# SYNTACTIC DE- AND ENCODING OF MEANING IN SENTENCE RECALL

Jens Roeser, Mark Andrews, Mark Torrance, Rodilene Gittoes (all Nottingham Trent University) | jens.roeser@ntu.ac.uk

NOTTINGHAM TRENT UNIVERSITY

## SUMMARY


- Long sentence-recall latencies for temporary compared to global ambiguities (**M2**) are better accounted for by a mixture process (Logačev & Vasishth, 2016a, 2016b; Vasishth et al., 2017) that applies to both ambiguity types (**M6**).
- Difficulty for temporary ambiguities occures then when a parse turned out to be incorrect (Logačev & Vasishth, 2016b).
- This, however, does not explain recall difficulty observed for global ambiguities (either parse is correct).
- Parses rapidly loose activation (Christiansen & Chater, 2016) but can be (re)generated from conceptual representations (e.g. Potter & Lombardi, 1998; Potter, 2012).
- Long latencies for both ambiguity types are consistent with demands that occure then when the syntactic encoder did not operate incrementally (e.g. Lee et al., 2013; Roeser, Andrews, et al., 2019; Roeser, Torrance, & Baguley, 2019); this is more likely for sentences with high attachment.
- Syntactic parsing in sentence recall is non-deterministic. This process can be captured in mixture models.


## SENTENCE RECALL

### EXPERIMENT 1

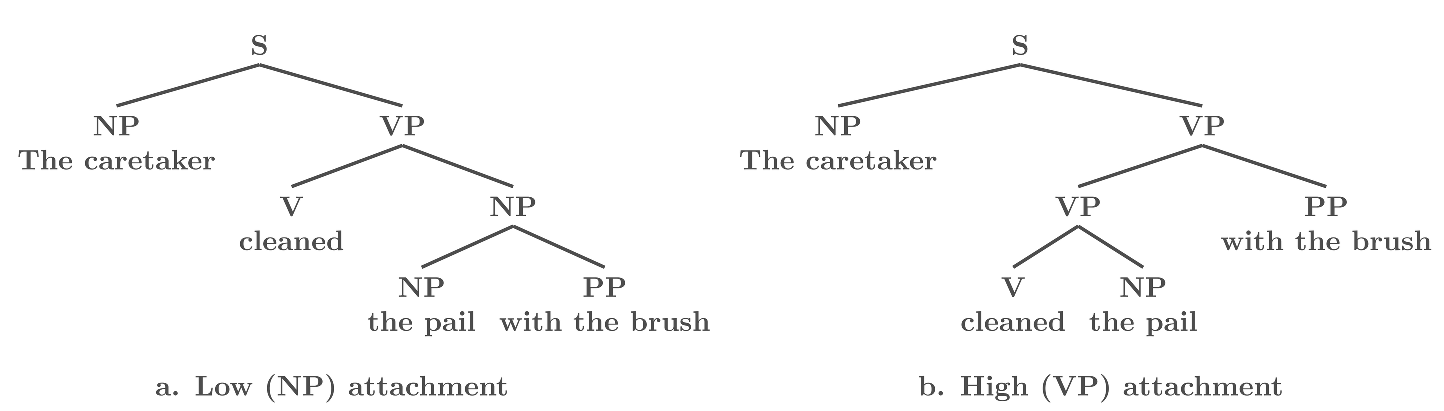
- 64 participants
- 24 items taken from Christianson et al. (2001):

1. While the man hunted the deer run into the woods. **Garden-path**
2. While the man hunted, the deer run into the woods. **Unambiguous**

