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

Jens Roeser

Mark Torrance Mark Andrews Thom Baguley

Nottingham Trent University, UK
jens.roeser@ntu.ac.uk

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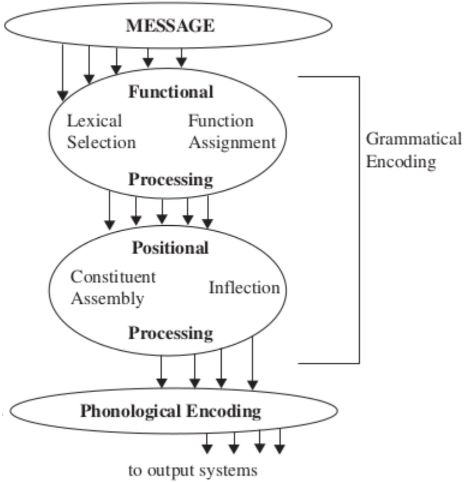
Turning ideas into language (Bock & Levelt, 1994)

- Message units are unordered.
- Output requires linearisation of words.
- Linearisation is subject to pragmatic, lexical and / or syntactic factors.

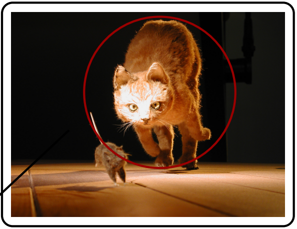


To what extent does syntax affect the linearisation of the output?

Syntax in language production (Bock & Ferreira, 2014)

1. Syntax is an emergent property of lexically-driven planning.
2. Syntactic relations guide lexical retrieval.
   a. **Deterministic:** syntax determines size of planning unit.
   b. **Non-deterministic:** multiple candidate structures (Kempen & Hoenkamp, 1987).
3. Either route (relational and non-relational) is available (at the message level; see Konopka & Meyer, 2014).

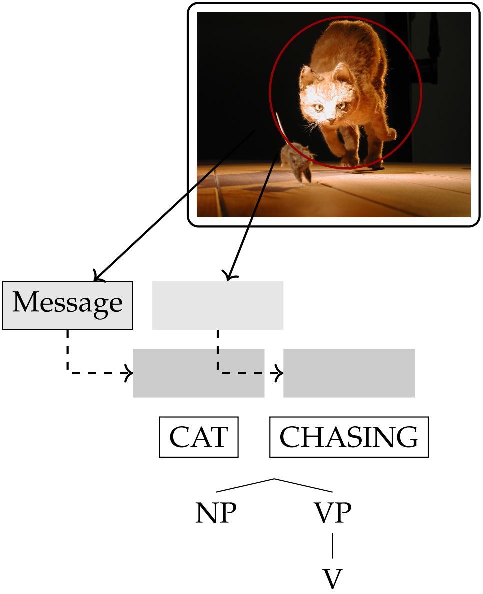
Consider the following evidence for possibility (2a).



Message

CAT

NP


Message
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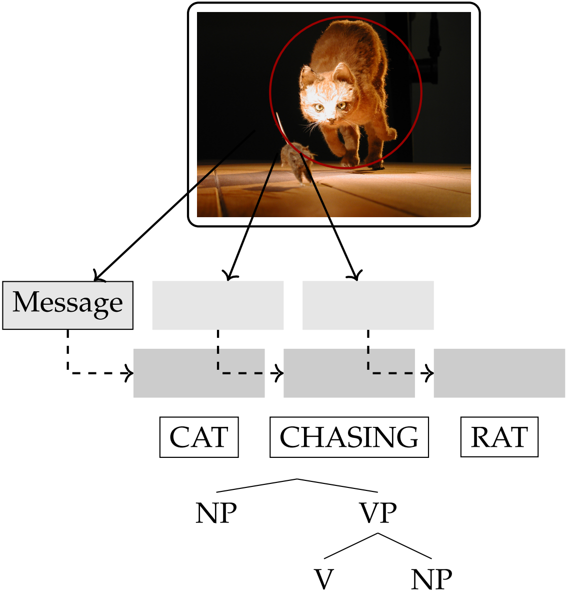
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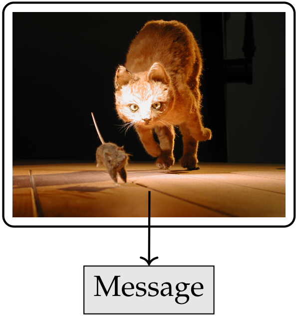
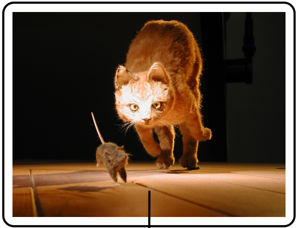
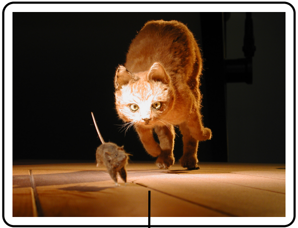

