No scope for planning – language pre-planning as mixture process

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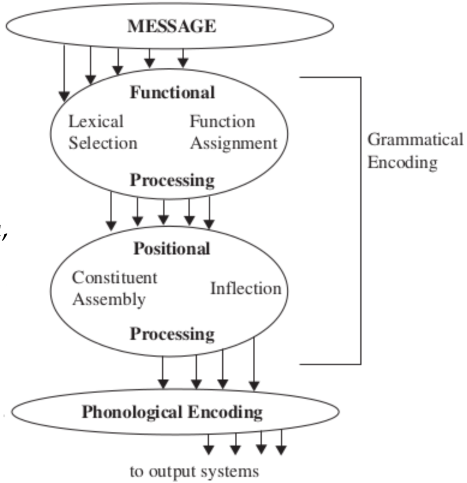
Turning ideas into language (Bock & Levelt, 1994)

- Unordered message units
- Output has linear order
- Linearisation via pragmatic, lexical and / or syntactic factors



To what extent does syntax affect the linearisation of the output before production onset?

Syntax in language production (Bock & Ferreira, 2014)

1. Syntax is emergent property of lexically-driven planning
2. Syntax is generated from message representation
   a. **Deterministic:** syntax determines size of planning unit
   b. **Non-deterministic:** multiple candidate structures (Kempen & Hoenkamp, 1987)
3. Both routes (relational and non-relational) are available (at the message level; see Konopka & Meyer, 2014).

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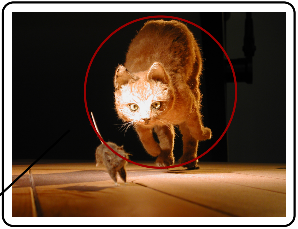
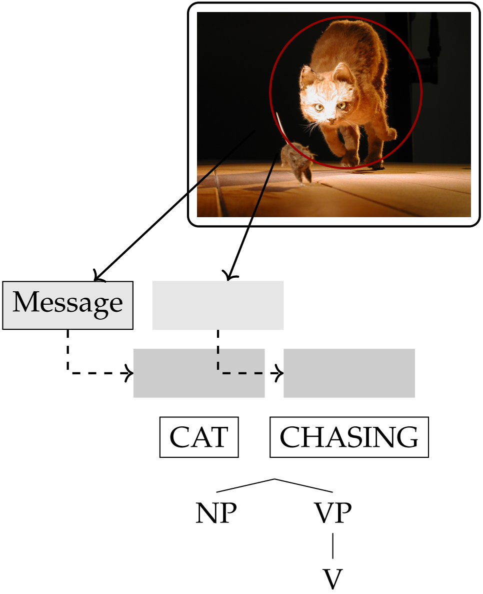


Message

CAT

NP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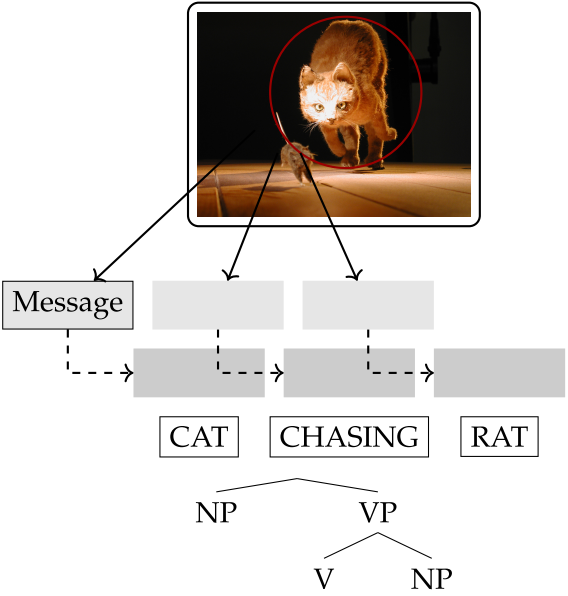
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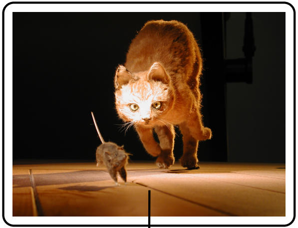
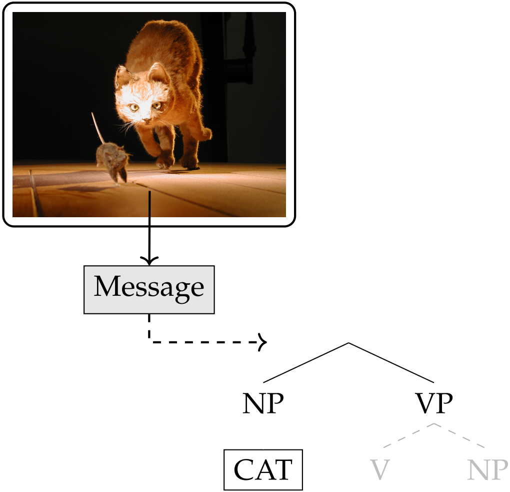


