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

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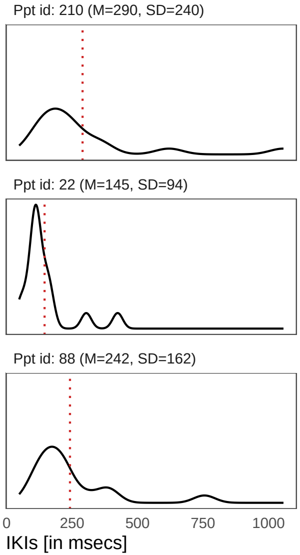
The problem: what's a pause?

- Keystroke data are heavily skewed.
- Skew reflects cognitive processes.
- How can we distinguish between fluent and disfluent key transitions?
- Fixed thresholds: 0.5 or 2 secs?
- A key transition normal for learner might be longer than a pause of an experienced writer.



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- Pause size depends on:
  - writing skills / style
  - position in text, sentence, word
  - experience with target language (in L2)
  - process of interest (lexical, motor, semantic)
  - writing task
  - …

Research focus

- How do we deal with the heavy tail statistically without losing information, trimming data, imposing pause thresholds?
- …and extract pause frequencies in a principled way?
- Mixture of log-normals (Almond et al., 2012; Baaijen et al., 2012)

→ More than one underlying data-generating process; i.e. normal key transitions and disfluencies.

- Compared to standard log-normal treatment.

→ One underlying data-generating process.

Method

- Implementation of the copy-typing process as statistical model in Stan (Carpenter et al., 2016); code based on Sorensen et al. (2016) and Vasishth et al. (2017).
- Bigram-keystroke interval data: Dutch subset of copy-task corpus (Van Waes et al., 2019; Van Waes et al., 2020)
- Lexical and non-lexical copy-typing context

Consonants task

tjxgfl pgkfkq dtdrgt npwdvf

LF-bigrams task

een chaotische cowboy

LF-bigrams task

een chaotische cowboy

$$\Downarrow$$

e^e^n   c^h^a^o^t^i^s^c^h^e   c^o^w^b^o^y

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LF-bigrams task

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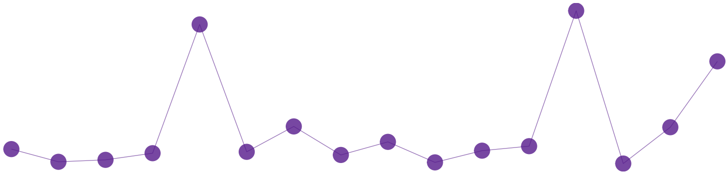
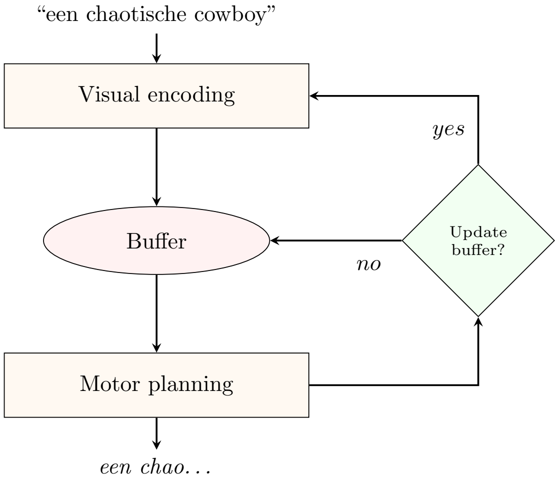
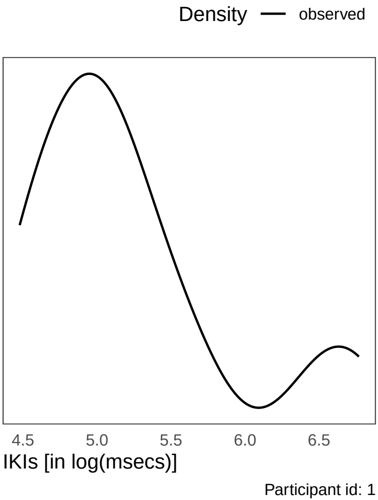


Disfluencies in a basic model of copy-typing



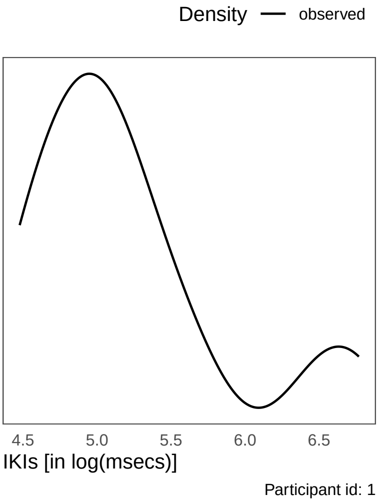
Mixed-Effects Model

$$y_{ij} \sim LogNormal(\mu_{ij}, \sigma_e^2)$$



Mixed-Effects Model

$$y_{ij} \sim LogNormal(\mu_{ij}, \sigma_e^2)$$
$$\mu_{ij} = \alpha + u_i + w_j$$



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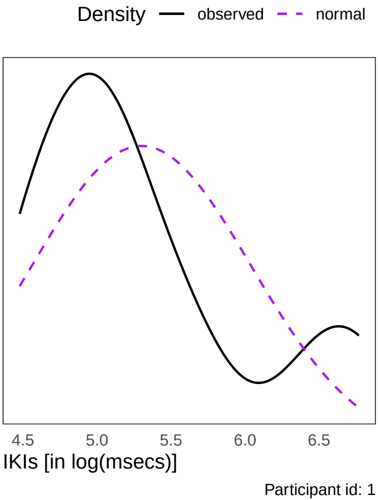
- α: average IKI
- σ_e^2: error variance
- Participants: u_i
- Bigrams: w_j