Message



Message

NP VP

CAT V NP

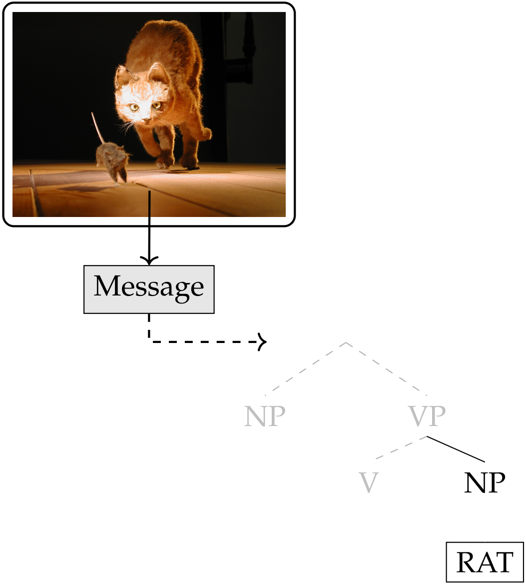


Message

NP VP

V NP

CHASE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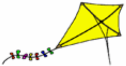
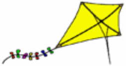
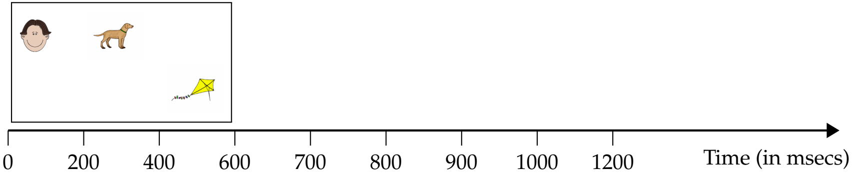




The boy and the dog moved above the kite.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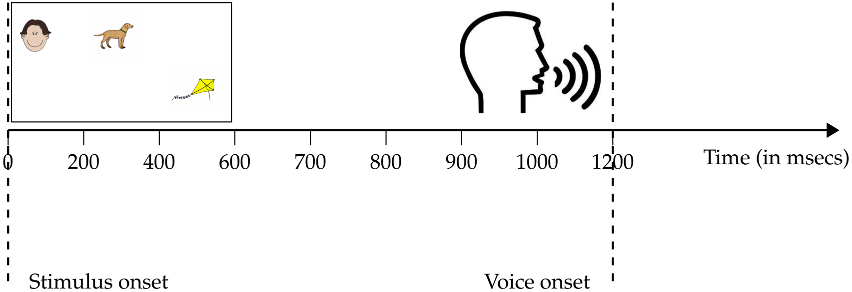
Time (in msecs)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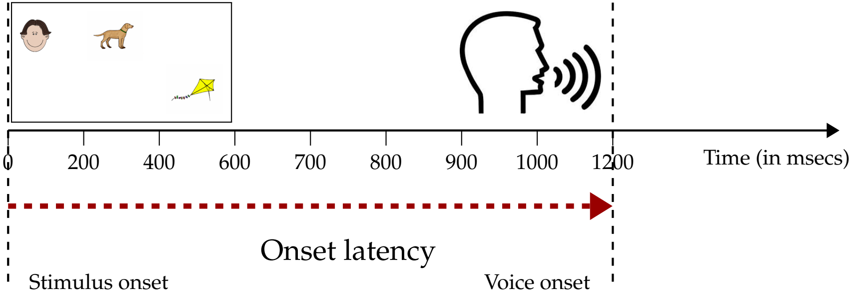
Time (in msecs)
Stimulus onset
Voice onset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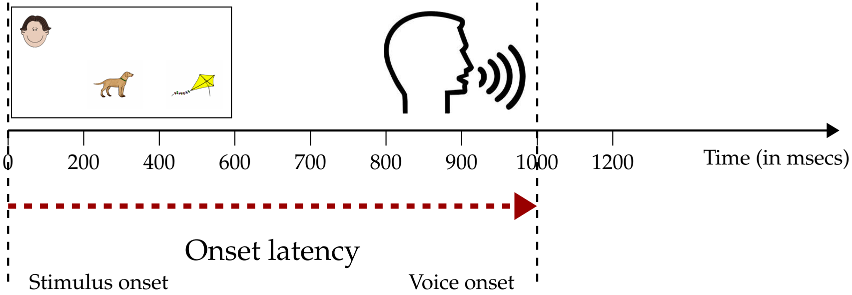
Time (in msecs)
Onset latency
Stimulus onset
Voice onset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Preplanning scope involves syntax