Message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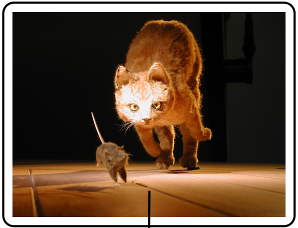

Message

NP VP

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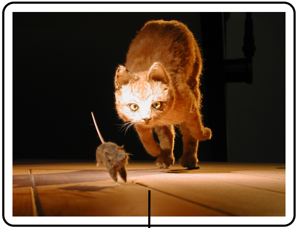
CHASE



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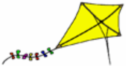
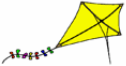
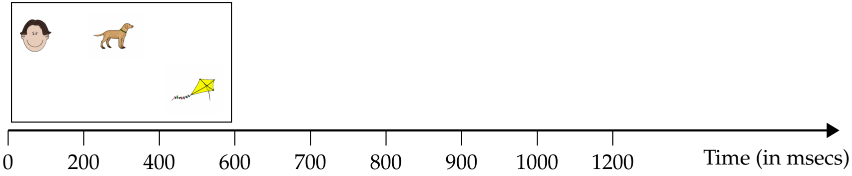




The boy and the dog moved above the kite.



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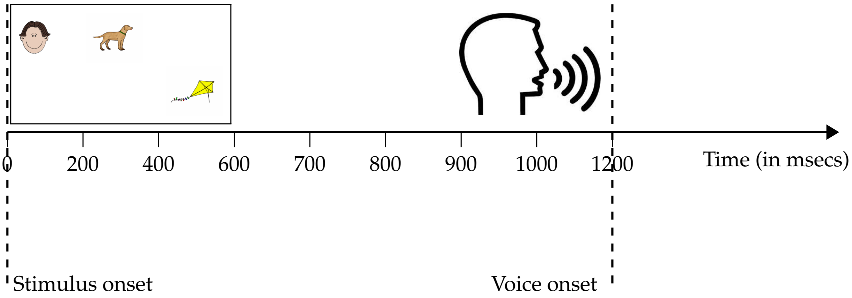

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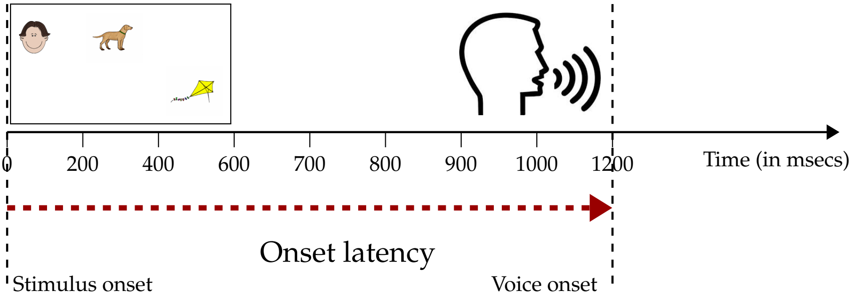

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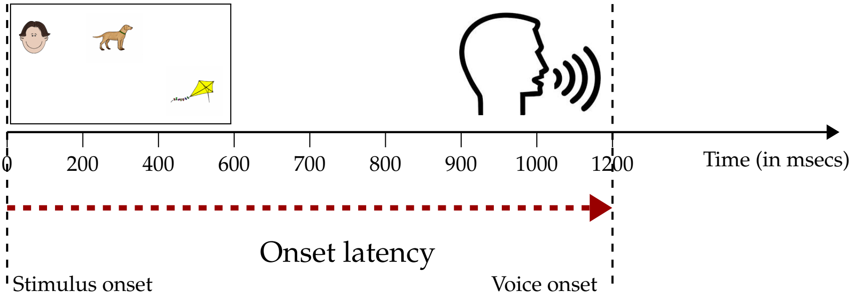