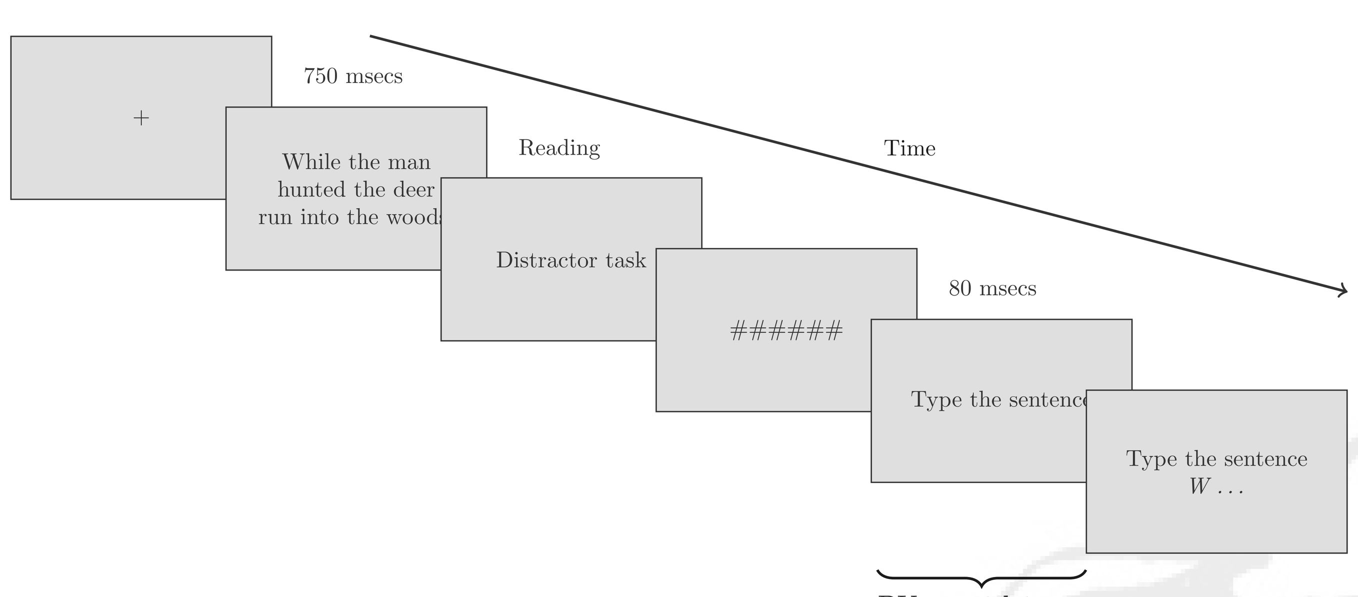
### EXPERIMENT 2

- 160 participants
- 24 simplified items taken from Van Gompel et al. (2001)
- Attachment type:

1. The caretaker cleaned the pail with the brush. **Global ambiguity**
2. The caretaker cleaned the suit with the brush. **High attachment**
3. The caretaker cleaned the pail with the holes. **Low attachment**