1. **The boy and the dog** moved above the kite.
2. **The boy** moved above the dog and the kite.

- Frequently reproduced effect (e.g. Martin et al., 2014; Smith & Wheeldon, 1999; Wagner et al., 2010).
- "Phrase as default planning scope" (Martin et al., 2010)
- NP syntax is planned before production onset.
- Lexical scope is smaller (Griffin, 2001) and flexible (Wheeldon et al., 2013).

Implication of the standard statistical treatment

- Statistical models used (LMM, ANOVA) map onto a deterministic syntax-driven model.
- Systematic difference between simple and conjoined NPs.
- Under these statistical models, the following alternative hypothesis couldn't be tested.

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Alternative hypothesis

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

1. Fluency pressure requires preplanning of B in *The A and the B moved …* if there is not enough time to plan B in parallel to articulation (Allum & Wheeldon, 2007; Griffin, 2003).
2. Activation of phrase syntax or use of the syntactic route is non-deterministic.

Research focus

- Direct comparison of two hypothesis.

i. Phrase scope obligated by the production system, leading to a systematic slowdown for conjoined NPs.
ii. Preplanning beyond the first noun is more likely in conjoined NPs but not obligated by the production system.

Pooled re-analysis

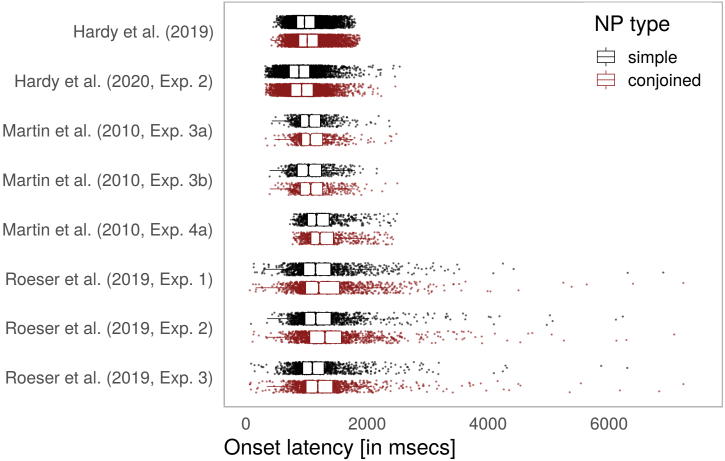
- Stimulus-to-onset latencies

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

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

- 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

Data overview



Model overview

1. Null LMM
2. **LMM (NP effect)**
3. LMM (unequal variance)
4. Null mixture model
5. **Mixture model**

- Stan code based on Sorensen et al. (2016) and Vasishth, Chopin et al. (2017); also Vasishth, Jäger et al. (2017).