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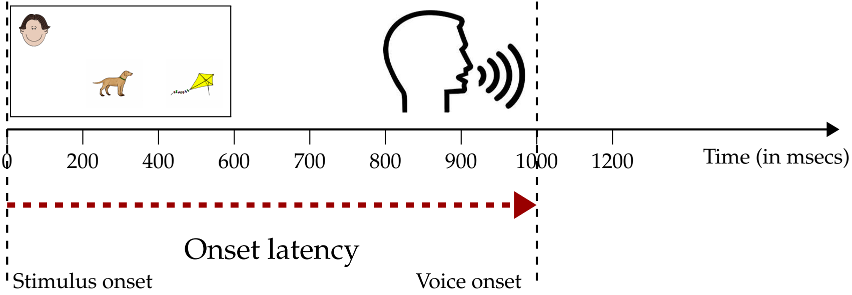

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Preplanning is guided by syntax

- Frequently reproduced systematic slowdown for conjoined NPs (e.g. Martin et al., 2014; Smith & Wheeldon, 1999; Wagner et al., 2010; Wheeldon et al., 2013).
- "Phrase as default planning scope" (Martin et al., 2010)
- NP syntax must be planned before onset; hence determines planning scope.

Alternative hypothesis

- **Preplanning beyond the first noun is more likely but not obligated by the phrase syntax** because, for example, …

1. Fluency requires preplanning of B in *The A and the B moved …* when there isn't enough time to plan B in parallel to articulation (Allum & Wheeldon, 2007; Griffin, 2003).
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Research focus

- Direct comparison of two hypotheses re onset-latency slowdown for conjoined NPs.
  i. Phrase scope obligated by the production system, leading to a systematic slowdown.
  ii. Preplanning beyond the first noun is more likely for conjoined NPs but not obligated by the production system.
- Implementation of both hypotheses as statistical models in Stan (Carpenter et al., 2017); code based on Sorensen et al. (2016) and Vasishth, Chopin et al. (2017); also Vasishth, Jäger et al. (2017).

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Pooled re-analysis of 8 experiments

- Hardy et al. (2019): 90 ppts; 36 items
- Hardy et al. (2020): 105 ppts; 80 items
- Martin et al. (2010): 3×12 ppts; 2×48 and 1×64 items
- Roeser et al. (2019): 3×32 ppts; 96 items

- 2 conditions

a. **Conjoined NPs:** *The boy and the dog moved above the kite.*

b. **Simple NPs:** *The boy moved above the dog and the kite.*

Pooled Linear Mixed Effects Model (null hypothesis)

$$y_{ijk} \sim LogNormal(\mu_{ijk}, \sigma^2_{e_k})$$
$$\mu_{ijk} = \alpha_k + u_i + w_j$$

- Non-centred mean α_k each for $k = 1, \ldots, K$ where K is the number of studies (Gelman et al., 2014) with pooled latency α_μ.
- Participants: $u_i \sim Normal(0, \sigma^2_u)$
- Items: $w_j \sim Normal(0, \sigma^2_w)$
- Pooled error variance σ^2_e

Pooled Linear Mixed Effects Model

$$y_{ijk} \sim LogNormal(\mu_{ijk}, \sigma^2_{e_k})$$
$$\mu_{ijk} = \alpha_k + \boxed{\beta_k \cdot x_{[0,1]}} + u_i + w_j$$

- $x = 0$ for simple NPs; $x = 1$ for conjoined NPs.
- β_k: by-study NP difference with pooled effect β_μ.
- **Conceptual idea:**
  - Underlying process can be characterised as **one distribution**.
  - Deterministic syntax-driven model: conjoined NPs slow down preplanning by β msecs.

Pooled Mixture of Gaussians

$$\begin{aligned} y_{ijk} \sim \theta_{NP_k} \cdot LogNormal(\mu_{ijk} + \delta_k, \sigma^2_{e'_k}) + \\ (1 - \theta_{NP_k}) \cdot LogNormal(\mu_{ijk}, \sigma^2_{e_k}) \\ \mu_{ijk} = \alpha_k + u_i + w_j \end{aligned}$$

- **Conceptual idea:**
- Underlying process is **mixture of two distributions**:

i. onset latency with variance $\sigma^2_{e_k}$

ii. slowdown δ with larger variance $\sigma^2_{e'_k}$

- θ captures the probability of long latencies by NP type.