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Extending mixed models to finite mixtures

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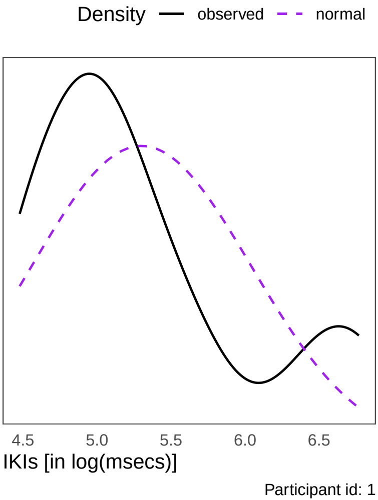

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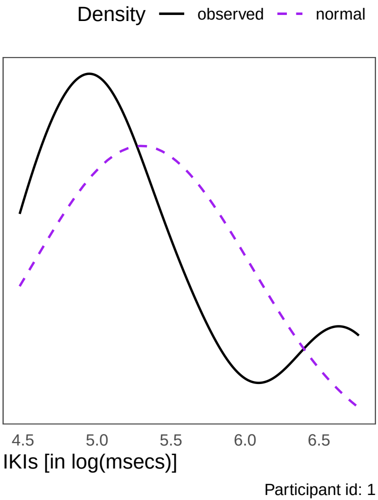
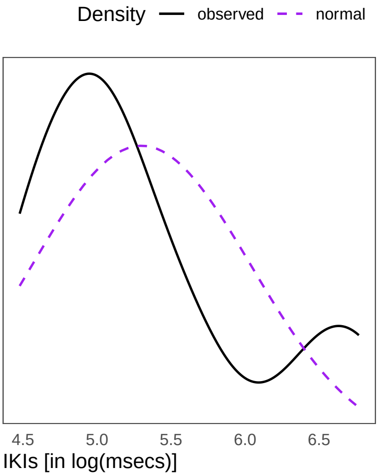


Extending mixed models to finite mixtures

$$y \sim \boxed{\theta} \cdot LogNormal(\mu, \sigma_e^2)$$
$$\theta = 1$$

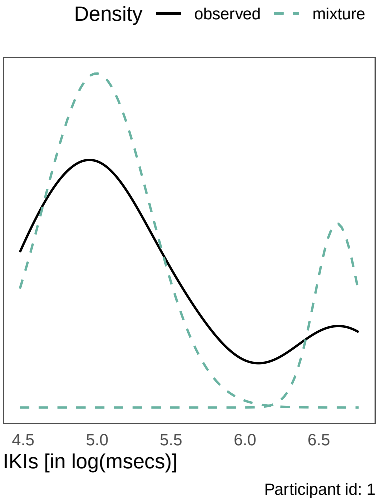


Participant id: 1

Extending mixed models to finite mixtures

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

$$\theta = 0.81$$

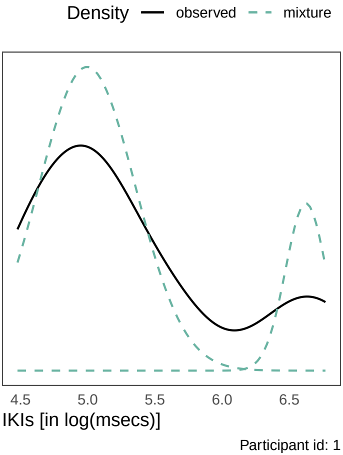


Finite mixture of two log-Gaussians

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

$$\mu_{ij} = \alpha + u_i + w_j$$

- α: fluent IKI
- δ: slowdown
- θ: disfluency probability
- $\sigma^2_{e'}$: larger variance



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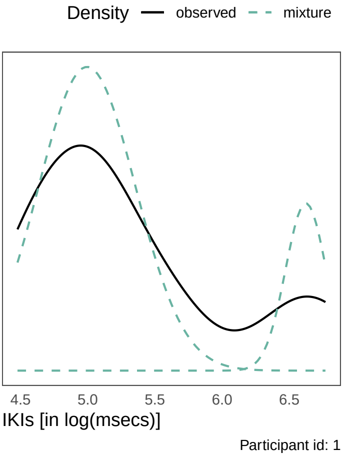

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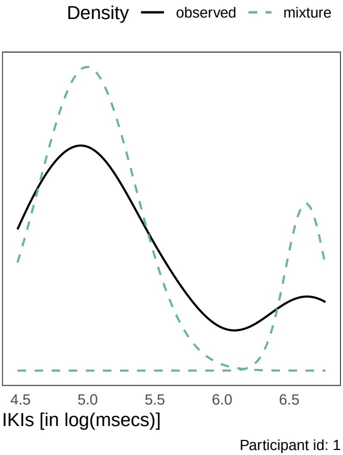

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\begin{aligned}
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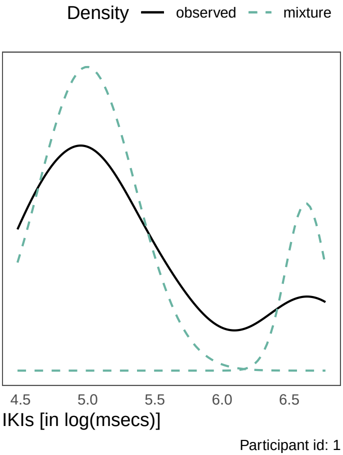

Model comparisons

Predictive performance estimated as the *expected log predictive density* ($\widehat{elpd}$) (Vehtari et al., 2015, 2017). Models are ordered by predictive performance (model with highest predictive performance in top row). Standard error in parentheses.

