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

Jens Roeser   Sven De Maeyer   Mark Torrance

Mariëlle Leijten   Luuk Van Waes

jens.roeser@ntu.ac.uk

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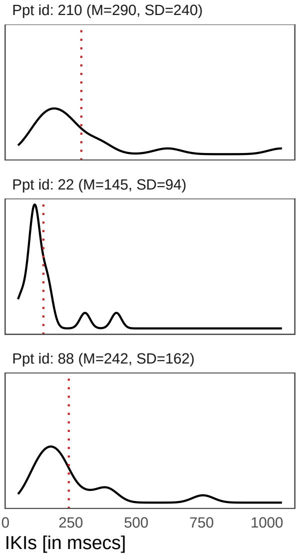
The problem: what's a pause?

- 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?
- Key transitions normal for a learner might be longer than pauses of experienced writers.



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- Pause sizes depend on:
  - writing skills / style
  - position in text, sentence, word
  - experience with target language (in L2)
  - cognitive process (lexical, motor, semantic)
  - writing task

Research focus

- How do we deal with the heavy tail without loosing data or imposing pause thresholds?
- Finding a principled way to extract:

1. by-ppt typing estimates
2. by-ppt pause frequencies

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).
- Key-interval data: Dutch subset (N=250) of copy-task corpus (Van Waes et al., 2019; Van Waes et al., 2020).
- Lexical vs non-lexical task

Consonants task

tjxgfl pgkfkq dtdrgt npwdvf

Low-Frequency (LF) bigrams task

een chaotische cowboy

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$\Downarrow$

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

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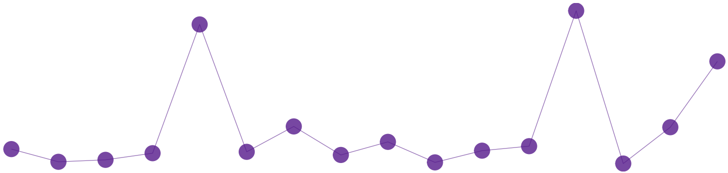

Standard analysis: Mixed-Effects Model

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

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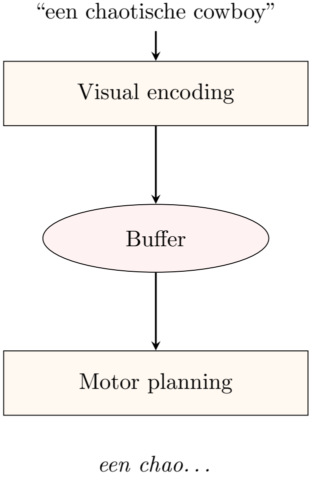
- α: population-level IKI
- σ_e^2: error variance
- Participants: u_i
- Bigrams: w_j

Model of copy-typing: standard analysis



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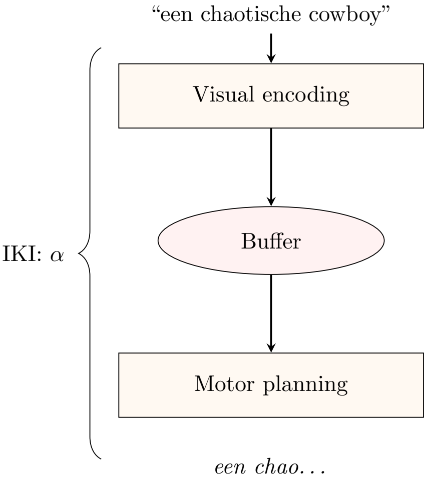
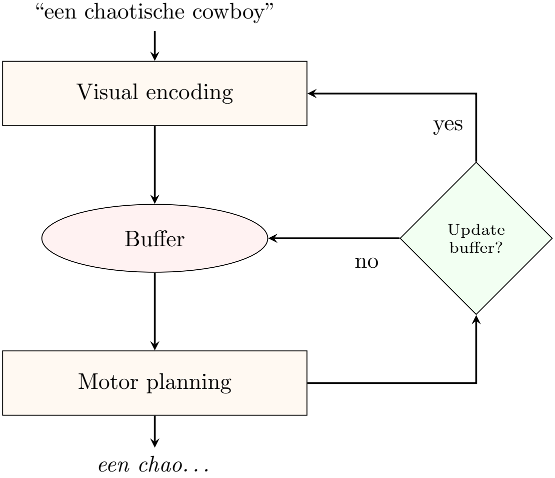


Model of copy-typing: disfluency model



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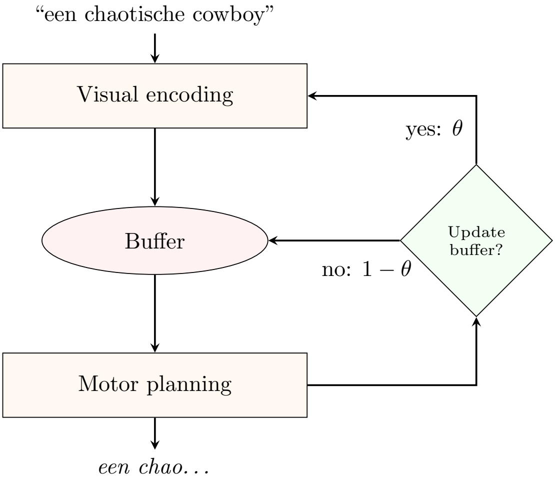