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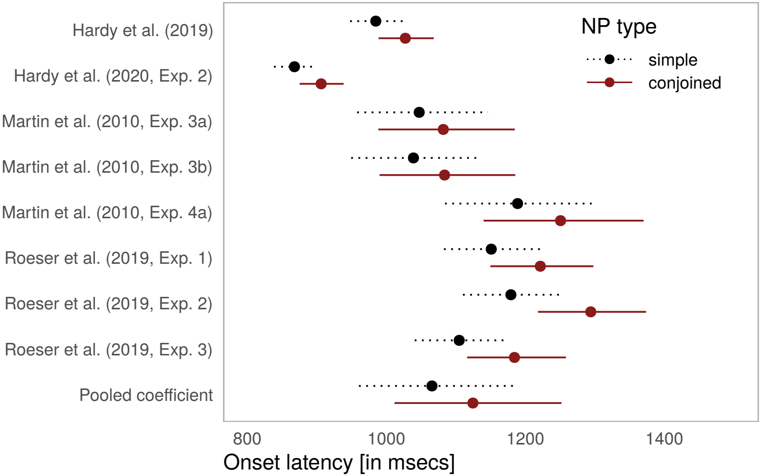
- **Conceptual idea:**
- Planning beyond first noun is possible for both NP types resulting in a slowdown δ.
- Non-deterministic model: planning beyond the first noun is more likely for conjoined NPs reflected in larger probability of long onset latencies θ.

NP effect (LMM)



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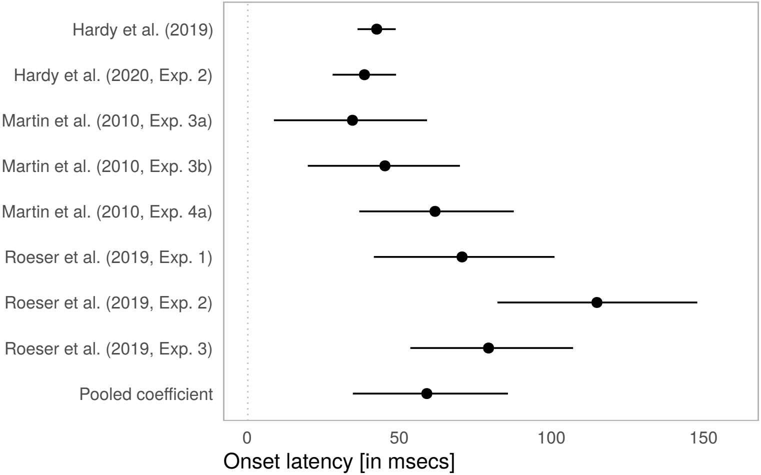

Model comparisons

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.

Models	$\Delta\widehat{elpd}$	$\widehat{elpd}$	Description
MoG-1			Mixing proportions by NP-type
MoG-0			Null model (no NP difference)
LMM-1			Slowdown for conjoined NPs
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LMM-2			Larger variance for conjoined NPs

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

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MoG-1	–	-201,486 (176)	Mixing proportions by NP-type
MoG-0	-15 (8)	-201,500 (176)	Null model (no NP difference)
LMM-1	-1,006 (97)	-202,492 (214)	Slowdown for conjoined NPs
LMM-0	-1,192 (92)	-202,678 (212)	Null model (no NP difference)
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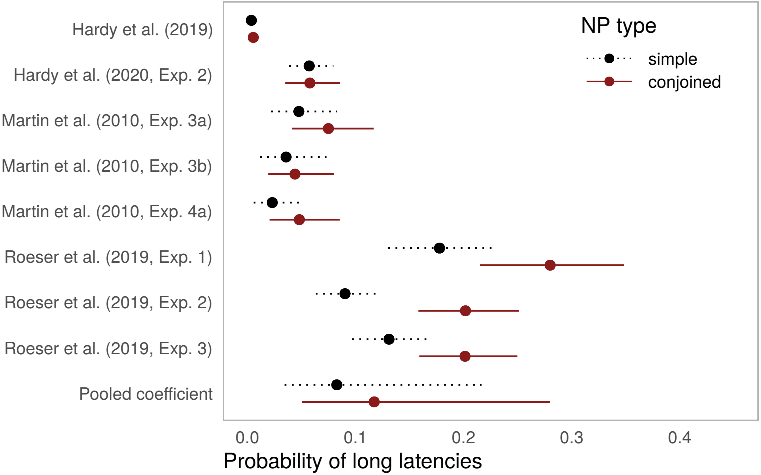
Probability of long latencies (MoG)



Bridge to follow-up experiments

- Slowdown for conjoined NPs is better explained by a larger, yet relatively small, probability of long latencies.
- Most studies in our pool included other manipulations.