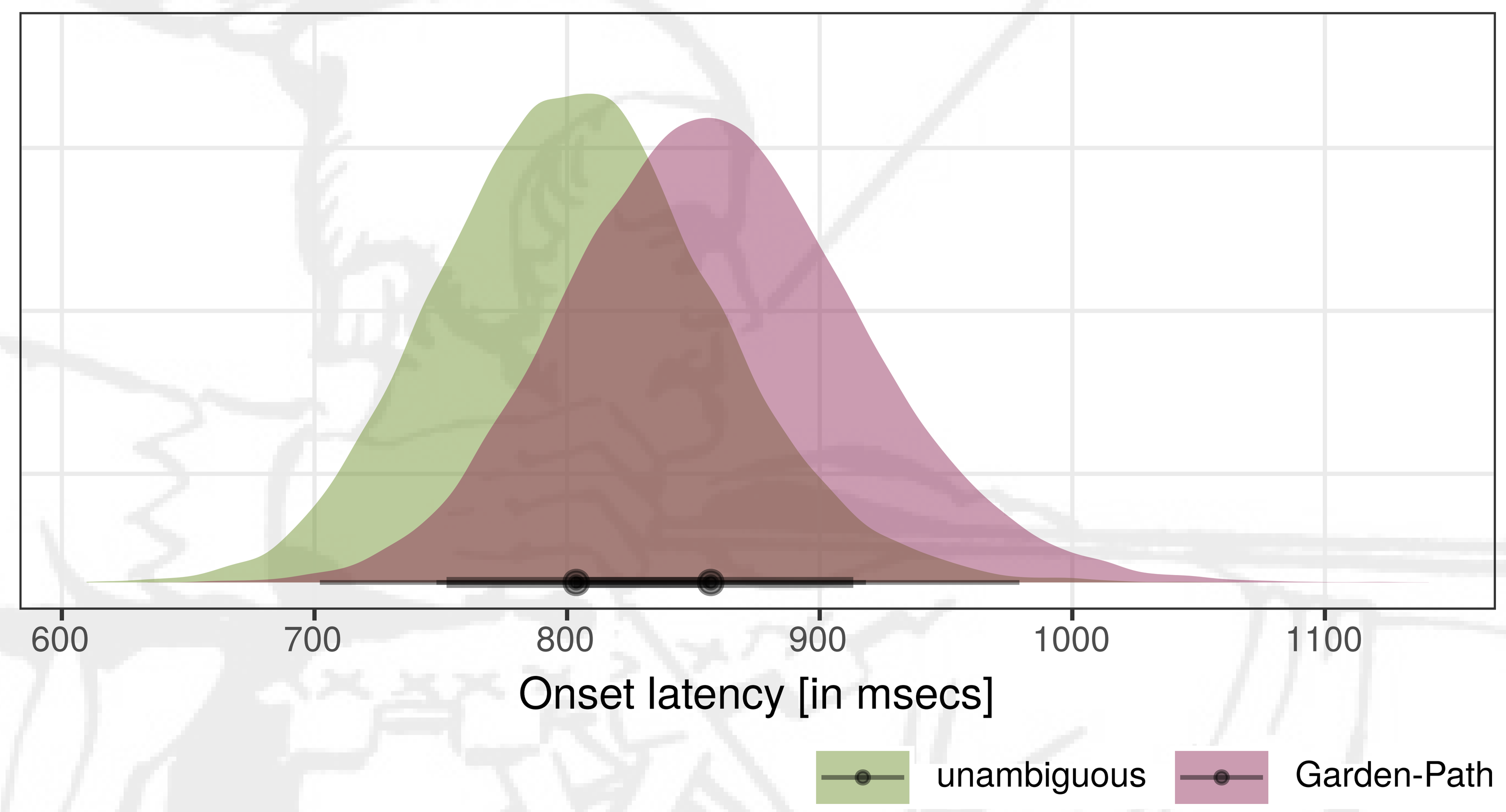

### PRESENTATION




## POSTERIOR PARAMETER DISTRIBUTIONS

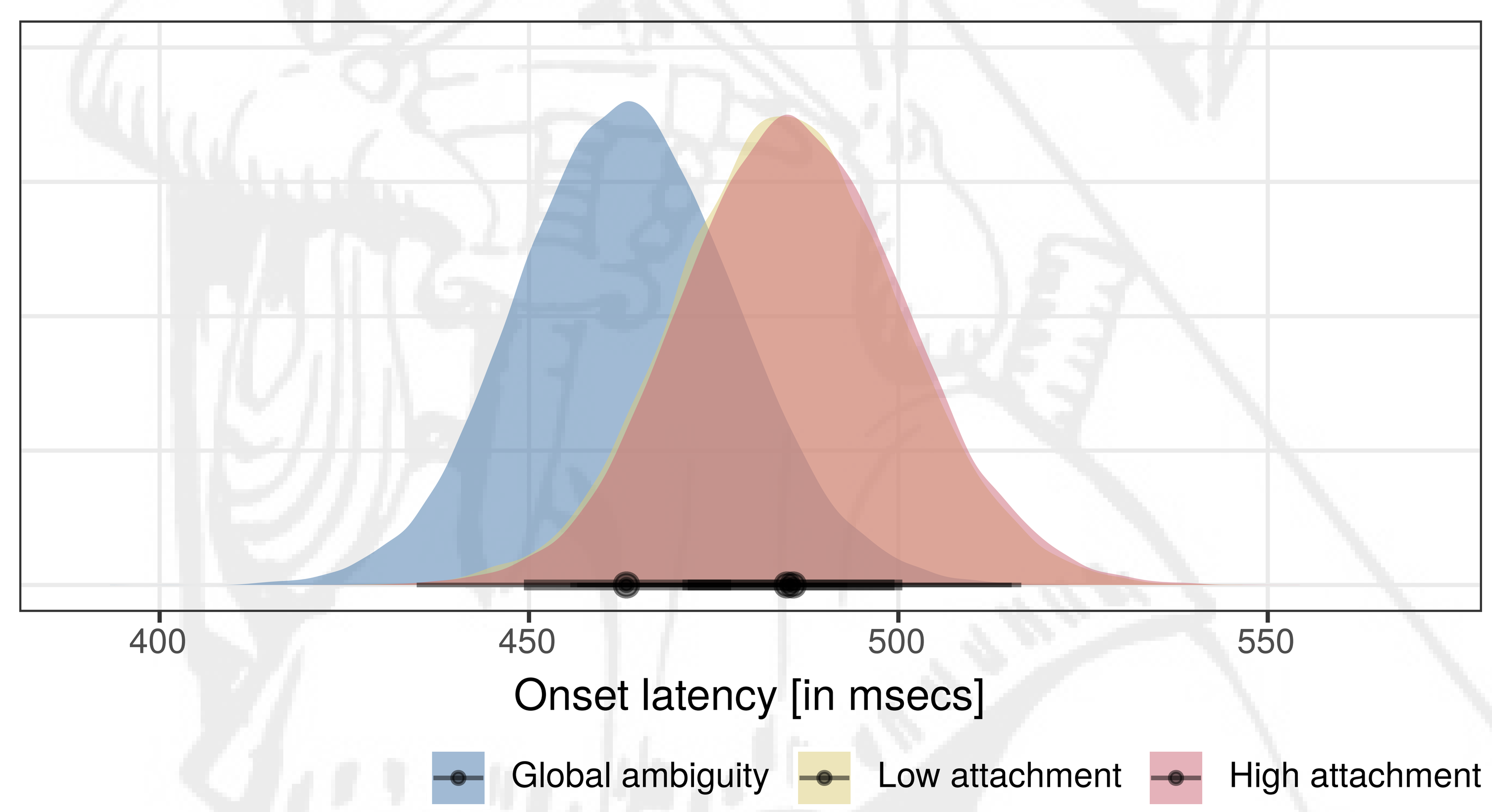
### Experiment 1: Slowdown for Garden-path sentences

Difference: $\Delta\hat{\beta}$ = 54 msecs; 95% PI[3, 105]