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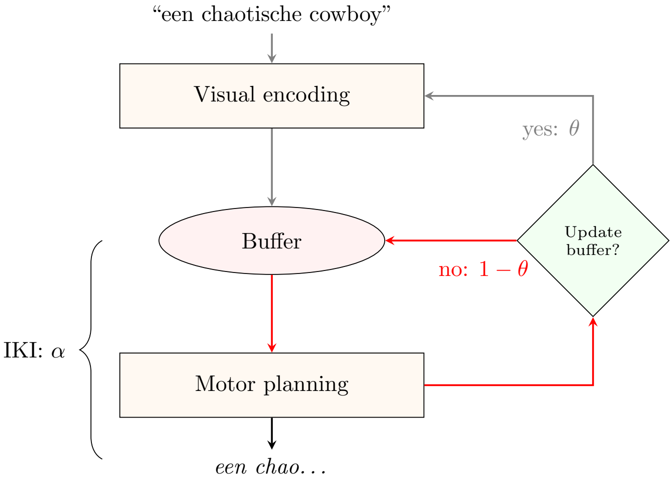

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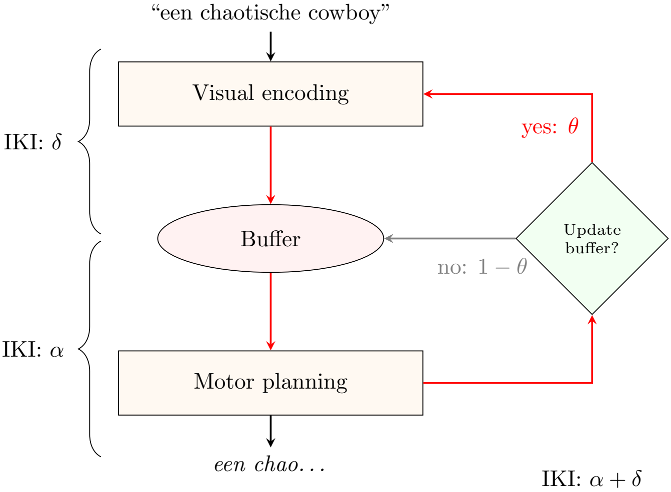

Finite Mixture of two log-Gaussians

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

- α: fluent IKI (e.g. no buffer update; no difficulty)
- δ: buffer update; other difficulty (finding correct key)
- θ: disfluency probability (by ppt *i*)
- $\sigma^2_{e'}$: variance larger than σ^2_e

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 $\times$ Log-normal	–	-37,069 (101)	–	-33,178 (113)
LMM	Log-normal	-281 (25)	-37,350 (99)	-994 (63)	-34,173 (121)

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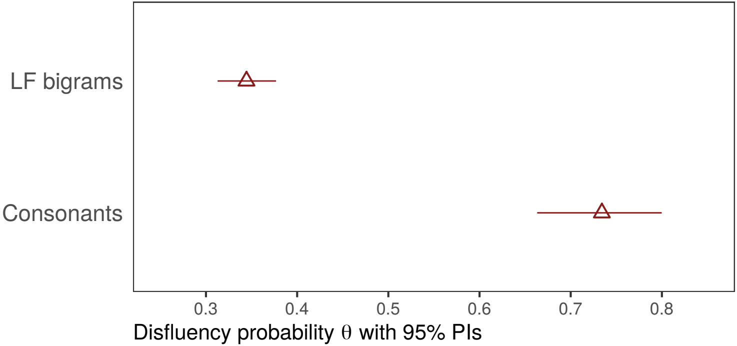
Population estimates



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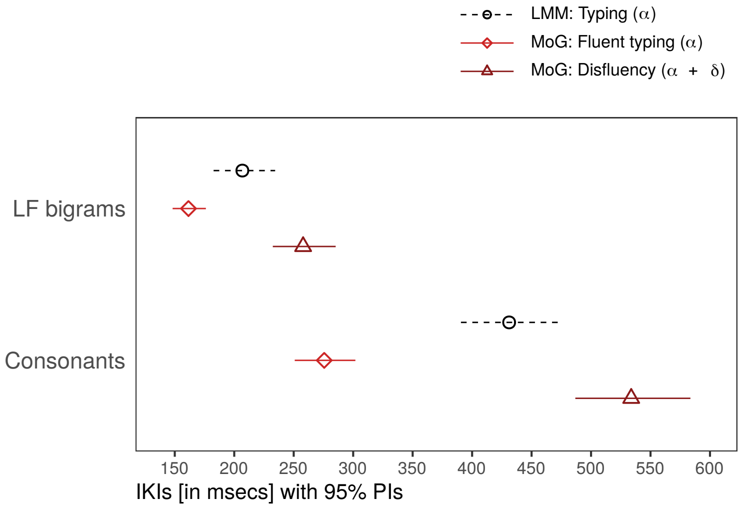