		Consonants task		LF-bigrams task	
Models	Distribution	$\Delta\widehat{elpd}$	$\widehat{elpd}$	$\Delta\widehat{elpd}$	$\widehat{elpd}$
MoG	$2 \times$ Log-normal				
LMM	Log-normal				

Note. LMM = Linear mixed effects model; MoG = Mixture of Gaussians

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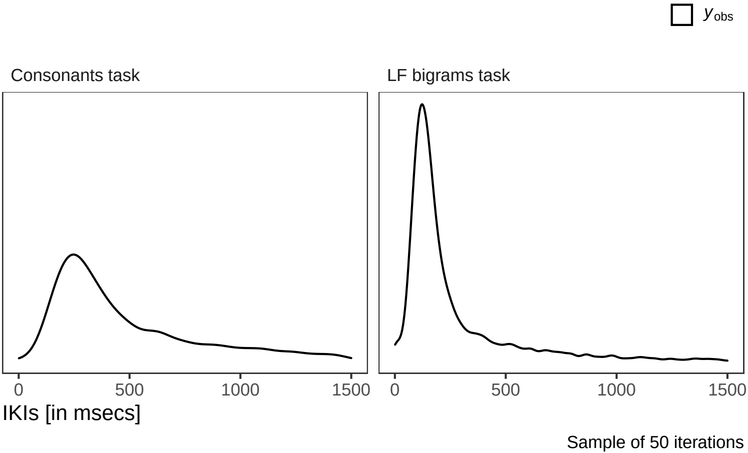
MoG	2 × Log-normal	–	-37,069 (101)	–	-33,178 (113)
LMM	Log-normal	-281 (25)	-37,350 (99)	-994 (63)	-34,173 (121)

Note. LMM = Linear mixed effects model; MoG = Mixture of Gaussians

Observed vs. predicted IKIs



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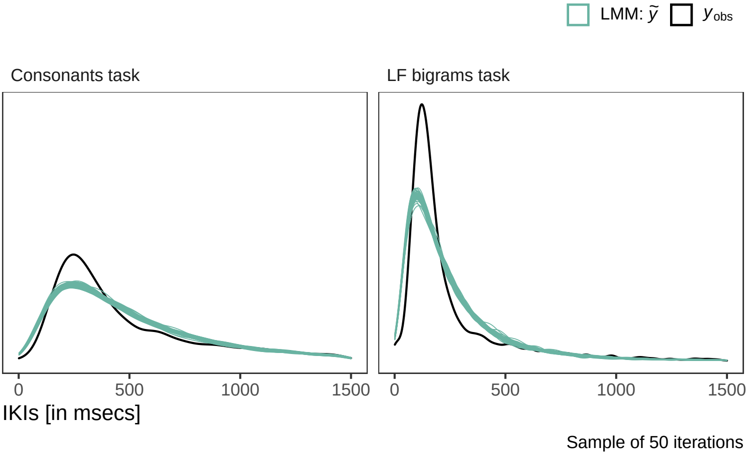

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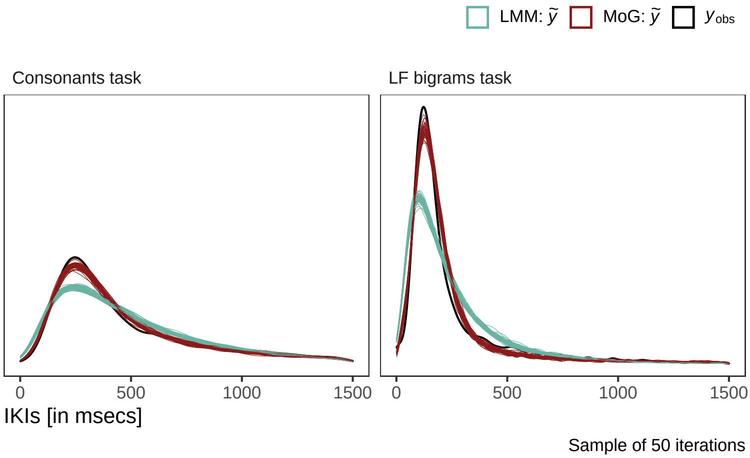
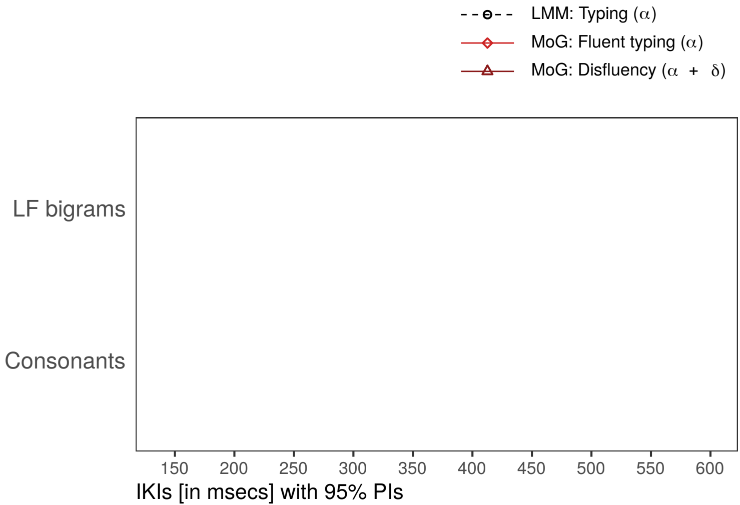