### Experiment 2: M2

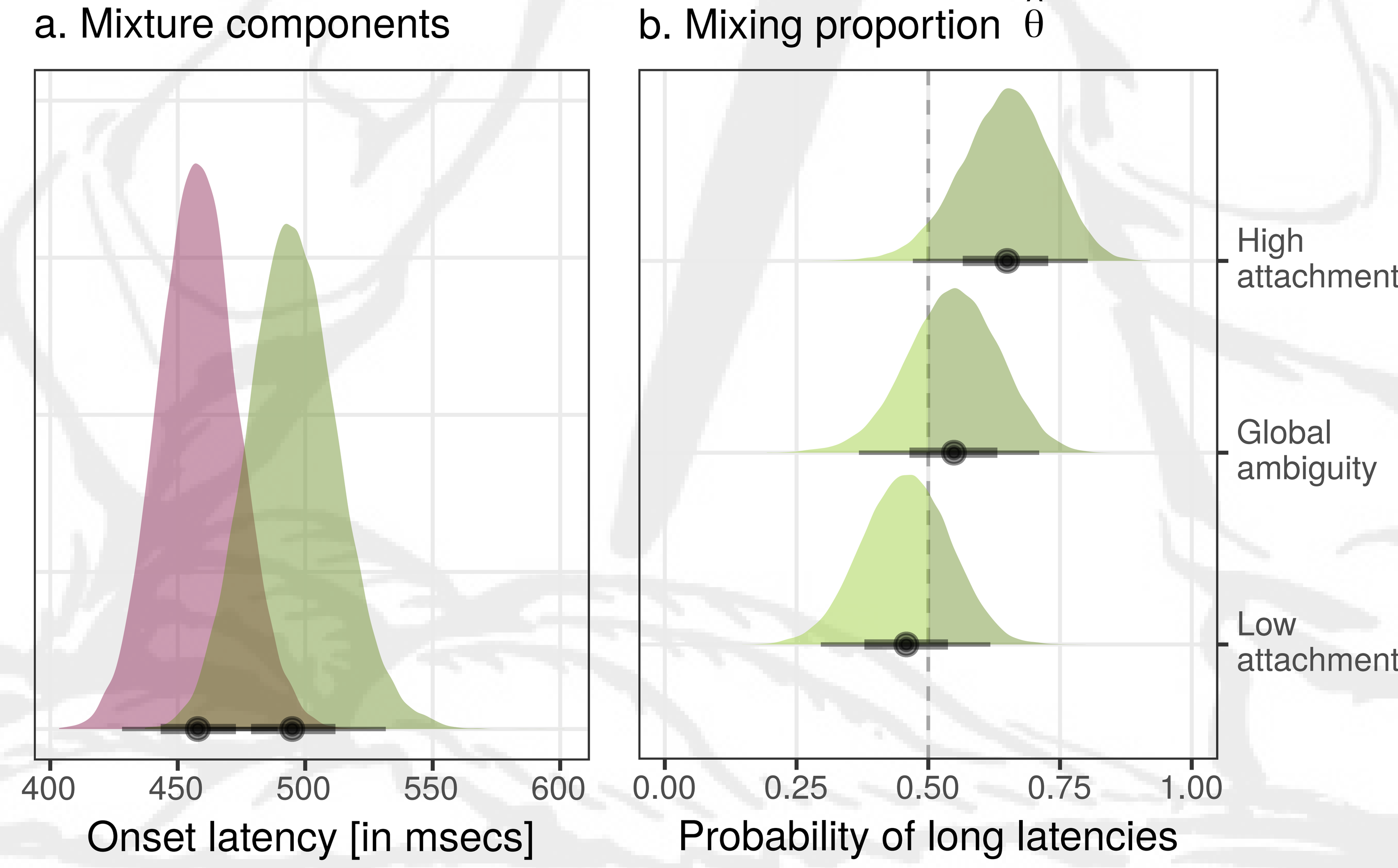
Difference: $\Delta\hat{\beta}$ = 22 msecs; 95% PI[6, 37]




### Experiment 2: M6

a. Mixture components

b. Mixing proportion $\hat{\theta}$




*Error bars represent 66% and 95% posterior probability intervals.

## STATISTICAL MODELLING

**M1:** Mean $\mu$ and variance $\sigma^2$:

$$y \sim LogNormal(\mu, \sigma^2)$$

**M2:** $k \in$ attachment type

$$y \sim LogNormal(\mu_k, \sigma^2)$$

**General model description:**

- Implementation in Stan (Carpenter et al., 2017)
- Random intercepts for subjects and items
- Latencies are LogNormal distributed
- M1 – M3: Linear mixed effects models
- M4 – M7: Mixture of Gaussians

**M3:** As M2 but with $\sigma^2$ smaller for global ambiguities than temporary ambiguities.

**M4:** Slowdown $\delta$ for high attachment with a probability $\theta$ in global ambiguities.

$$y \sim \begin{cases} \left\{ \begin{matrix} \theta \cdot LogNormal(\mu + \delta, \sigma_2^2) \\ 1 - \theta \cdot LogNormal(\mu, \sigma_1^2) \end{matrix} \right\} & \text{if Attachment = Global,} \\ LogNormal(\mu, \sigma_1^2) & \text{if Attachment = Low,} \\ LogNormal(\mu + \delta, \sigma_2^2) & \text{if Attachment = High.} \end{cases}$$

**M5:** Slowdown $\delta$ with a probability $\theta_k$ with $k \in$ temporary ambiguities.

$$y \sim \begin{cases} LogNormal(\mu, \sigma_1^2) & \text{if Attachment = Global,} \\ \left\{ \begin{matrix} \theta_k \cdot LogNormal(\mu + \delta, \sigma_2^2) \\ 1 - \theta_k \cdot LogNormal(\mu, \sigma_1^2) \end{matrix} \right\} & \text{otherwise. } k \in \{\text{High, Low}\} \end{cases}$$