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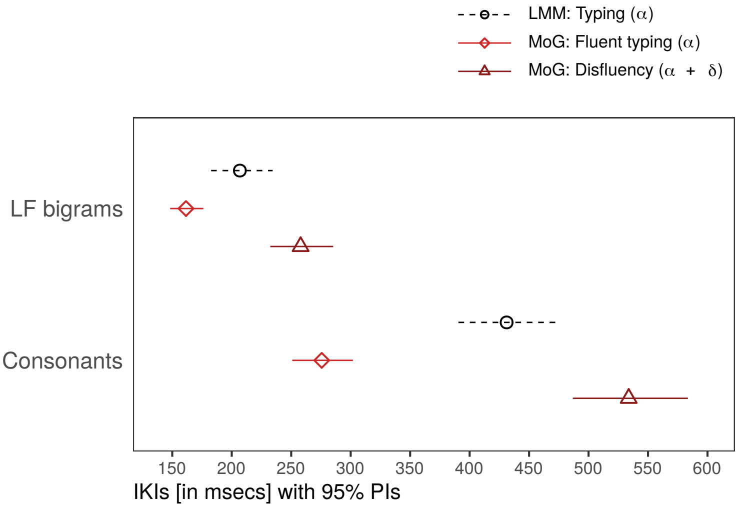

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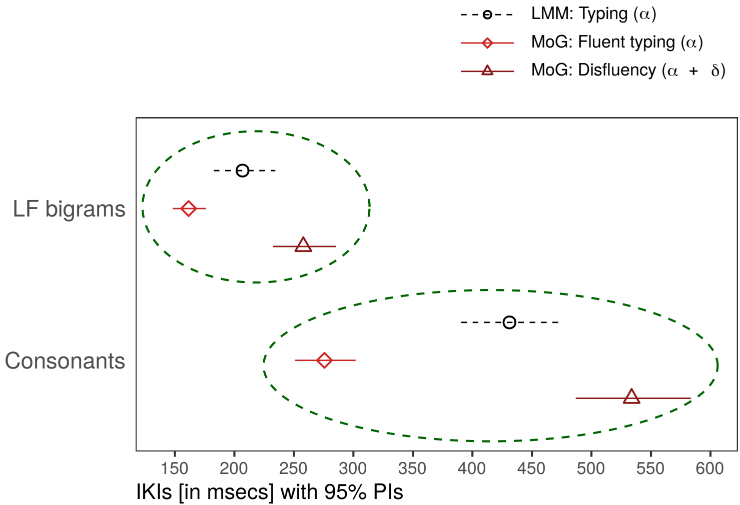

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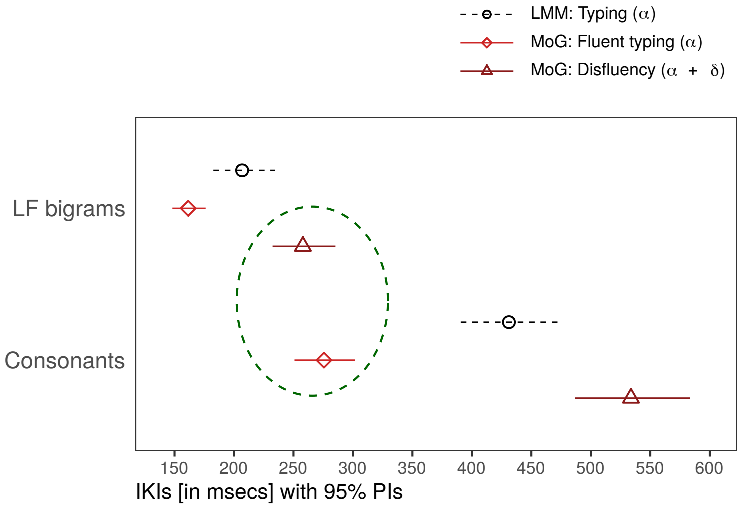
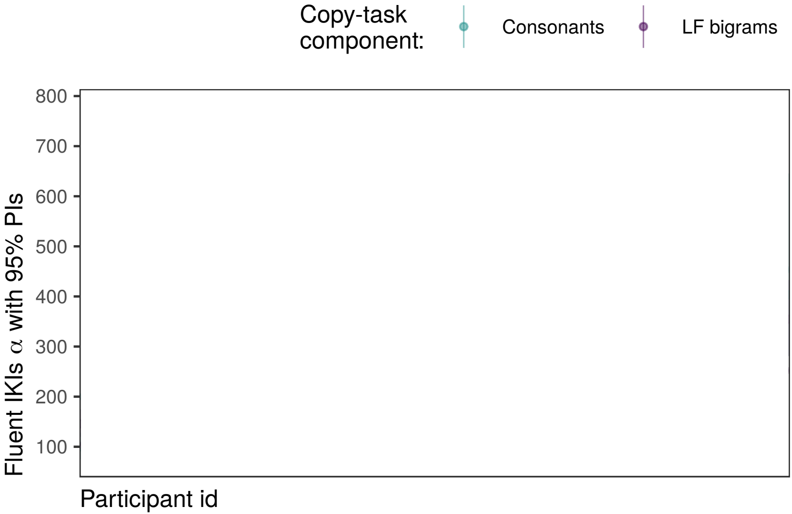


