Analysing inter-key intervals: Beyond means, medians and pause frequencies

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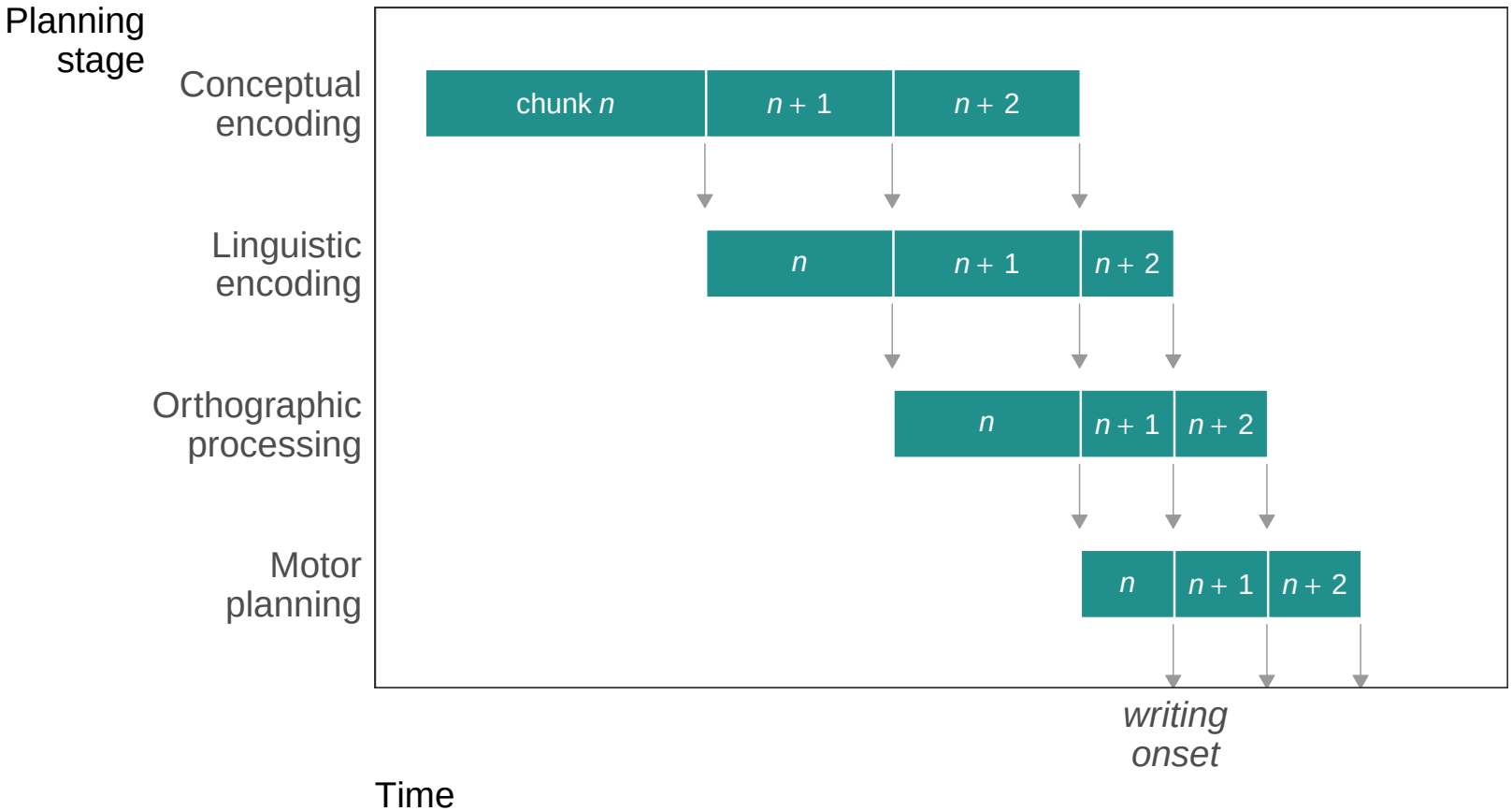
Planning cascade in writing