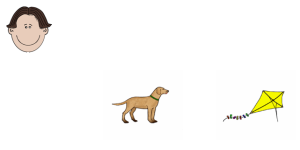
- **Experiment 1:**
  - Reproduce analysis after …

  i. Reducing the manipulation to simple and conjoined NPs.

  ii. Controlling image names
- **Experiment 2:**
  - Assess impact of visual manipulation (as in Martin et al., 2010).

Methods

Condition 1: A and B moved above C



Condition 2: A moved above B and C

- 48 items; 96 fillers; 6 practice trials
- First noun: *Peter* or *Tania*
- Image names: high frequency and naming agreement.

- **Experiment 1:**
  - 1a. **Peter and the dog** moved above the kite
  - 1b. **Peter** moved above the dog and the kite
  - 78 ppts (after cleaning)
- **Experiment 2:**
  - 2. Peter, the dog, the kite
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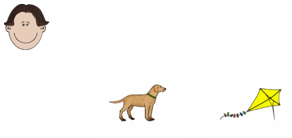

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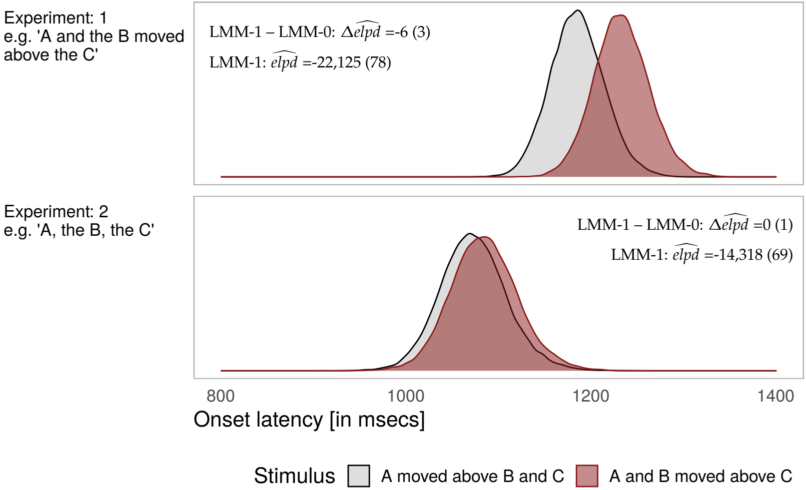
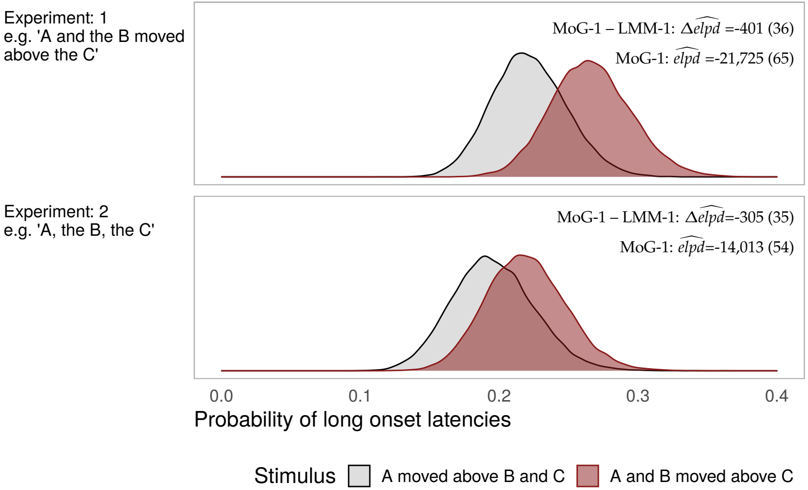
NP-type effect (LMM)



Probability of long latencies (MoG)



Summary

- No evidence for phrase-as-planning-unit hypothesis: NP syntax isn't obligated by production system.
- Instead, the slowdown for conjoined NPs (as in Martin et al., 2010; Smith & Wheeldon, 1999) is better explained by a larger probability of long latencies which, however, remained in a minority.
- Syntax in language production must result from a non-deterministic planning mechanism.