By-participant fluent-typing intervals



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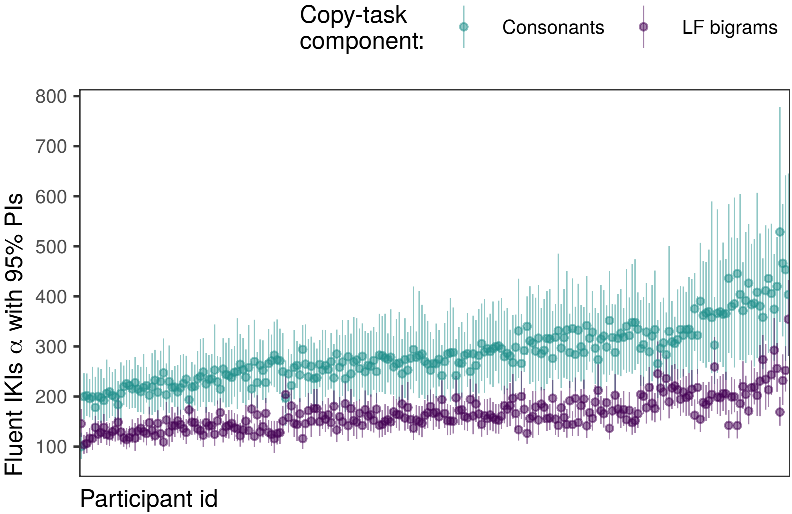
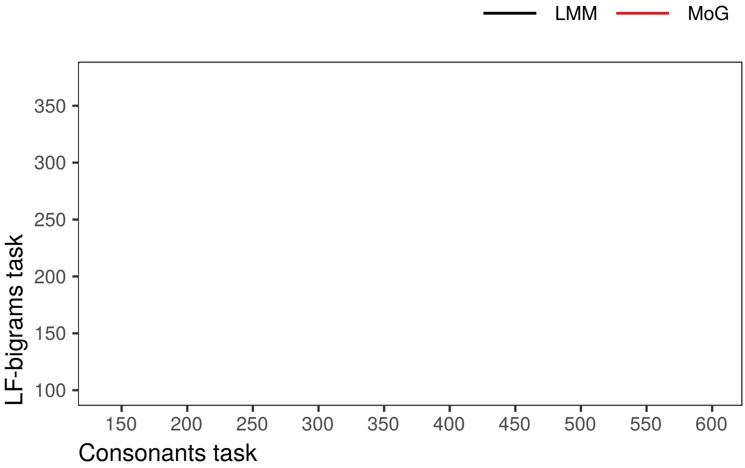


Estimated (fluent) keystroke transitions



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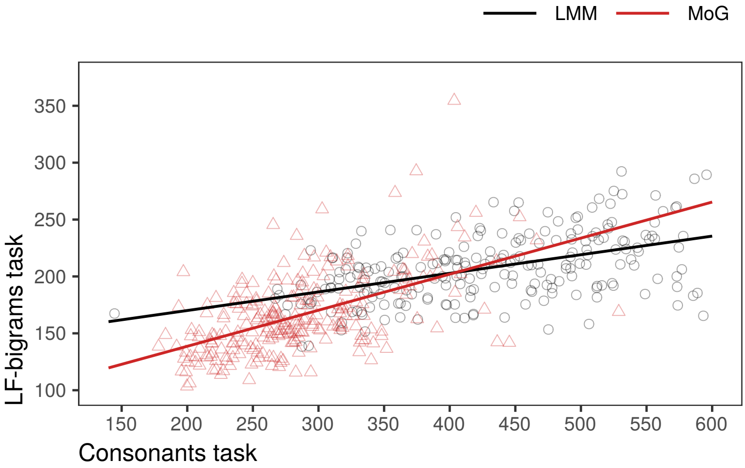
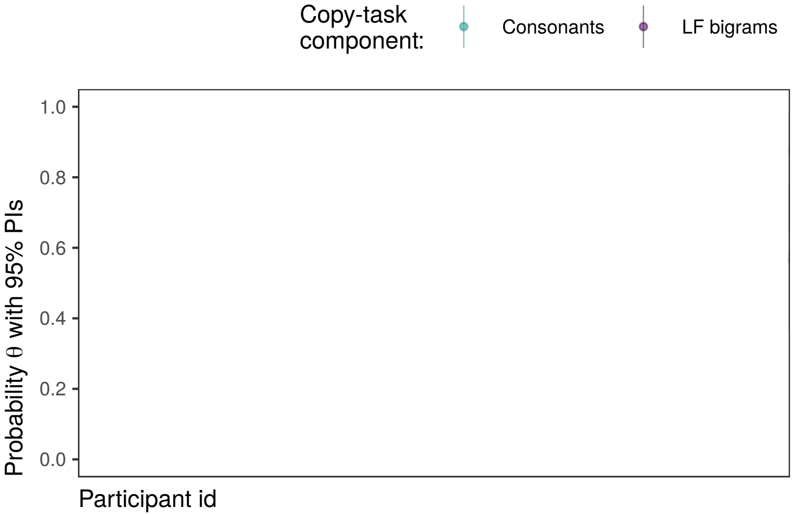