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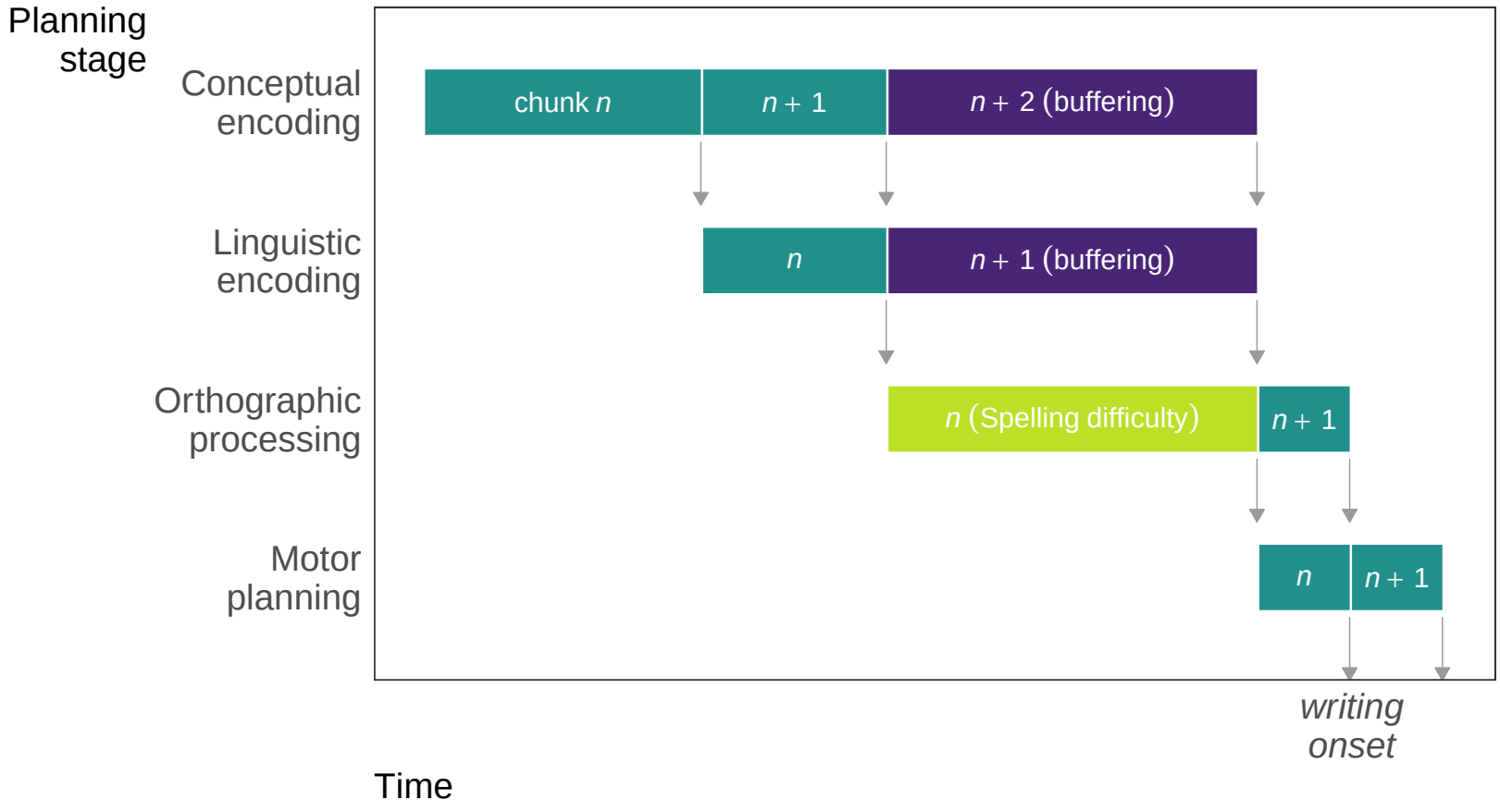
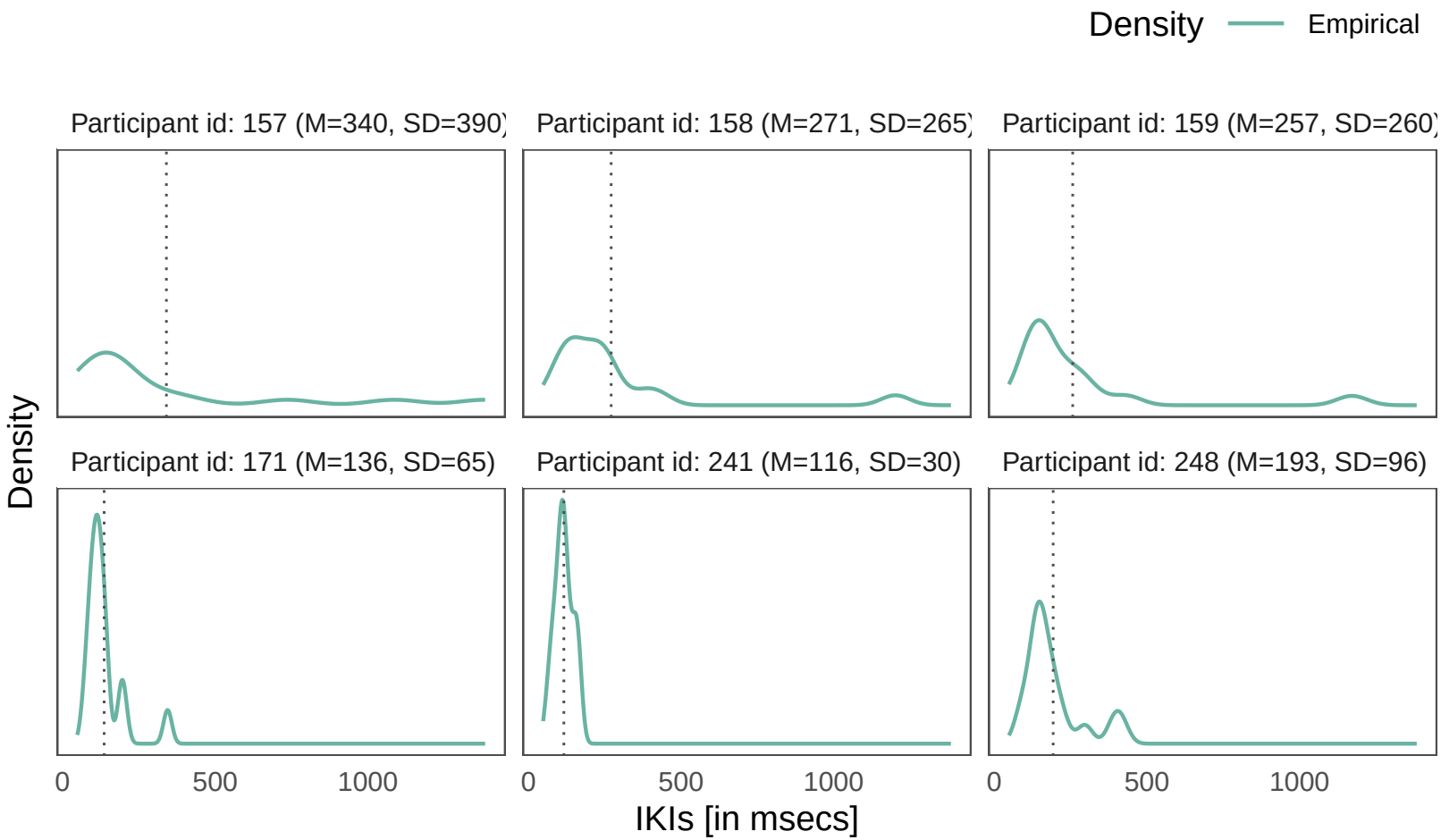