Thank you for listening!

…and **Randi Martin**, **Jason Crowther**, and **Sophie Hardy** (et al.) for sharing their data,
…and **Dora Kramar** and **Andra Tanasescu** for supporting the data collection.

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R and *Stan* code: github.com/jensroes/NP-effect

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Meta LMM

$$
\begin{aligned}
y_{ijk} &\sim LogNormal(\mu_{ijk}, \sigma^2_{e_k}) \\
\mu_{ijk} &= \alpha_k + \beta_k \cdot x_{[0,1]} + u_i + w_j \\
\alpha_k &= \alpha_\mu + \alpha_\tau \cdot \alpha_{\eta_k} \\
\beta_k &= \beta_\mu + \beta_\tau \cdot \beta_{\eta_k} \\
\text{constraint: } \sigma^2_{e_k} &> 0
\end{aligned}
$$

- $x = 0$ for simple NPs; $x = 1$ for conjoined NPs.

Meta LMM (unequal variance)

$$y_{ijk} \sim \begin{cases} LogNormal(\mu_{ijk}, \sigma^2_{e_k}), & \text{if NP}_{ijk} = \text{simple} \\ LogNormal(\mu_{ijk} + \beta_k, \sigma^2_{e'_k}) & \text{else if NP}_{ijk} = \text{conjoined} \end{cases}$$

$$\mu_{ijk} = \alpha_k + u_i + w_j$$

$$\alpha_k = \alpha_\mu + \alpha_\tau \cdot \alpha_{\eta_k}$$

$$\beta_k = \beta_\mu + \beta_\tau \cdot \beta_{\eta_k}$$

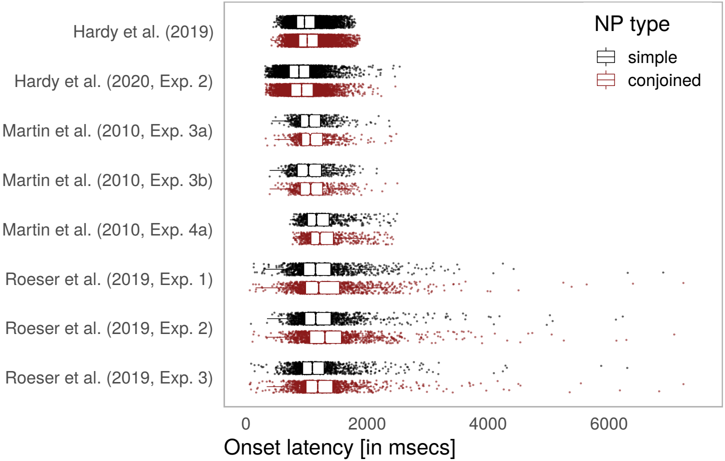
$$\text{constraint: } \sigma^2_{e_k} > 0$$

$$\sigma^2_{e'_k} > \sigma^2_{e_k}$$

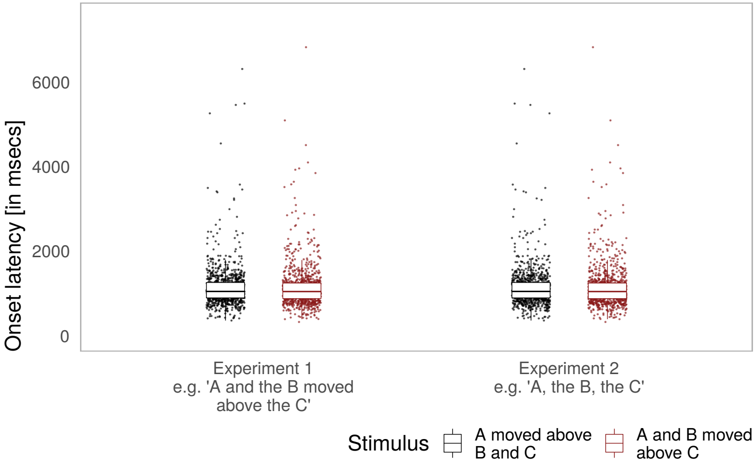
Meta mixture model (alternative hypothesis)