By-participant disfluency probability



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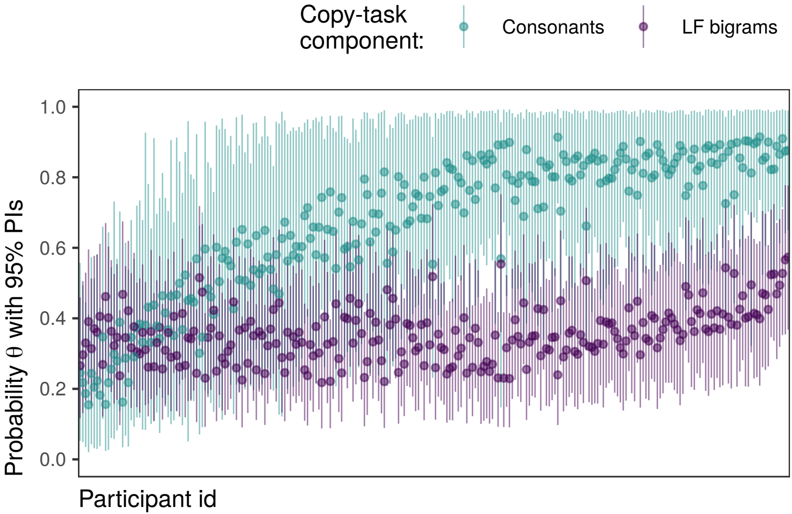

Conclusion

- Better fit for mixture models over standard analysis.
- Capture writing process as a mixture of fluent and disfluent key transitions.
- Advantages of mixture models for writing research:
  1. map on cascading models of writing.
  2. capture disfluencies in a principled way.
  3. represent the probabilistic nature of disfluencies.
  4. provide reliable typing estimates and pause frequencies.

Thanks for listening!

email: jens.roeser@ntu.ac.uk
R-scripts, *Stan*-code, slides, preprint:
https://github.com/jensroes/Typing-disfluency

References I

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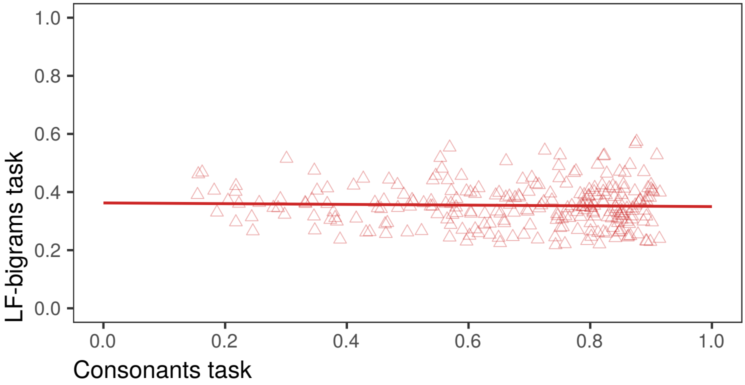
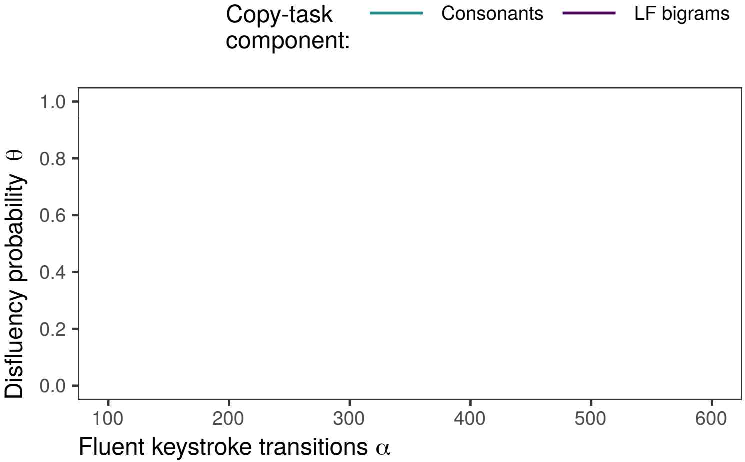


