms) which quickly shift the gaze to other regions of interest, usually preventing information uptake. Data in reading consists of time ordered sequences of fixations with fixation *positions* and fixation *durations*.

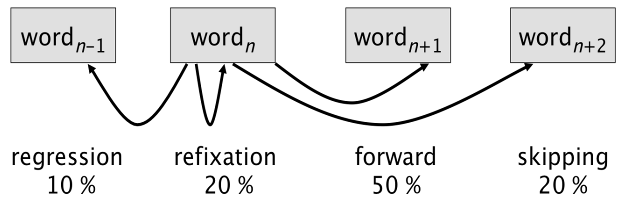



Figure 2. Saccade types and relative frequencies during reading. About half of all saccades move the foveal part of the visual field from word $n$ to the next word $n+1$. Other saccade types generate refixations, word skipping, and regressions.

## SWIFT: a cognitive model of eye movement control during reading

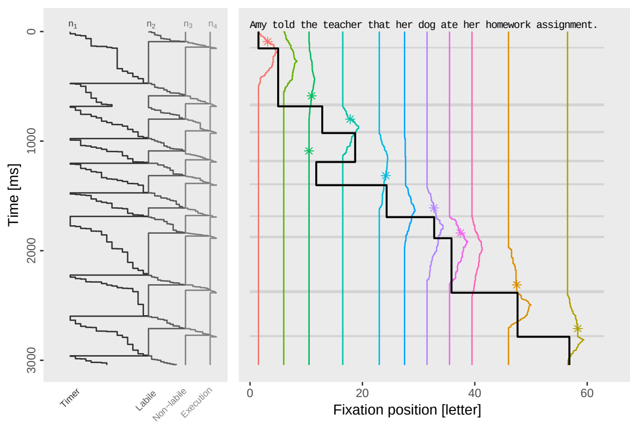



Figure 3. Single trial example of SWIFT reading a sentence. Words within the processing span centered around the current **fixation position** (black line) are processed in parallel via a temporally evolving activation field. **Word activations** (colored lines) govern saccade target selection and continuously inhibit the **saccadic timer cascade** (left), spawning **saccadic gaze shifts** (asterisks).

### Spatial and temporal likelihood contributions

A fixation $f_i = (x_i, T_i, s_i)$ is generated from the sequence of previous fixations $f_1 \ldots f_{i-1}$ under the control of the set of parameters $\boldsymbol{\theta}$ and, possibly, influenced by internal degrees of freedom $\boldsymbol{\xi}$,

$$L_M(\boldsymbol{\theta}|F) = L_M(\boldsymbol{\theta}|f_1, f_2, \ldots, f_n) = P_M(f_1|\boldsymbol{\theta}) \prod_{i=2}^{n} P_M(f_i|f_1, \ldots, f_{i-1}, \boldsymbol{\theta}) \quad (1)$$

The likelihood of fixation $f_i$ is composed of a spatial contribution $P_{\mathrm{spat}}$ and a temporal contribution $P_{\mathrm{temp}}$ (we use $F_{i-1} \equiv \{f_1, f_2, \ldots, f_{i-1}\}$ to simplify the notation),

$$P_M(v_i, l_i, T_i|F_{i-1}, \boldsymbol{\theta}, \boldsymbol{\xi}) = P_{\mathrm{temp}}(T_i|v_i, l_i, F_{i-1}, \boldsymbol{\theta}, \boldsymbol{\xi}) \cdot P_{\mathrm{spat}}(v_i, l_i|F_{i-1}, \boldsymbol{\theta}, \boldsymbol{\xi}) \quad (2)$$

$P_{\mathrm{temp}}(T_i|v_i, l_i, F_{i-1}, \boldsymbol{\theta}, \boldsymbol{\xi})$ is computed using kernel density approximation of the generated fixation durations, where internal degrees of freedom were addressed $\boldsymbol{\xi}$. $P_{\mathrm{spat}}(v_i, l_i|F_{i-1}, \boldsymbol{\theta}, \boldsymbol{\xi})$ is a stochastic pseudo-likelihood function due to internal degrees of freedom $\boldsymbol{\xi}$.