Keystroke transitions are not normal distributed



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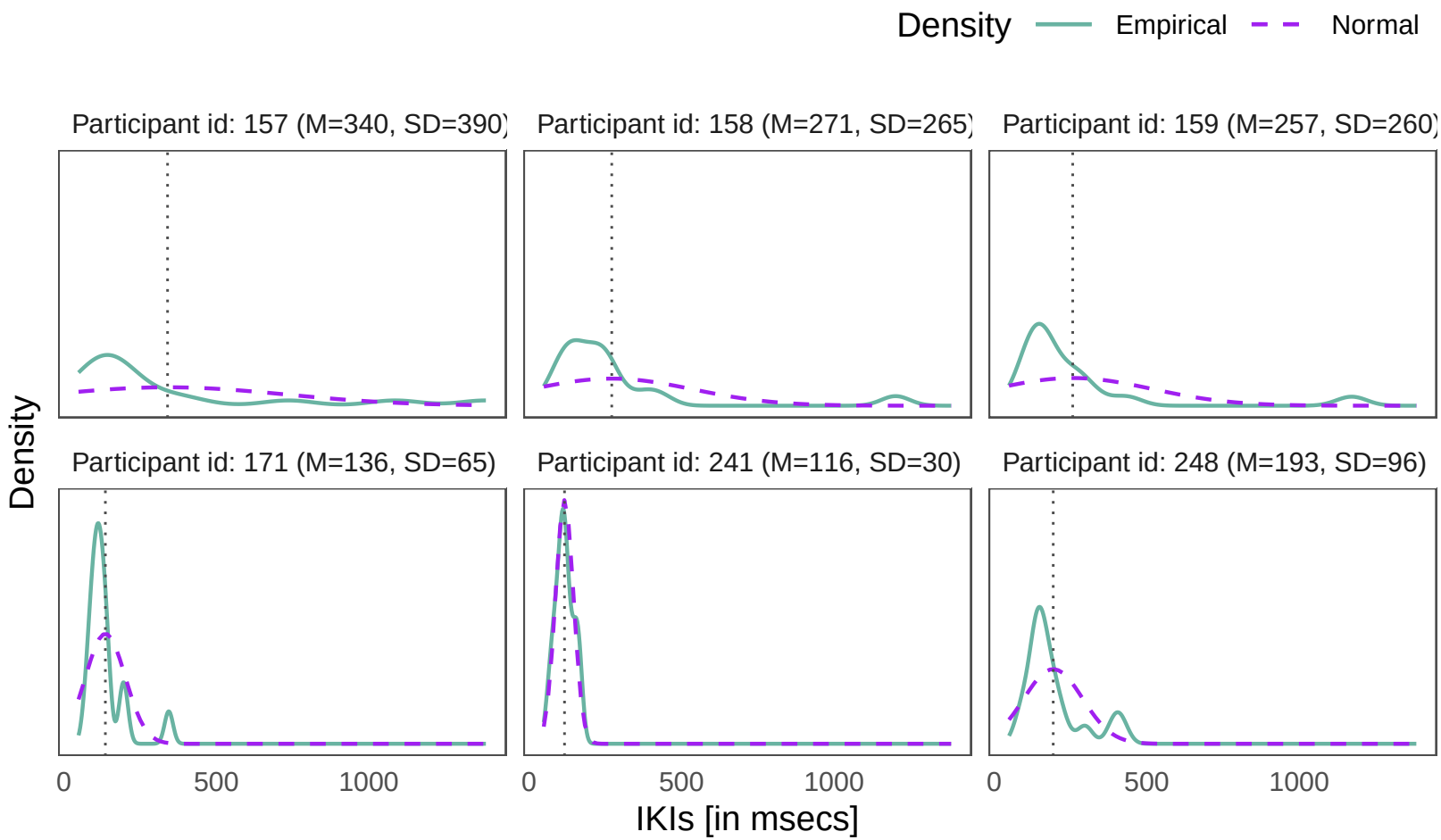