Disfluency typing-speed trade-off



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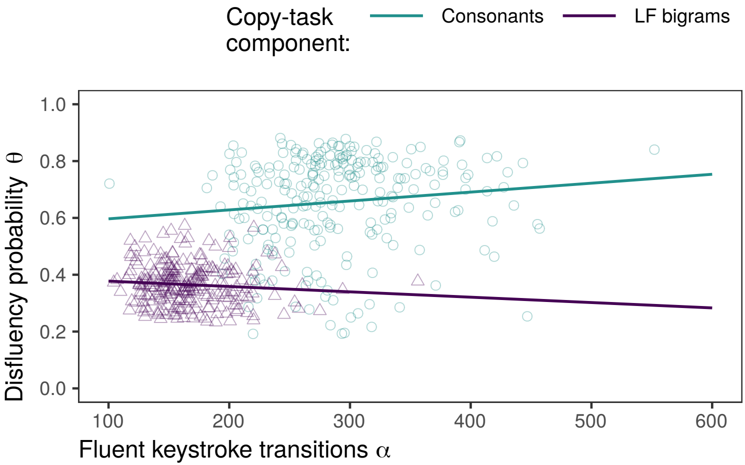
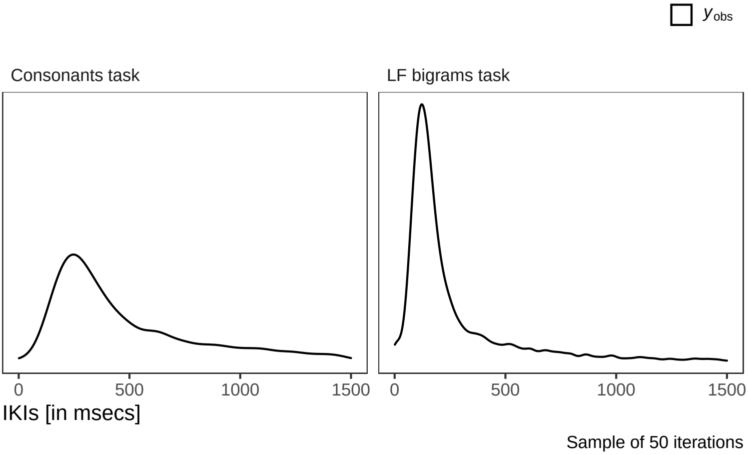


Observed vs. predicted IKIs



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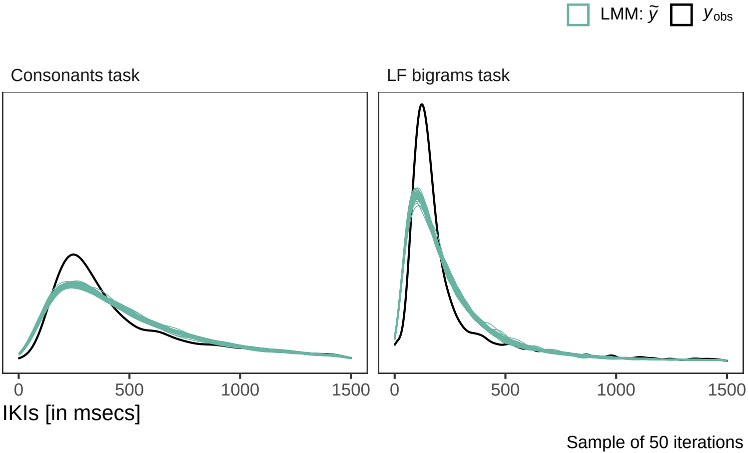

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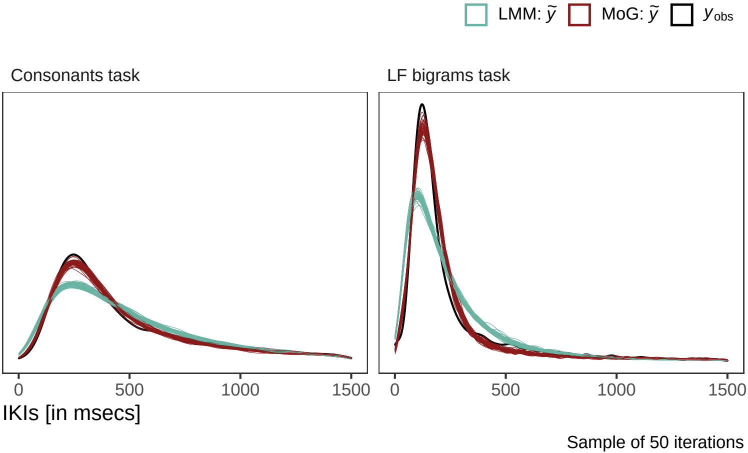