Population estimates



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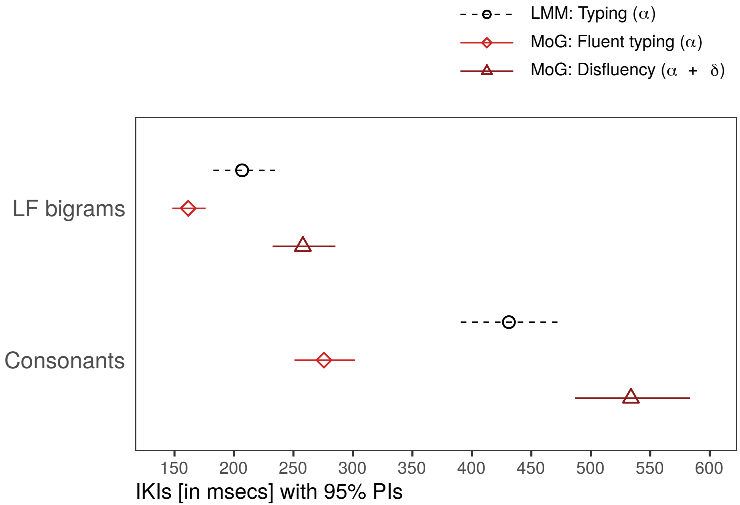

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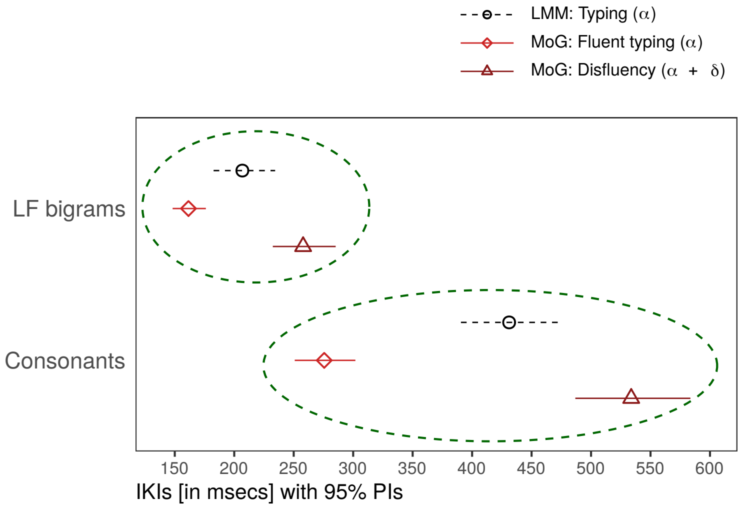

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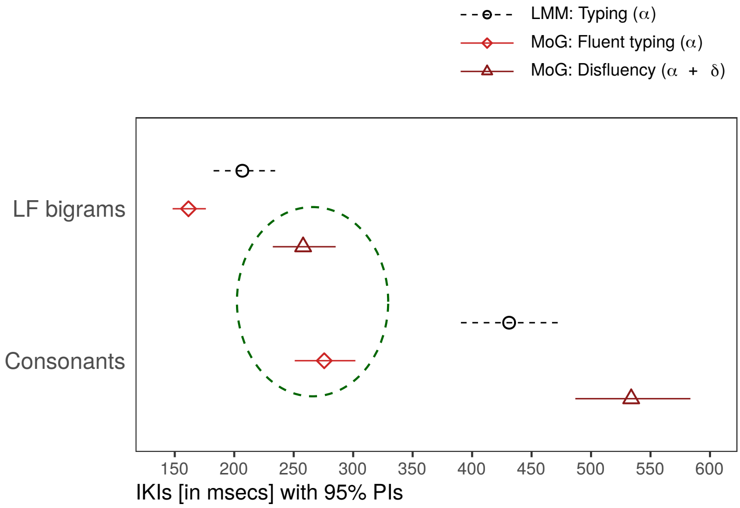

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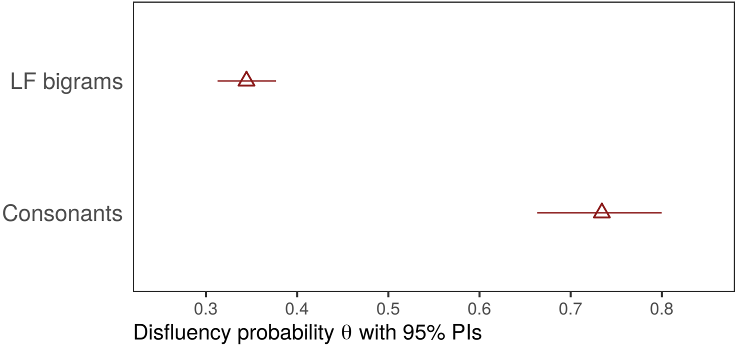
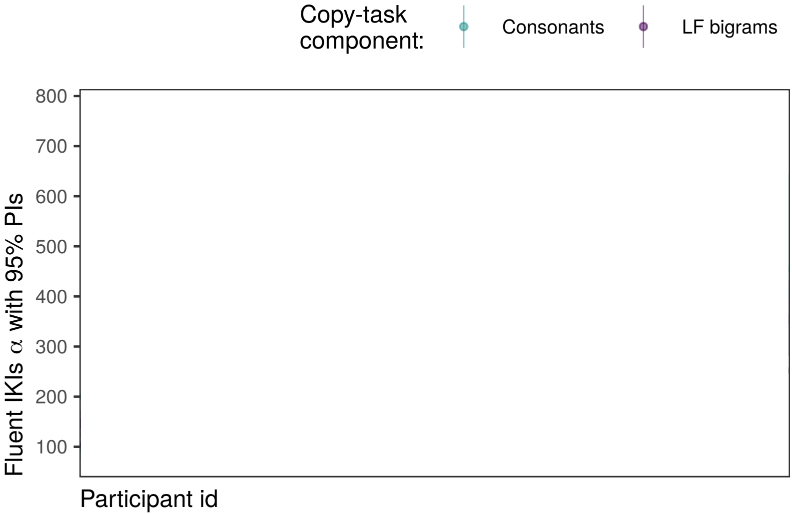