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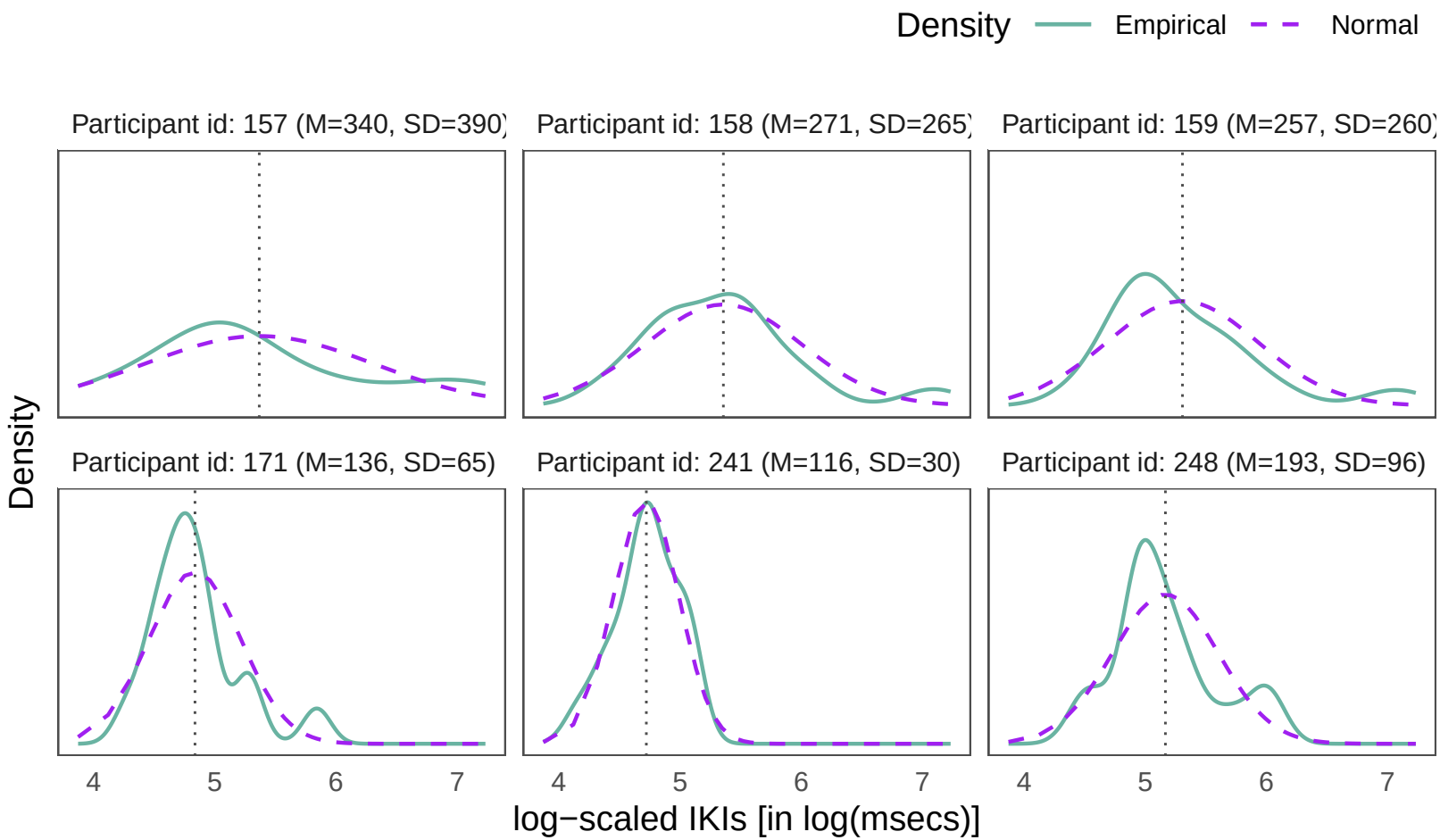
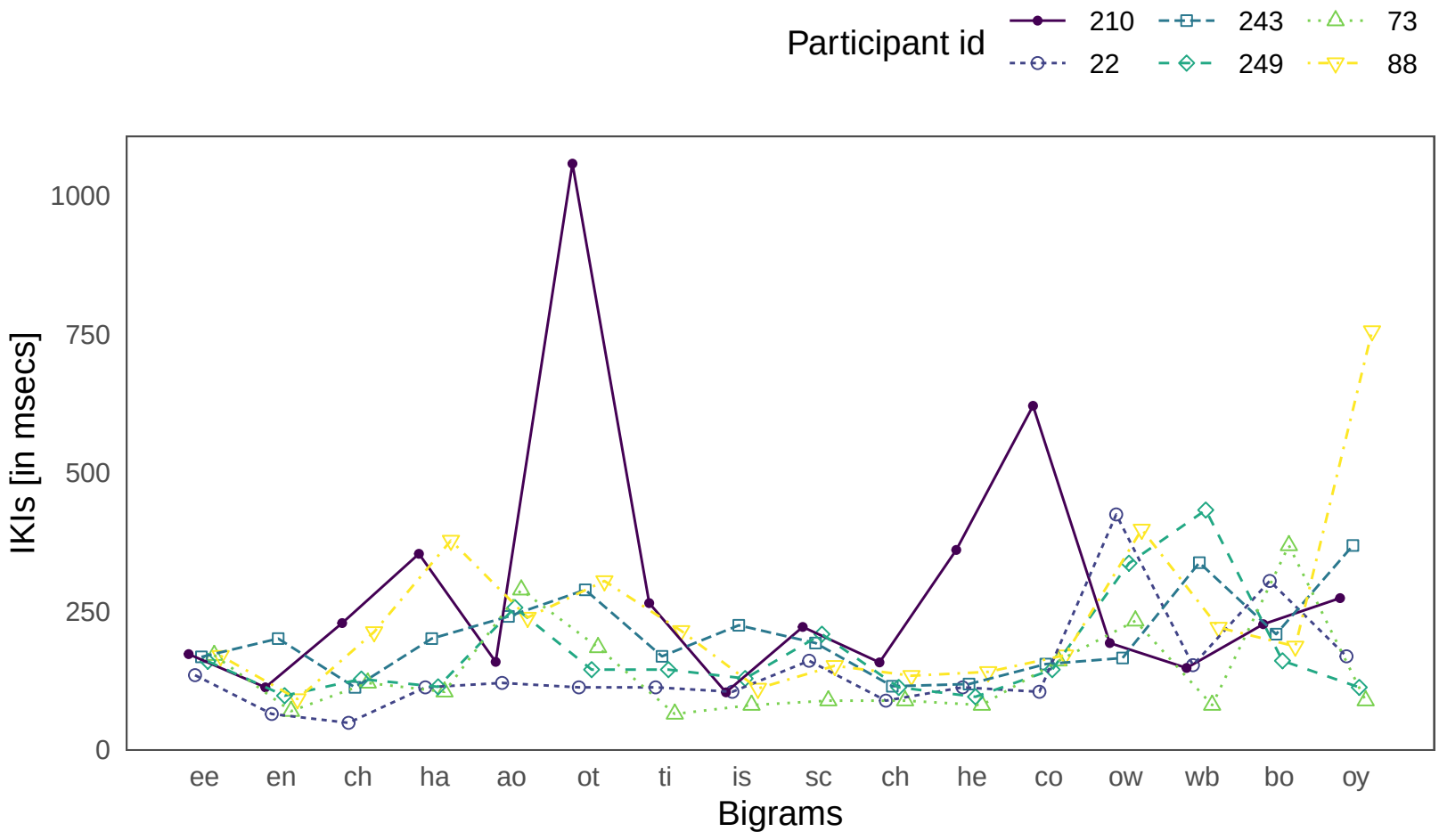