- *LogNormal* distribution with mean μ and error variance σ_e^2
- Random intercepts
  - participants: $u_i \sim Normal(0, \sigma_u^2)$
  - items: $w_j \sim Normal(0, \sigma_w^2)$
- Weakly informative priors (McElreath, 2016)

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Null model (null hypothesis)

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

Meta null model (null hypothesis)

$$
\begin{aligned}
y_{ijk} \sim LogNormal(\mu_{ijk}, \sigma^2_{e_k}) \\
\mu_{ijk} = \alpha_k + u_i + w_j \\
\alpha_k = \alpha_\mu + \alpha_\tau \cdot \alpha_{\eta_k}
\end{aligned}
$$

- For $k = 1, \ldots, K$ where K is the number of studies.
- α_k is the latency coefficient for the kth study.
- α_μ is the pooled latency coefficient.
- Non-centred parametrisation for α_k (Gelman et al., 2014).

Meta LMM (standard analysis)

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

- $x = 0$ for simple NPs; $x = 1$ for conjoined NPs.
- β_k is the latency change for conjoined NPs for the kth study.
- β_μ is the pooled latency change for conjoined NPs.

Mixture model (alternative hypothesis)

$$
\begin{aligned}
y_{ij} \sim \theta_{NP} \cdot LogNormal(\mu_{ij} + \delta, \sigma^2_{e'}) + \\
(1 - \theta_{NP}) \cdot LogNormal(\mu_{ij}, \sigma^2_{e}) \\
\mu_{ij} = \alpha + u_i + w_j \\
\text{constraint: } \delta > 0 \\
\sigma^2_{e'} > \sigma^2_{e}
\end{aligned}
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- Probability of long latencies θ by NP type.
- μ and σ^2 constant across NP type.

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

- α_k, $\sigma^2_{e'_k}$, $\sigma^2_{e_k}$ defined as before.
- Pooled coefficient for parameters: θ_{NP}, δ

Meta LMM (unequal variance)

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

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

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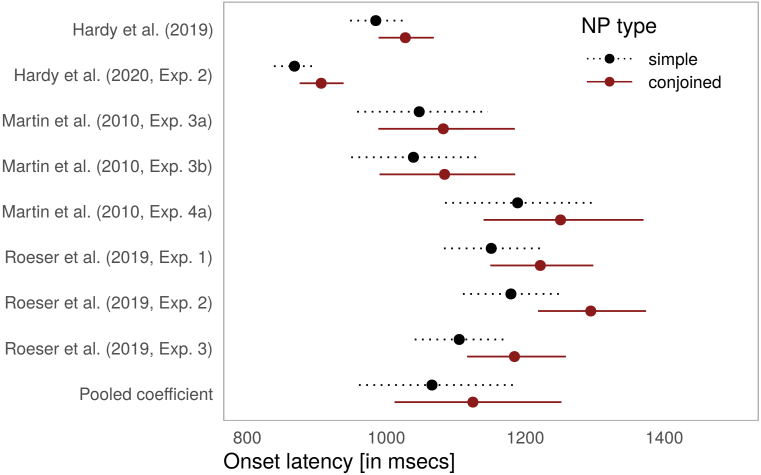
$$\beta_k = \beta_\mu + \beta_\tau \cdot \beta_{\eta_k}$$

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

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

NP effect (LMM)



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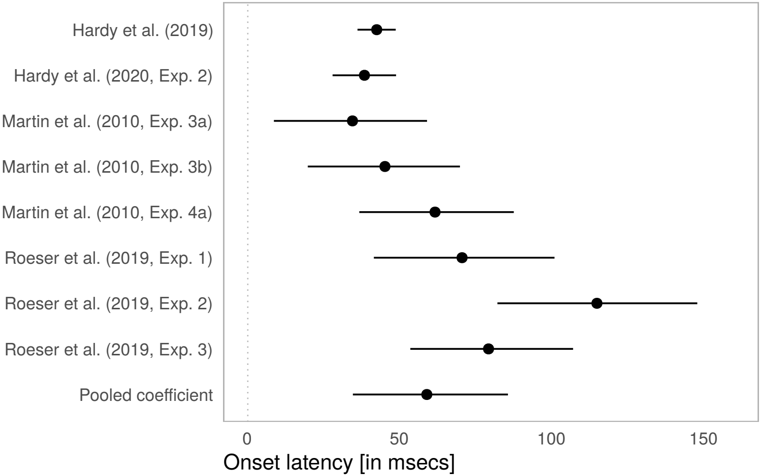