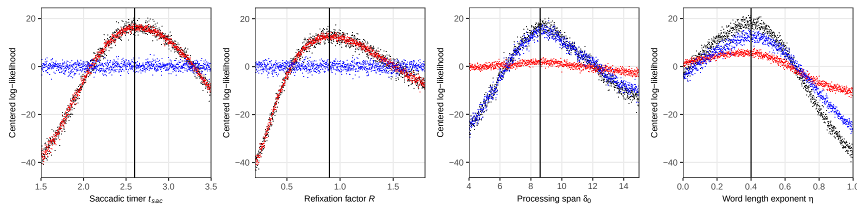



Figure 4. **Temporal**, **spatial** and **combined** likelihood profiles for four different parameters for which specific temporal and/or spatial likelihood contributions are expected.

## Estimation algorithm

### Algorithm

We are using *Differential Evolution Adaptive Metropolis (DREAM)* [2], a differential evolution algorithm with adaptive randomized subspace sampling. Due to stochasticity of likelihood, in addition to evaluating the likelihood function for the proposal $Y_i$, we also evaluate $X_{i-1}$ at each iteration.

### Parameter recovery from simulated data

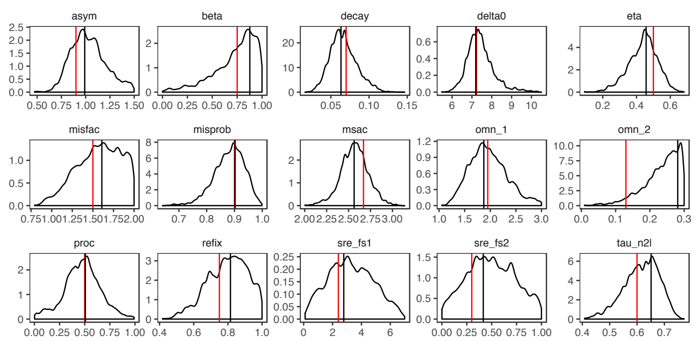



Figure 5. Pooled posterior densities with 30% HPDI mean (black) and true parameter value (red).

## Data assimilation

Eye-tracking experiment [3] (36 participants read 150 sentences on a computer screen). For every participant, posterior densities of 25 parameters were estimated using 6 chains with 15.000 iterations on 70% of each participant's data. Estimates were then used to generate simulations for the other 30%.

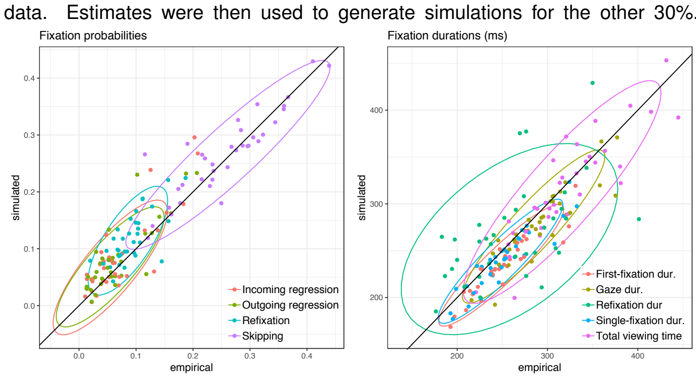
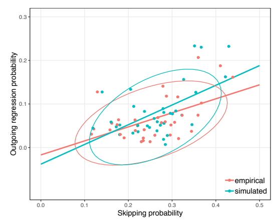



Figure 6. Relationship between mean fixation durations (right) and first-pass fixation probabilities (left) of simulated and experimental data. Each datapoint represents one participant.

Figure 7. For higher skipping rates, more regressions are expected. The same linear relationship is found in empirical (red) and simulated (blue) data.




## References

[1] 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.* Manuscript submitted for publication. (http://arxiv.org/abs/1901.11110)

[2] Vrugt, J. A., ter Braak, C. J. F., Diks, C. G. H., Robinson, B. A., Hyman, J. M., & Higdon, D. (2009). Accelerating Markov Chain Monte Carlo simulation by differential evolution with self-adaptive Randomized subspace sampling. *International Journal of Nonlinear Sciences & Numerical Simulation, 10*(3), 271–288. (http://dx.doi.org/10.1515/ijnsns.2009.10.3.273)

[3] Chandra, J., Krügel, A., & Engbert, R. (2019) *Modulation of oculomotor control during reading of mirrored and inverted texts.* Manuscript in preparation.