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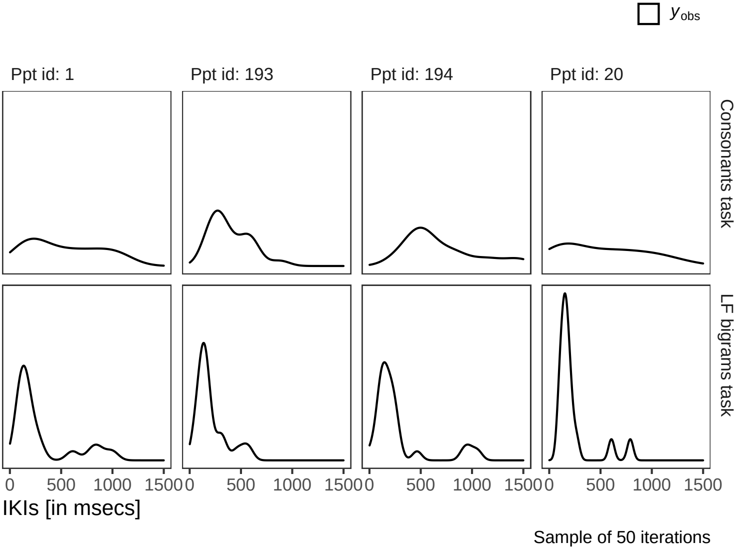

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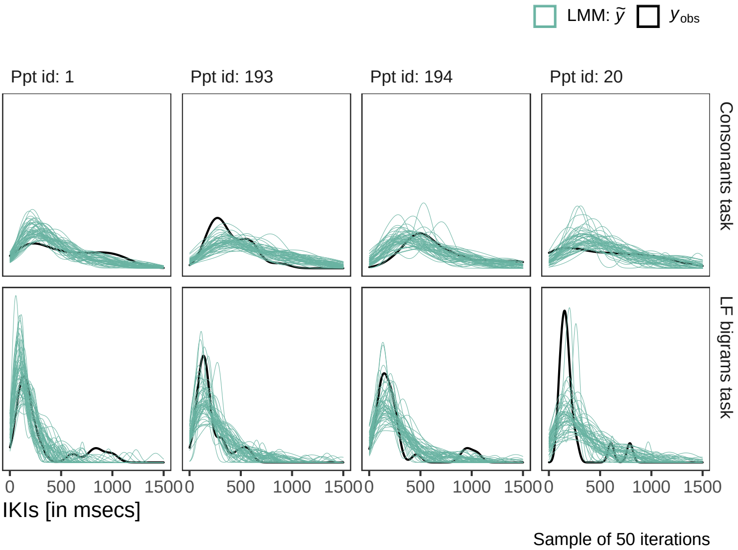

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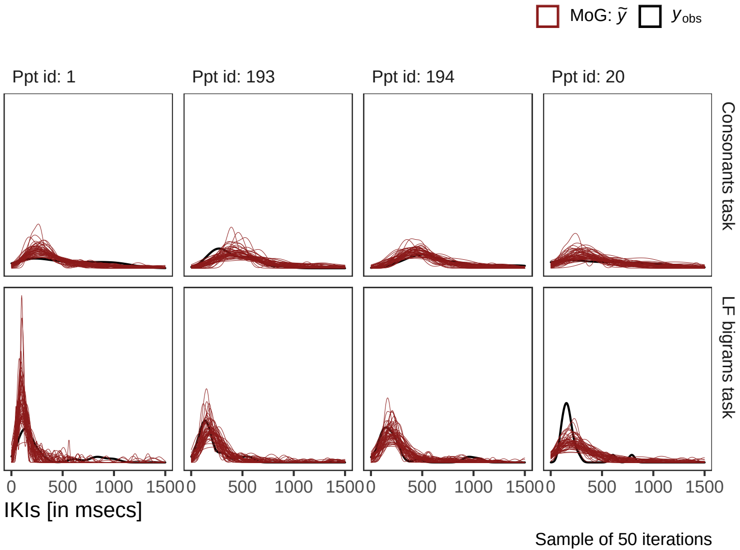
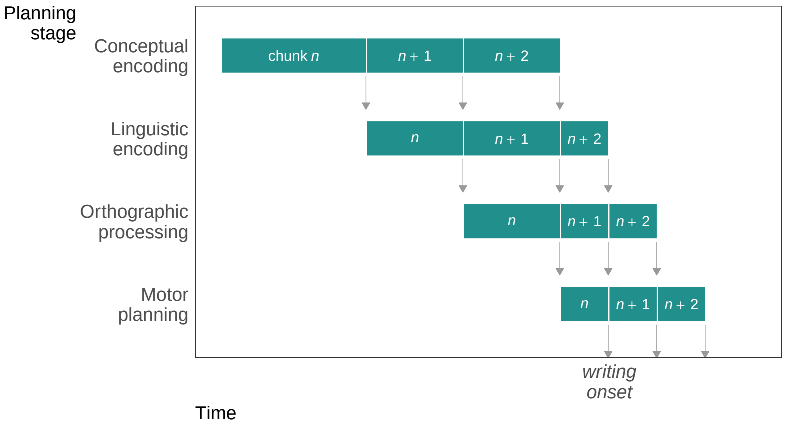