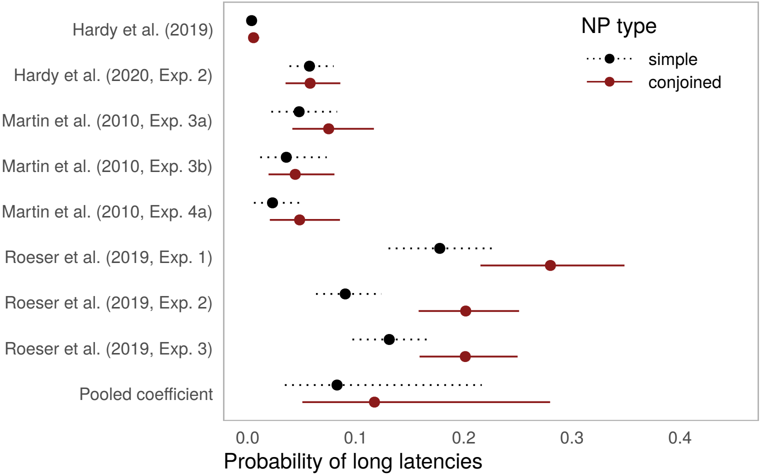
Model comparisons

Predictive performance estimated as the *expected log pointwise 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	–	-201,486 (176)	Mixing proportions by NP
MoG-0	-15 (8)	-201,500 (176)	Null model
LMM-1	-1,006 (97)	-202,492 (214)	NP effect
LMM-0	-1,192 (92)	-202,678 (212)	Null model
LMM-2	-3,537 (214)	-205,022 (307)	Unequal variance

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

Probability of long latencies (MoG)



Summary

- The frequently observed slowdown for conjoined NPs is better explained by a larger, yet relatively small, probability of long latencies.
- Different pattern for Hardy et al. (2019, 2020) compared to Martin et al. (2010) and Roeser et al. (2019); possibly because of data trimming threshold.
- Most studies in our pool included other manipulations.

Follow-up experiments

Experiment 1:

- Reproduce analysis after …

  i. Reducing the manipulation to simple and conjoined NPs.

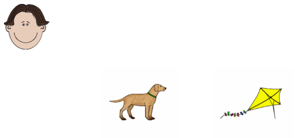
  ii. Controlling image names

Experiment 2:

- Assess the impact of the visual manipulation independently of utterance sytnax.
- Elicit name lists instead of sentences (as in Martin et al., 2010)

Methods

Condition 1: A and B moved above C



Condition 2: A moved above B and C

- **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

  - 45 ppts (after cleaning)

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

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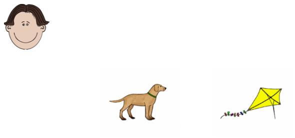

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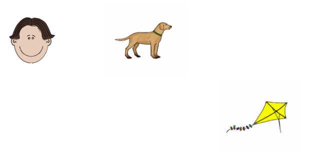

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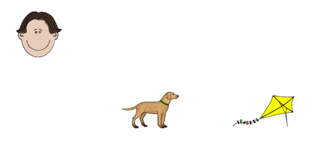