$$
\begin{aligned}
y_{ijk} \sim \theta_{NP_k} \cdot LogNormal(\mu_{ijk} + \delta_k, \sigma^2_{e'_k}) + \\
(1 - \theta_{NP_k}) \cdot LogNormal(\mu_{ijk}, \sigma^2_{e_k}) \\
\mu_{ijk} = \alpha_k + u_i + w_j \\
\alpha_k = \alpha_\mu + \alpha_\tau \cdot \alpha_{\eta_k} \\
\theta_{NP_k} = Logit^{-1}(\phi_{NP_k}) \\
\theta_{\mu_{NP}} = Logit^{-1}(\phi_{\mu_{NP}}) \\
\phi_{NP_k} \sim Normal(\phi_{\mu_{NP}}, \phi^2_\tau) \\
\delta_k \sim Normal(\delta_\mu, \delta^2_\tau) \\
\text{constraint: } \delta_k, \sigma^2_{e_k}, \phi_\tau, \delta_\tau > 0 \\
\sigma^2_{e'_k} > \sigma^2_{e_k}
\end{aligned}
$$

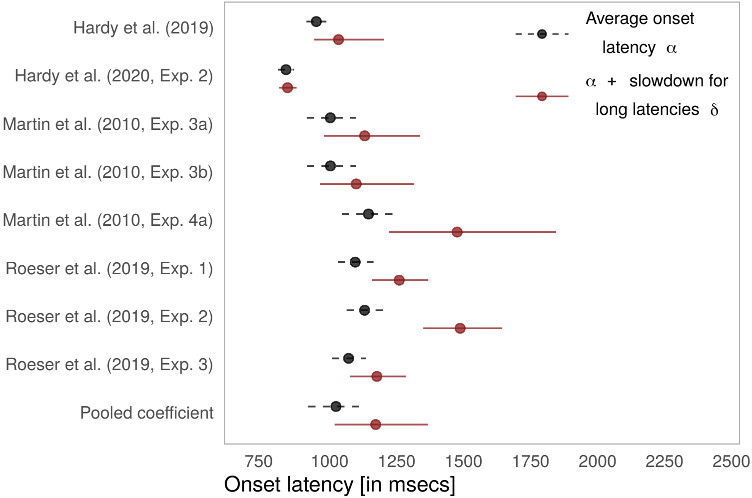
Data overview (pooled data)



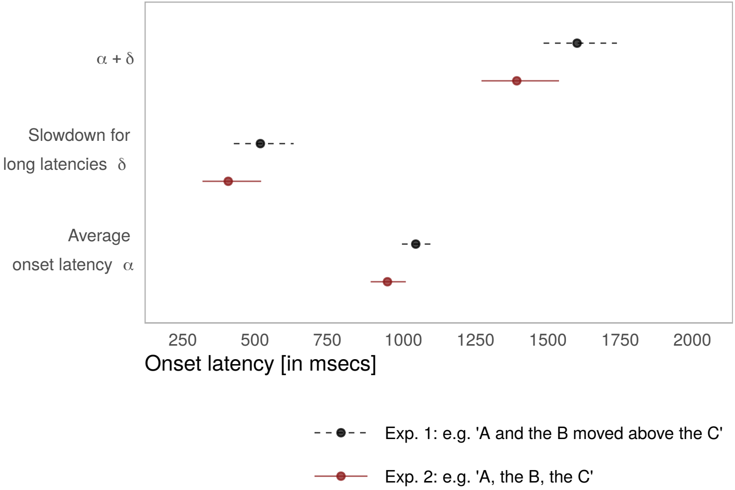
Data overview (Experiments 1& 2)



Onset-latency coefficients (pooled mixture components)



Onset-latency coefficients (mixture components)



Model comparisons

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

	Model	$\Delta\widehat{elpd}$	$\widehat{elpd}$
Expeirment 1	MoG-1	–	-21,724 (65)
	MoG-0	-1 (2)	-21,725 (65)
	LMM-1	-401 (36)	-22,125 (78)
	LMM-2	-402 (36)	-22,126 (78)
	LMM-0	-406 (36)	-22,131 (78)
Expeirment 2	MoG-0	–	-14,012 (54)
	MoG-1	-1 (1)	-14,013 (54)
	LMM-0	-306 (35)	-14,318 (69)
	LMM-1	-306 (35)	-14,318 (69)
	LMM-2	-308 (35)	-14,319 (69)

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