Long intervals are not bigram specific



Research focus

- How do we address the long right tail in statistical models without losing information, trimming data, imposing pause thresholds?
- log-Gaussian stable distribution (Guo et al., 2018)
- ex-Gaussian (Chukharev-Khudilaynen, 2014)
- Mixture of processes (Almond et al., 2012; Baaijen et al., 2012)
- Implementation of the copy-typing process as statistical models in Stan (Carpenter et al., 2016); code based on Sorensen et al. (2016) and Vasishth, Chopin et al. (2017); also Vasishth, Jäger et al. (2017).

LogNormal Mixed-Effects Model

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- Average IKI α.
- Participants: $u_i \sim Normal(0, \sigma_u^2)$
- Bigrams: $w_j \sim Normal(0, \sigma_w^2)$
- Error variance σ_e^2

Extending mixed models to mixtures

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$$\theta = 1$$

Extending mixed models to mixtures

$$y \sim \theta \cdot LogNormal(\mu_1, \sigma^2_{e_1}) +$$
$$(1 - \theta) \cdot LogNormal(\mu_2, \sigma^2_{e_2})$$
$$\theta = \ ?$$

Mixture of Gaussians

$$y_{ij} \sim \theta_i \cdot LogNormal(\mu_{ij} + \delta, \sigma^2_{e'}) +$$
$$(1 - \theta_i) \cdot LogNormal(\mu_{ij}, \sigma^2_e)$$
$$\mu_{ij} = \alpha + u_i + w_j$$

- Disfluencies result in a slowdown δ.
- happening with a probability θ; differs by-participant i
- associated with larger variance $\sigma^2_{e'_k}$

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Mixture of Gaussians

$$y_{ij} \sim \theta_i \cdot \textit{LogNormal}(\mu_{ij} + \delta, \sigma^2_{e'}) + (1 - \theta_i) \cdot \textit{LogNormal}(\mu_{ij}, \sigma^2_e)$$

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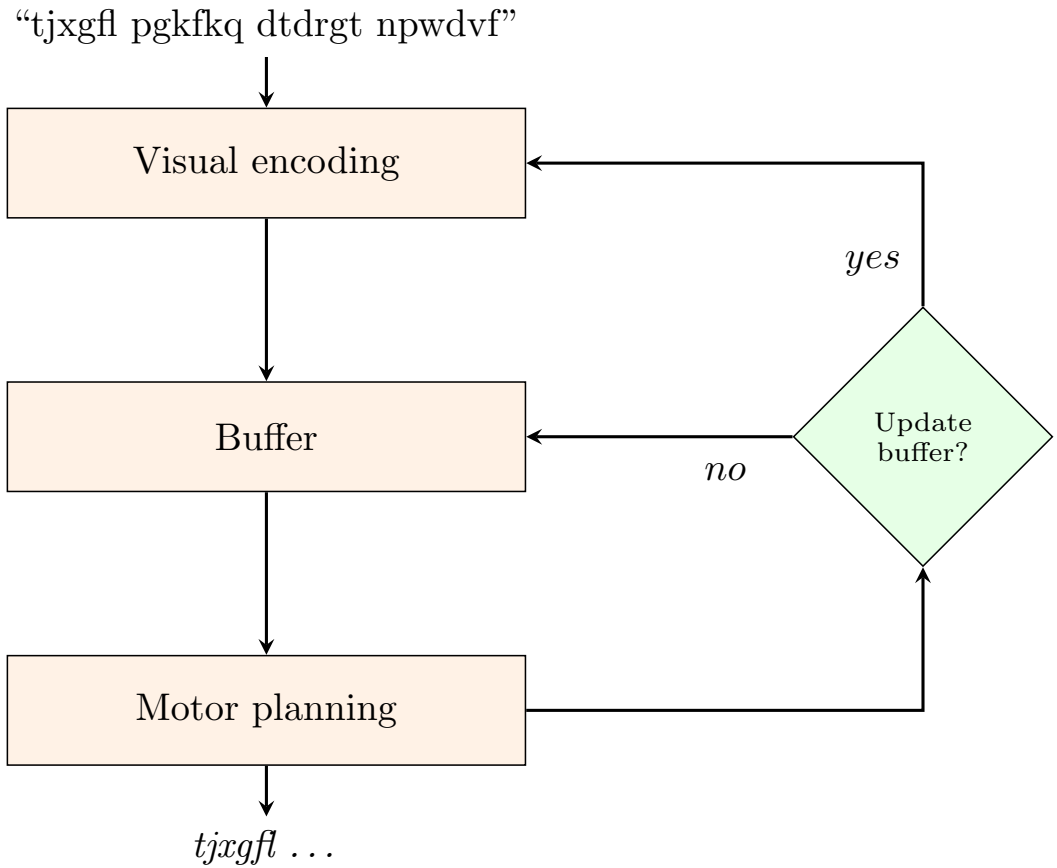
Method