Planning cascade in writing



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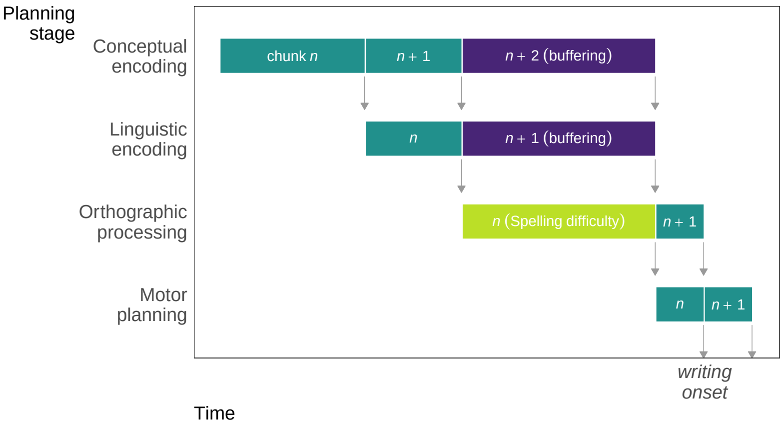

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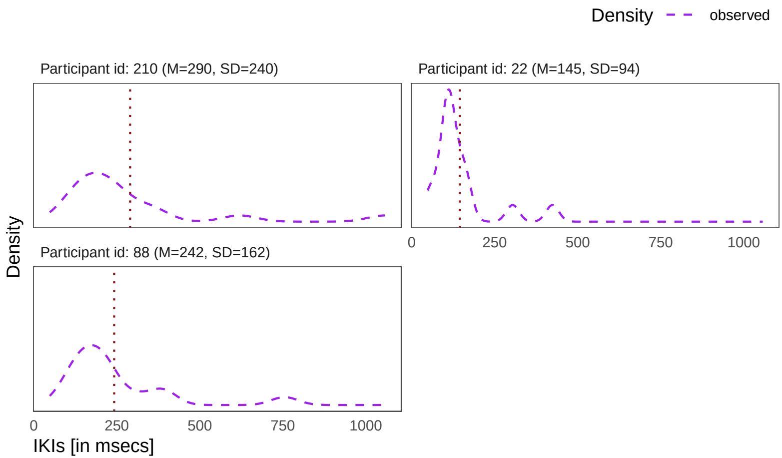

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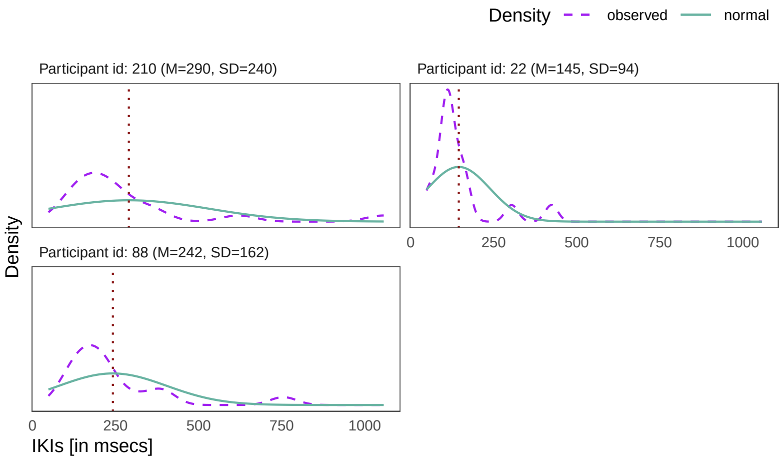

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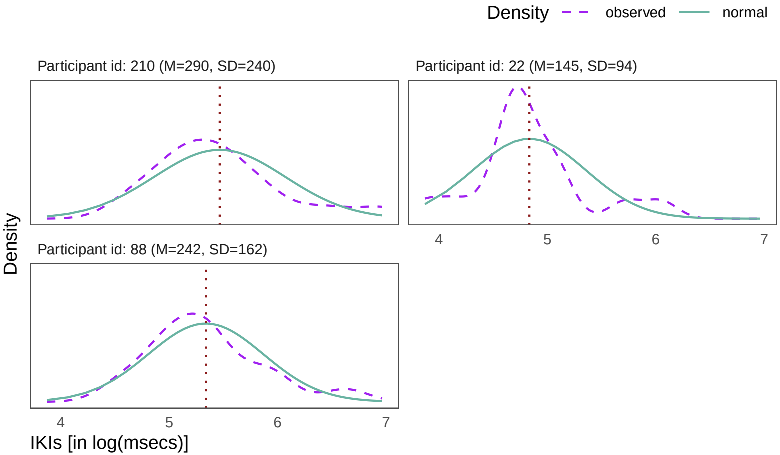

Long intervals are not bigram specific