By-participant fluent-typing intervals



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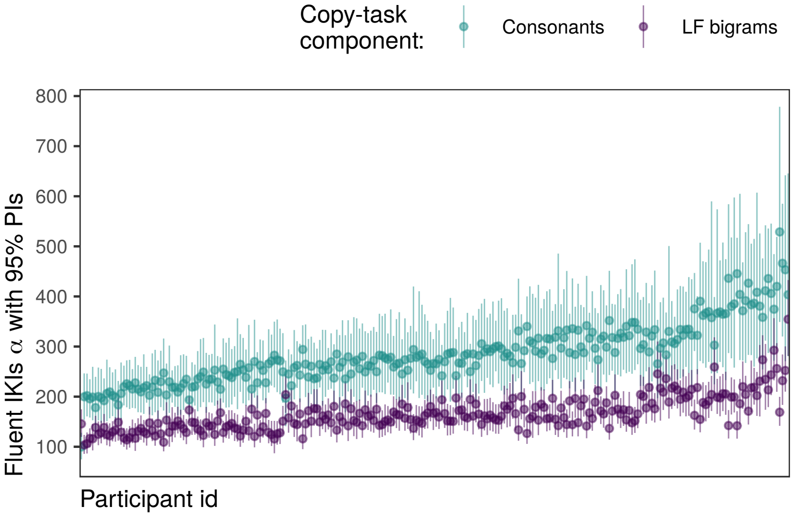
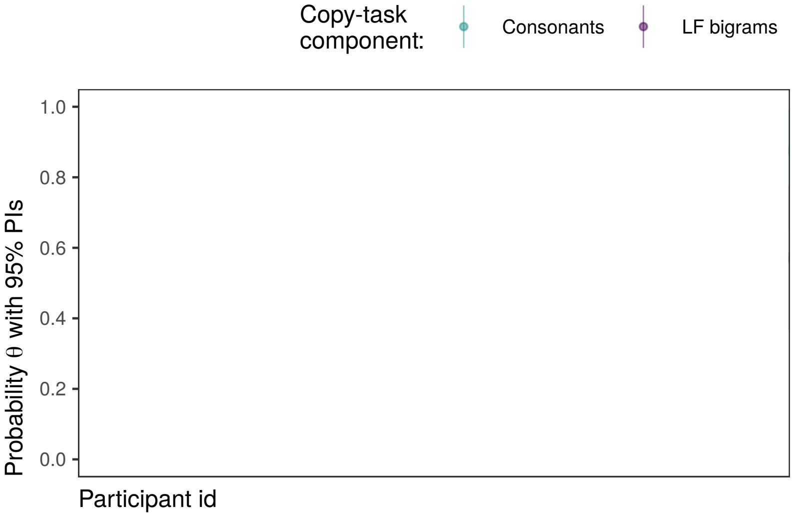


By-participant disfluency probability



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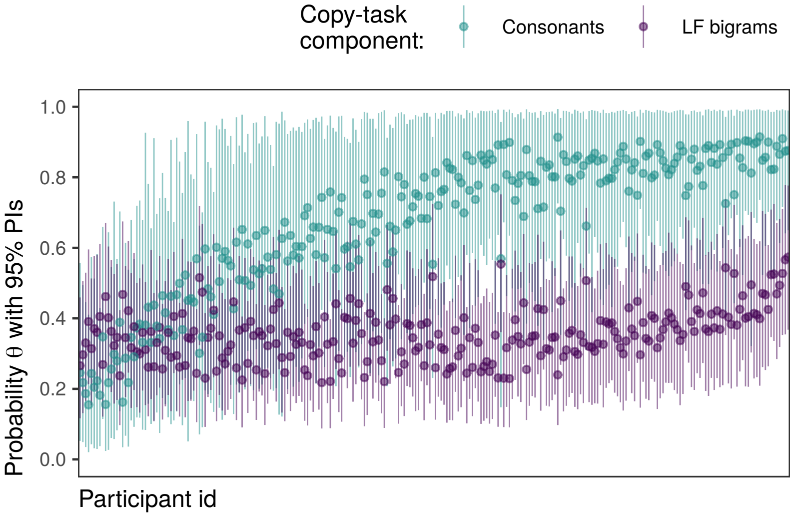

Conclusion

- Better fit for mixture models over standard analysis.
- Data come from a mixture of processes reflected in fluent and disfluent keystroke transitions.
- Advantages for writing research:
  1. map on cascading models of writing (ask me why).
  2. represent the probabilistic nature of disfluencies.
  3. capture disfluencies in a principled way.
  4. provide reliable typing estimates and pause frequencies

Discussion

- Our statistical techniques need to align closely with the cognitive process we're trying to understand.
- …and represent our current understanding of the underlying cognitive process.
- To achieve this we need to model the raw data possible rather than summary statistics.
- Otherwise we risk incorrect conclusions about our data.