- Bigram-keystroke interval data: Dutch subset of copy-task corpus (Van Waes et al., 2019; Van Waes et al., 2020)
- **Consonants task:** "tjxgfl pgkfkq dtdrgt npwdvf"
- **LF-bigrams task:** "een chaotische cowboy"
- Lexical and non-lexical copy-typing context
- Random sample of 250 ppts (18-25 years of age)

Copy-typing sequences of characters



References I

Almond, R., Deane, P., Quinlan, T., Wagner, M. & Sydorenko, T. (2012). *A preliminary analysis of keystroke log data from a timed writing task* (tech. rep. Research Report No. RR-12-23). Princeton, NJ, Educational Testing Service.

Baaijen, V. M., Galbraith, D. & de Glopper, K. (2012). Keystroke analysis: Reflections on procedures and measures. *Written Communication, 29*(3), 246–277.

Carpenter, B., Gelman, A., Hoffman, M. D., Lee, D., Goodrich, B., Betancourt, M., Brubaker, M. A., Guo, J., Li, P. & Riddell, A. (2016). Stan: A probabilistic programming language. *Journal of Statistical Software, 20*.

Chukharev-Khudilaynen, E. (2014). Pauses in spontaneous written communication: A keystroke logging study. *Journal of Writing Research, 6*(1), 61–84.

Guo, H., Deane, P. D., van Rijn, P. W., Zhang, M. & Bennett, R. E. (2018). Modeling basic writing processes from keystroke logs. *Journal of Educational Measurement, 55*(2), 194–216.

Sorensen, T., Hohenstein, S. & Vasishth, S. (2016). Bayesian linear mixed models using Stan: A tutorial for psychologists, linguists, and cognitive scientists. *Quantitative Methods for Psychology, 12*(3), 175–200.

Van Waes, L., Leijten, M., Pauwaert, T. & Van Horenbeeck, E. (2019). A multilingual copy task: Measuring typing and motor skills in writing with inputlog. *Journal of open research software, 7*(30), 1–8.

Van Waes, L., Leijten, M., Roeser, J., Olive, T. & Grabowski, J. (2020). Designing a copy task to measure typing and motor skills in writing research [submitted]. *Journal of Writing Research*.

References II

Vasishth, S., Chopin, N., Ryder, R. & Nicenboim, B. (2017). Modelling dependency completion in sentence comprehension as a Bayesian hierarchical mixture process: A case study involving Chinese relative clauses. *ArXiv e-prints*.

Vasishth, S., Jäger, L. A. & Nicenboim, B. (2017). Feature overwriting as a finite mixture process: Evidence from comprehension data. *arXiv preprint arXiv:1703.04081*.