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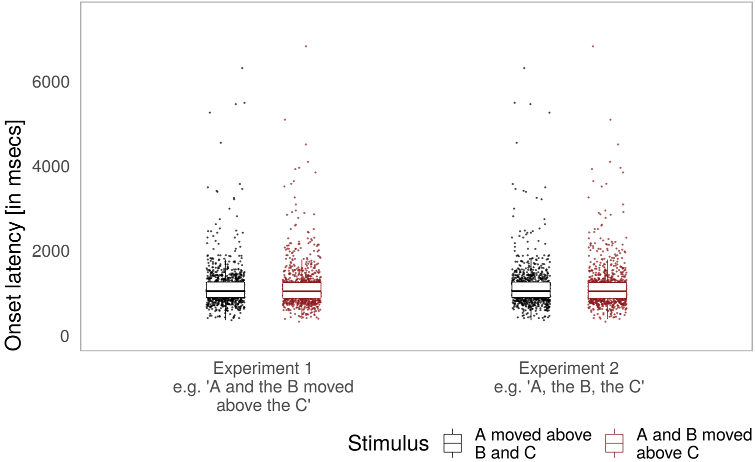
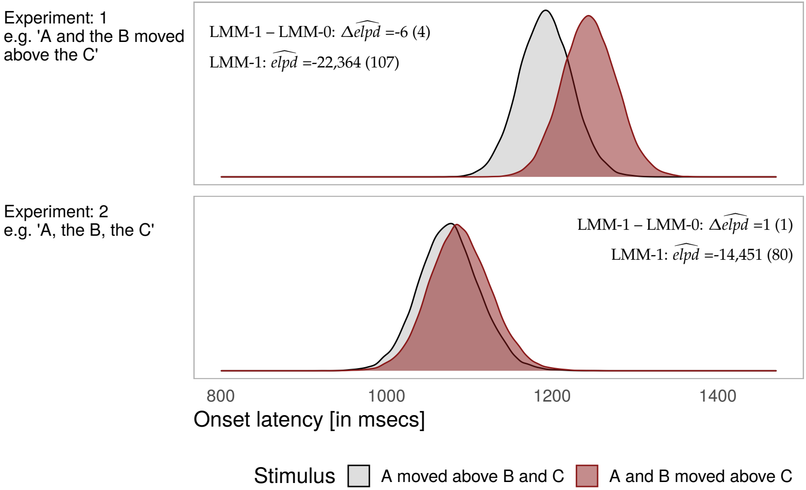
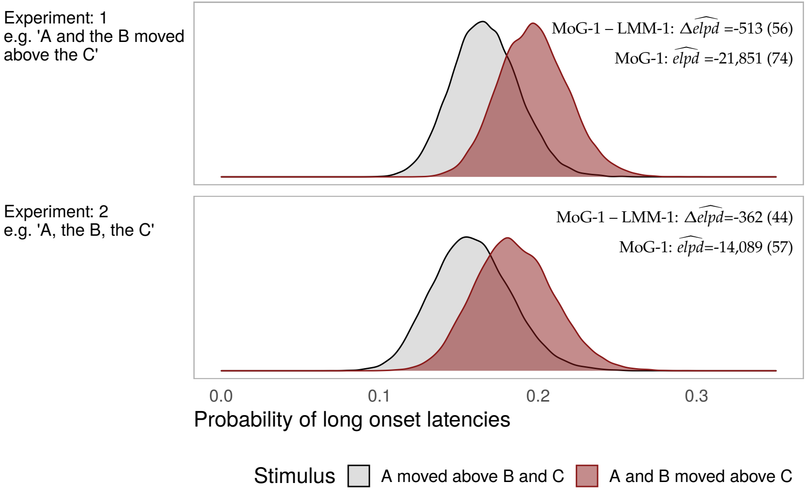
Onset latencies



NP-type effect (LMM)



Probability of long latencies (MoG)



Summary

- Evidence against the phrase-as-planning-unit hypothesis: preplanning NP syntax is not obligated by the language production system.
- Instead, the slowdown for conjoined NPs (as in Martin et al., 2010; Smith & Wheeldon, 1999) is better explained by a larger tendency to exhibit long onset latencies.

Alternative explanations

- Preplanning scope is in-line with non-deterministic theories of language production.
- Together with Exp. 2, results suggest that the slowdown observed in a subset of trials origins during visual rather than grammatical encoding.
- Both a relational and non-relational route are available during high level encoding (Konopka & Meyer, 2014; Kuchinsky et al., 2011).

Thank you for listening!

jens.roeser@ntu.ac.uk

nottinghamtrent.academia.edu/JensRoeser

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

…and **Randi Martin**, **Jason Crowther**, and **Sophie Hardy** for sharing their data.

…and **Dora Kramar** and **Andra Tanasescu** for help with the data collection.