Prospects

- Shiny-app: calculate disfluencies from keystroke data.
- Manuscript: extension to autoregression.
- Application of models for data in which pause frequencies play a central role: group comparisons, diagnostic tool?
- Application picture description data with spelling manipulation.

Thanks for listening!

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R-scripts, *Stan*-code, slides, preprint:
https://github.com/jensroes/Typing-disfluency

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*.

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*.

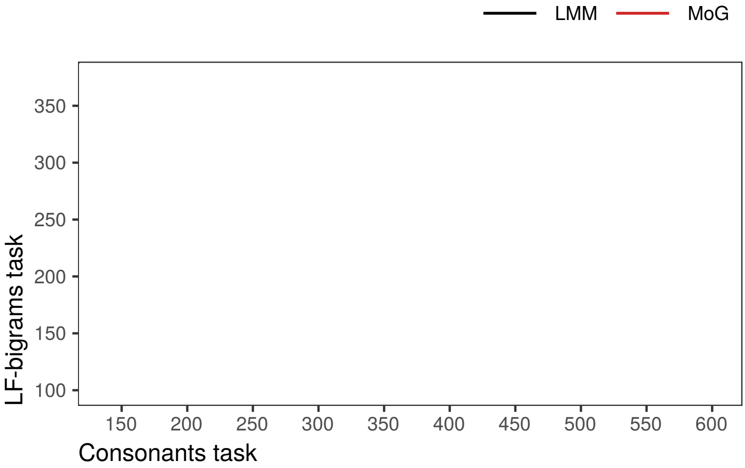
References II

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*.

Vehtari, A., Gelman, A. & Gabry, J. (2015). Pareto smoothed importance sampling. *arXiv preprint arXiv:1507.02646*.

Vehtari, A., Gelman, A. & Gabry, J. (2017). Practical Bayesian model evaluation using leave-one-out cross-validation and WAIC. *Statistics and Computing*, *27*(5), 1413–1432.

Estimated (fluent) keystroke transitions



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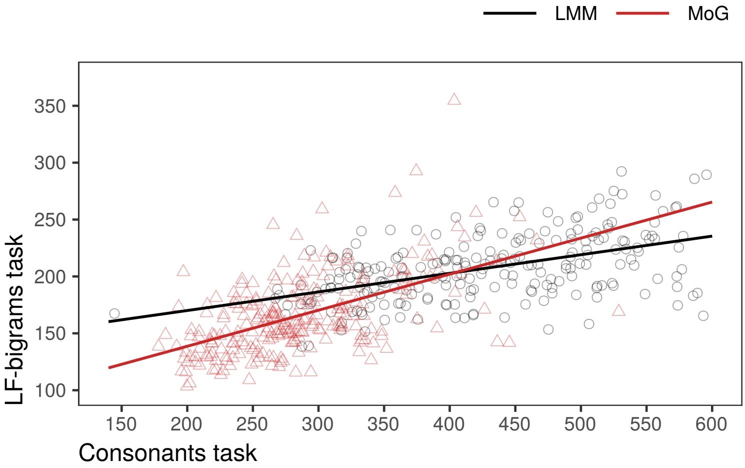
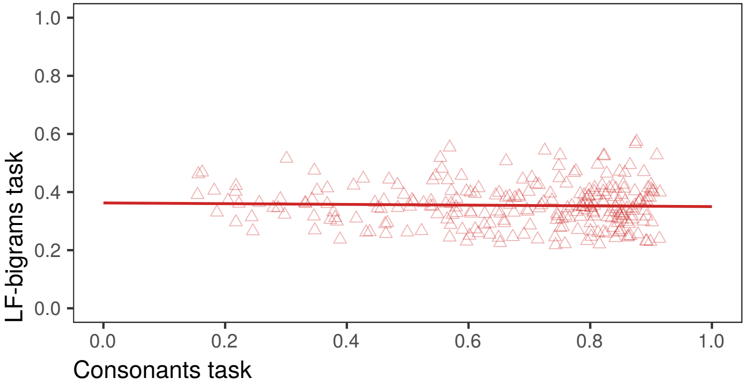
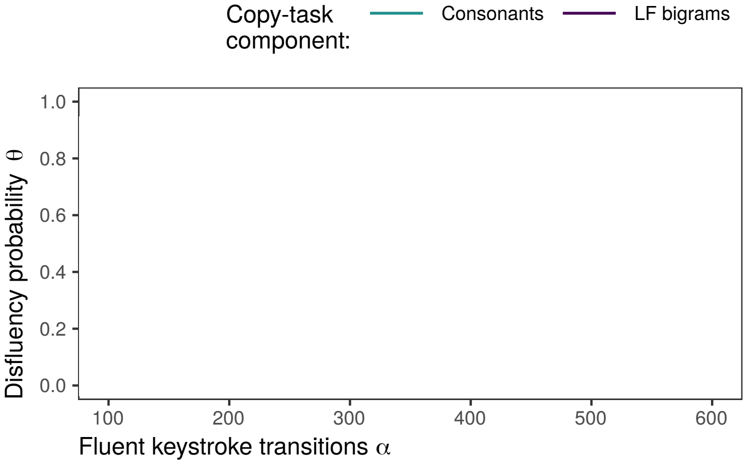