**M6:** Slowdown $\delta$ with a probability $\theta_k$ with $k \in$ attachment type.

$$y \sim \begin{cases} \theta_k \cdot LogNormal(\mu + \delta, \sigma_2^2) \\ 1 - \theta_k \cdot LogNormal(\mu, \sigma_1^2) \end{cases}$$

**M7:** As M6 but without $k$ for $\theta$.

**Details and Stan code:**

## MODEL COMPARISONS

**Experiment 2:** Difference in expected log predictive density ($\Delta\widehat{elpd}$) and standard errors (SE) (Vehtari et al., 2017). The model with the highest predictive performance in top row.

| Model | Description | $\Delta\widehat{elpd}$ | SE |
|---|---|---|---|
| **M6** | **$\theta$ by attachment types** | 0 | 0 |
| M7 | $\theta$ without attachment types | -2.5 | 3.1 |
| M5 | $\theta$ for each temporary ambiguity | -15.9 | 9.0 |
| M4 | $\theta$ for global ambiguities; $\delta$ high attachment | -29.2 | 11.1 |
| M3 | $\sigma^2$ smaller for global ambiguities | -29.3 | 10.0 |
| **M2** | **$\mu$ by attachment type (standard analysis)** | -30.2 | 11.1 |
| M1 | Null model | -33.1 | 10.7 |

*Note.* Leave-one-out cross-validation penalises models with more parameters

## REFERENCES


Carpenter, B., Gelman, A., Hoffman, M. D., Lee, D., Goodrich, B., Betancourt, M., … Riddell, A. (2017). Stan: A probabilistic programming language. *Journal of Statistical Software*, *76*(1), 1–32.

Christiansen, M. H., & Chater, N. (2016). The now-or-never bottleneck: A fundamental constraint on language. *Behavioral and Brain Sciences*, *39*, 1–72.

Christianson, K., Hollingworth, A., Halliwell, J. F., & Ferreira, F. (2001). Thematic roles assigned along the Garden Path linger. *Cognitive psychology*, *42*(4), 368–407.

Lee, E.-K., Brown-Schmidt, S., & Watson, D. G. (2013). Ways of looking ahead: Hierarchical planning in language production. *Cognition*, *129*(3), 544–562.

Logačev, P., & Vasishth, S. (2016a). A multiple-channel model of task-dependent ambiguity resolution in sentence comprehension. *Cognitive Science*, *40*(2), 266–298.

Logačev, P., & Vasishth, S. (2016b). Understanding underspecification: A comparison of two computational implementations. *The Quarterly Journal of Experimental Psychology*, *69*(5), 996–1012.

Potter, M. C. (2012). Conceptual short term memory in perception and thought. *Frontiers in Psychology*, *3*, 113.

Potter, M. C., & Lombardi, L. (1998). Syntactic priming in immediate recall of sentences. *Journal of Memory and Language*, *38*(3), 265–282.

Roeser, J., Andrews, M., Torrance, M., & Baguley, T. (2019). No scope for planning: latent mixture modelling of sentence onsets. In *32nd Annual CUNY Conference on Human Sentence Processing.*

Roeser, J., Torrance, M., & Baguley, T. (2019). Advance planning in written and spoken sentence production. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *45*(11), 1983–2009.

Van Gompel, R. P. G., Pickering, M. J., & Traxler, M. J. (2001). Reanalysis in sentence processing: Evidence against current constraint-based and two-stage models. *Journal of Memory and Language*, *45*(2), 225–258.

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. (2017). Practical bayesian model evaluation using leave-one-out cross-validation and WAIC. *Statistics and Computing*, *27*(5), 1413–1432.


*Presented at 33rd Annual CUNY Conference on Human Sentence Processing*
*March 19–21, 2020 at the University of Massachusetts, Amherst*
A PDF of this poster can be found at nottinghamtrent.academia.edu/JensRoeser