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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.
- β_k is the latency change for conjoined NPs for the *k*th study.
- β_μ is the pooled latency change for conjoined NPs.

Meta LMM (unequal variance)

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

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

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

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

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

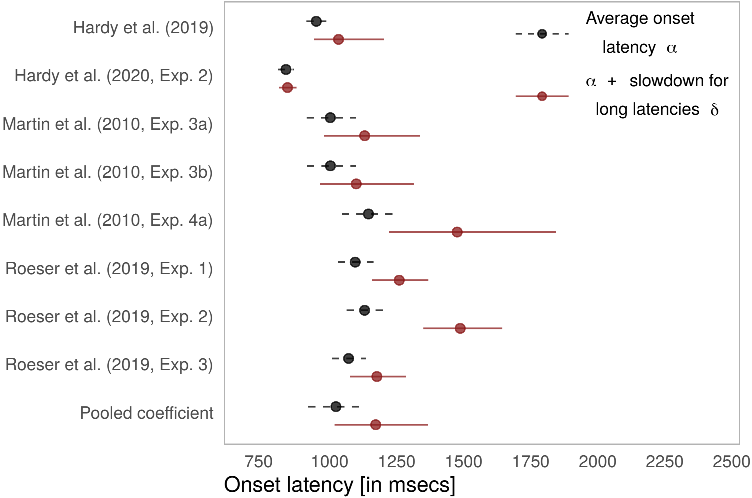
$$\sigma^2_{e'_k} > \sigma^2_{e_k}$$

Meta mixture model (alternative hypothesis)

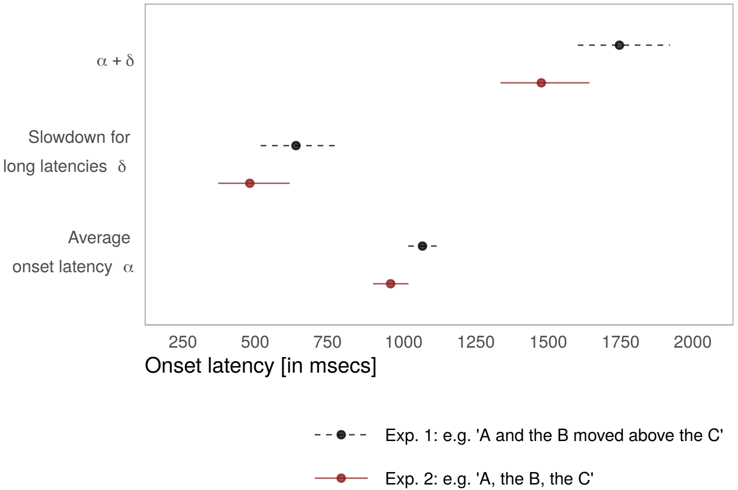
$$
\begin{aligned}
y_{ijk} \sim \theta_{NP_k} \cdot LogNormal(\mu_{ijk} + \delta_k, \sigma^2_{e'_k}) + \\
(1 - \theta_{NP_k}) \cdot LogNormal(\mu_{ijk}, \sigma^2_{e_k}) \\
\mu_{ijk} = \alpha_k + u_i + w_j \\
\alpha_k = \alpha_\mu + \alpha_\tau \cdot \alpha_{\eta_k} \\
\theta_{NP_k} = Logit^{-1}(\phi_{NP_k})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

- Pooled coefficient for parameters: θ_{NP}, δ

Onset-latency coefficients (meta 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	$\Delta\widehat{elpd}$	$\widehat{elpd}$
Experiment 1	MoG-0	–	-21,851 (74)
	MoG-1	0 (2)	-21,851 (74)
	LMM-1	-513 (56)	-22,364 (107)
	LMM-2	-515 (57)	-22,366 (107)
	LMM-0	-519 (56)	-22,369 (107)
Experiment 2	MoG-0	–	-14,088 (57)
	MoG-1	-1 (1)	-14,089 (57)
	LMM-0	-362 (44)	-14,450 (80)
	LMM-1	-363 (44)	-14,451 (80)
	LMM-2	-364 (44)	-14,452 (81)

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