Estimated disfluency probability



Disfluency typing-speed trade-off



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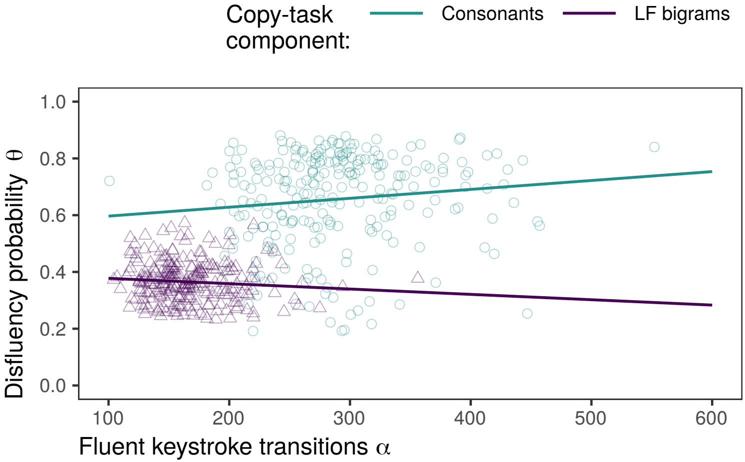

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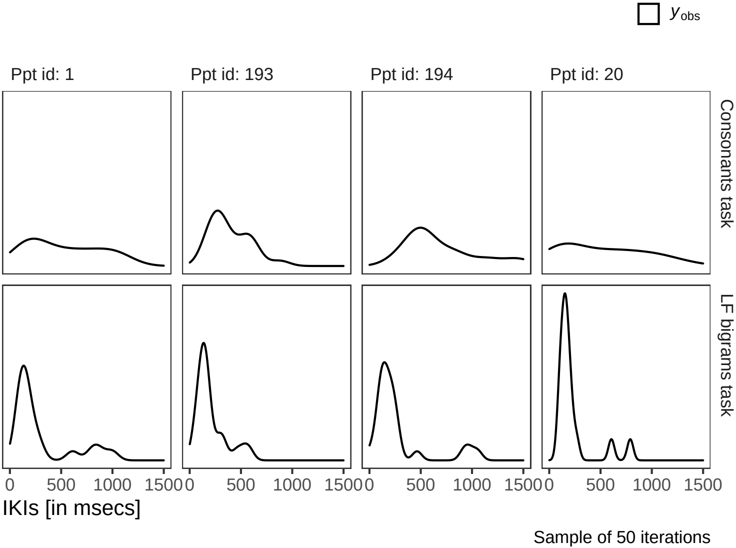

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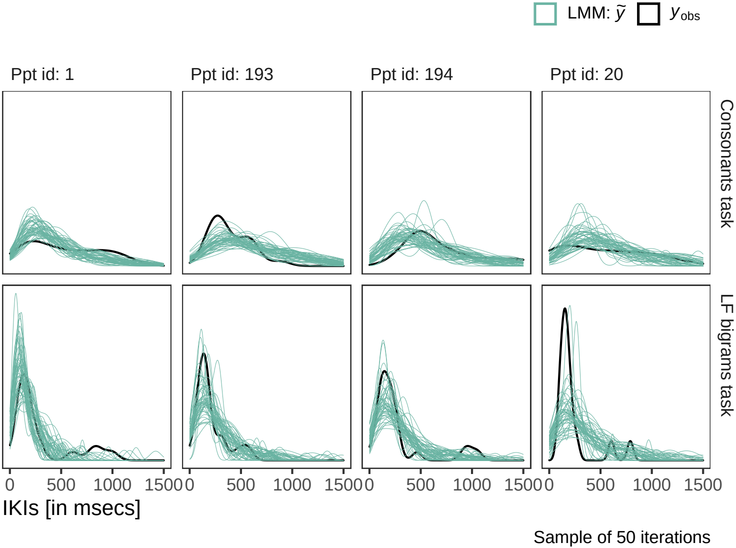

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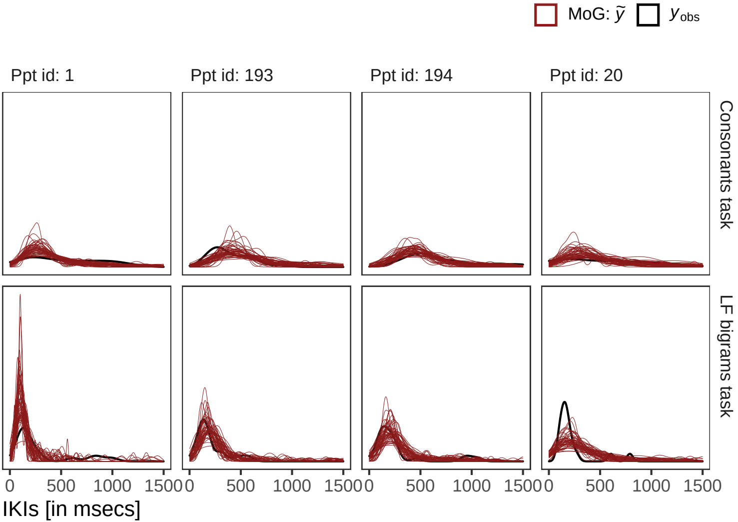
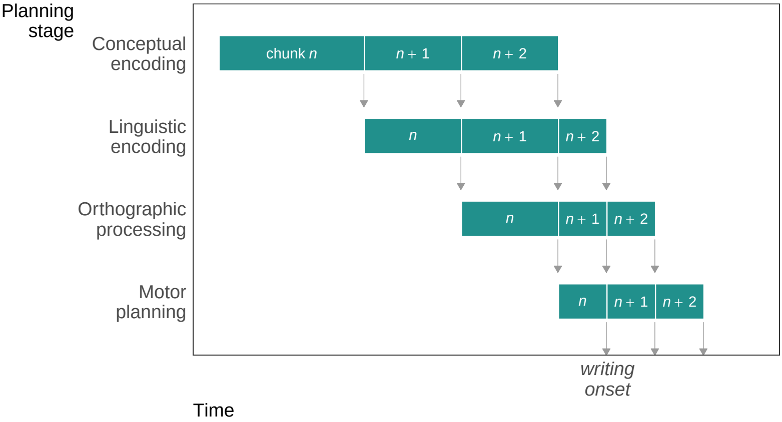


Sample of 50 iterations

Planning cascade in writing



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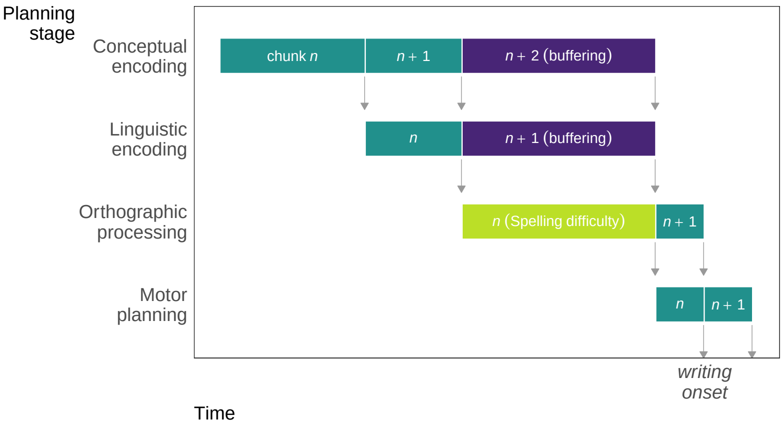
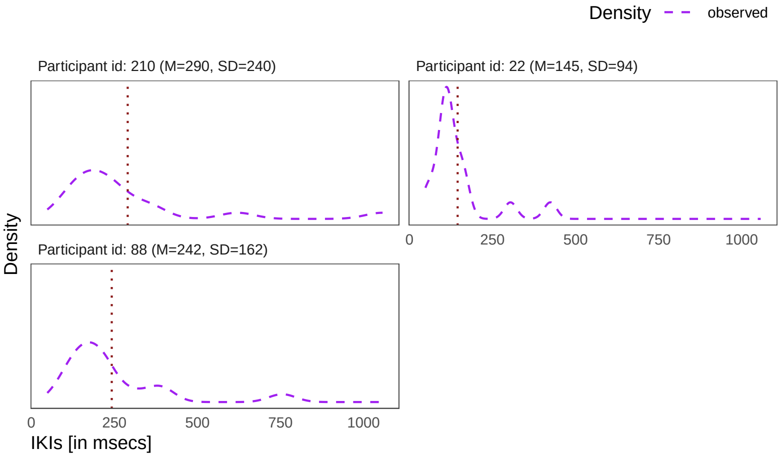


Keystroke transitions are not normal distributed



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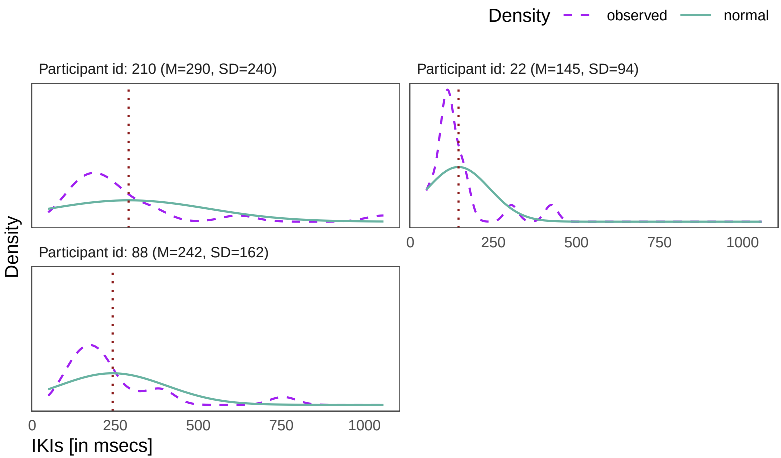

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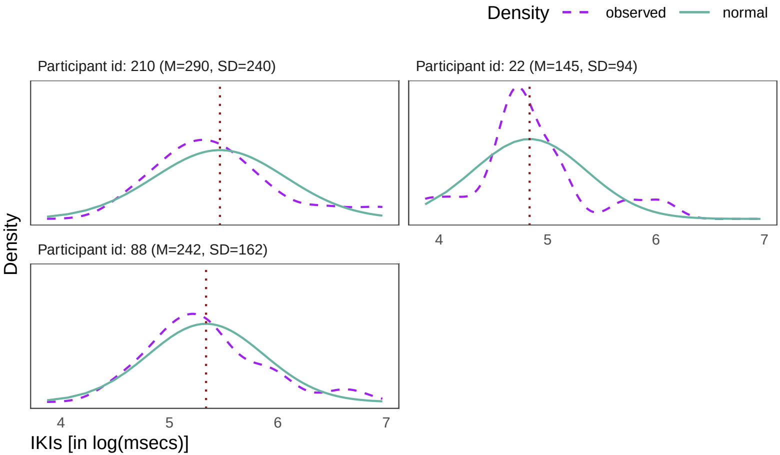

Long intervals are not bigram specific