

Maze Correlates of N400 Responses in English Argument Structure Processing

Montana Thommes, Dawn Lau, Thea Kendall-Green, Lisa Levinson (University of Michigan)



Can a behavioral tasks like **maze** provide insight into whether apparent 'delays' in argument structure processing are due to timing or the presence of intervening linguistic material? YES!

Background

Chow et al. (2016) proposal: **slow prediction** for structurally-sensitive argument structure predictions such as predicting the **verb** based on **specific argument roles**.

Empirical support: No N400 observed for low cloze verb in structurally-sensitive argument reversal stimuli (1-2), vs. lexically-biased argument substitution (3-4).

Chow et al. (2018): N400 with more intervening words (time?).

Stimuli

Table 1: Chow et al (2016) Exp 1 Stimuli. 120 pairs, 60 per type.

Ex	Sentence	Type	Cloze	N400
1	...which customer the waitress had served ...	rev	high	
2	...which waitress the customer had served ...	rev	low	N
3	...which tenant the landlord had evicted ...	sub	high	
4	...which realtor the landlord had evicted ...	sub	low	Y

Table 2: Kutas (1993) Stimuli. 60 pair subset.

Ex	Sentence	Type
5	She put on her high heeled shoes .	Highest cloze
6	She put on her high heeled boots .	Related to highest cloze
7	They went as far as they dared .	Highest cloze
8	They went as far as they could .	Unrelated to highest cloze

Current Study

Goal: test slow prediction hypothesis by lengthening argument-verb SOA via the maze task (see right).

Prediction: RTs will be longer for low cloze verbs in both substitution AND reversal stimuli.

Stimuli from Kutas (1993) to confirm "classic" N400-associated effect (Table 2).

Results

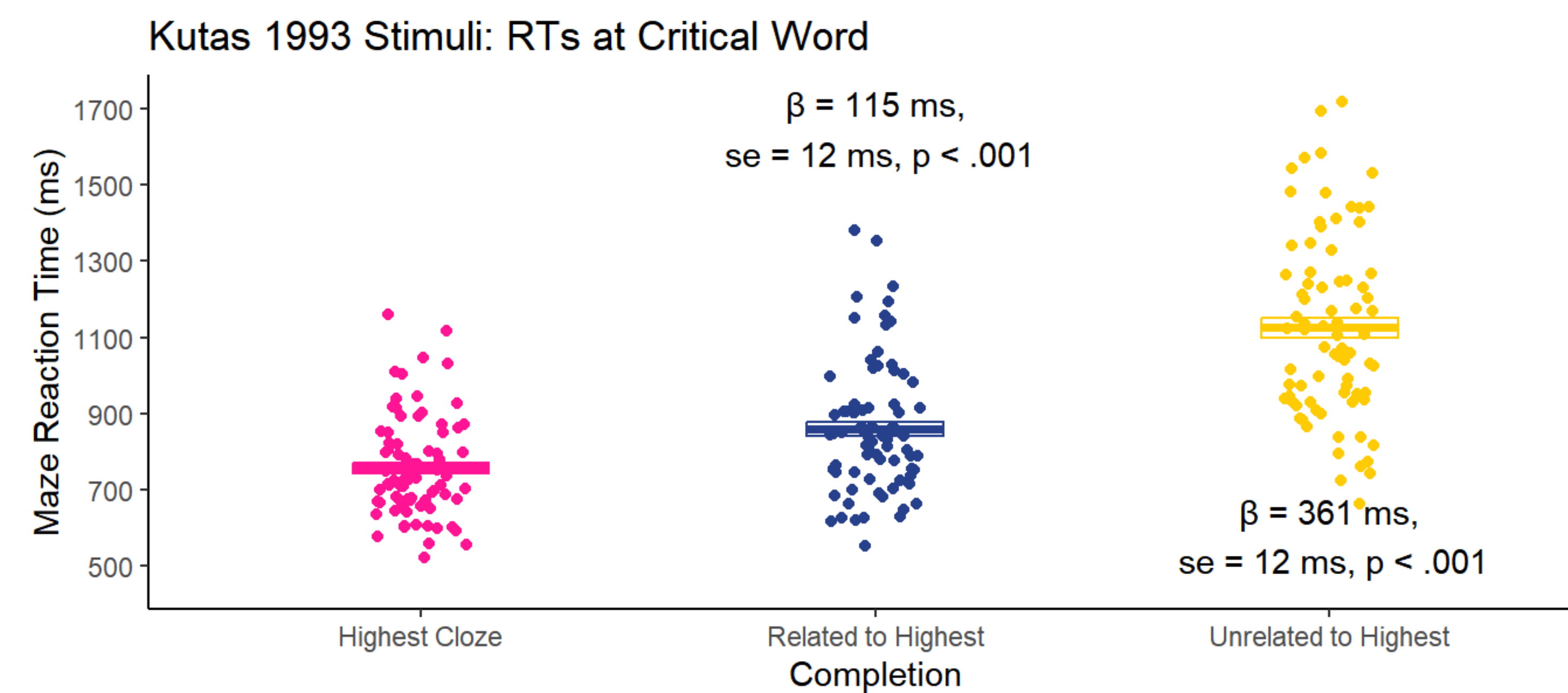


Figure 1: Points represent participant means. Crossbars represent mean and standard error. $\text{Imer}(\log(\text{rt}) \sim \text{relatedness} + (1|\text{part}) + (1|\text{item}))$

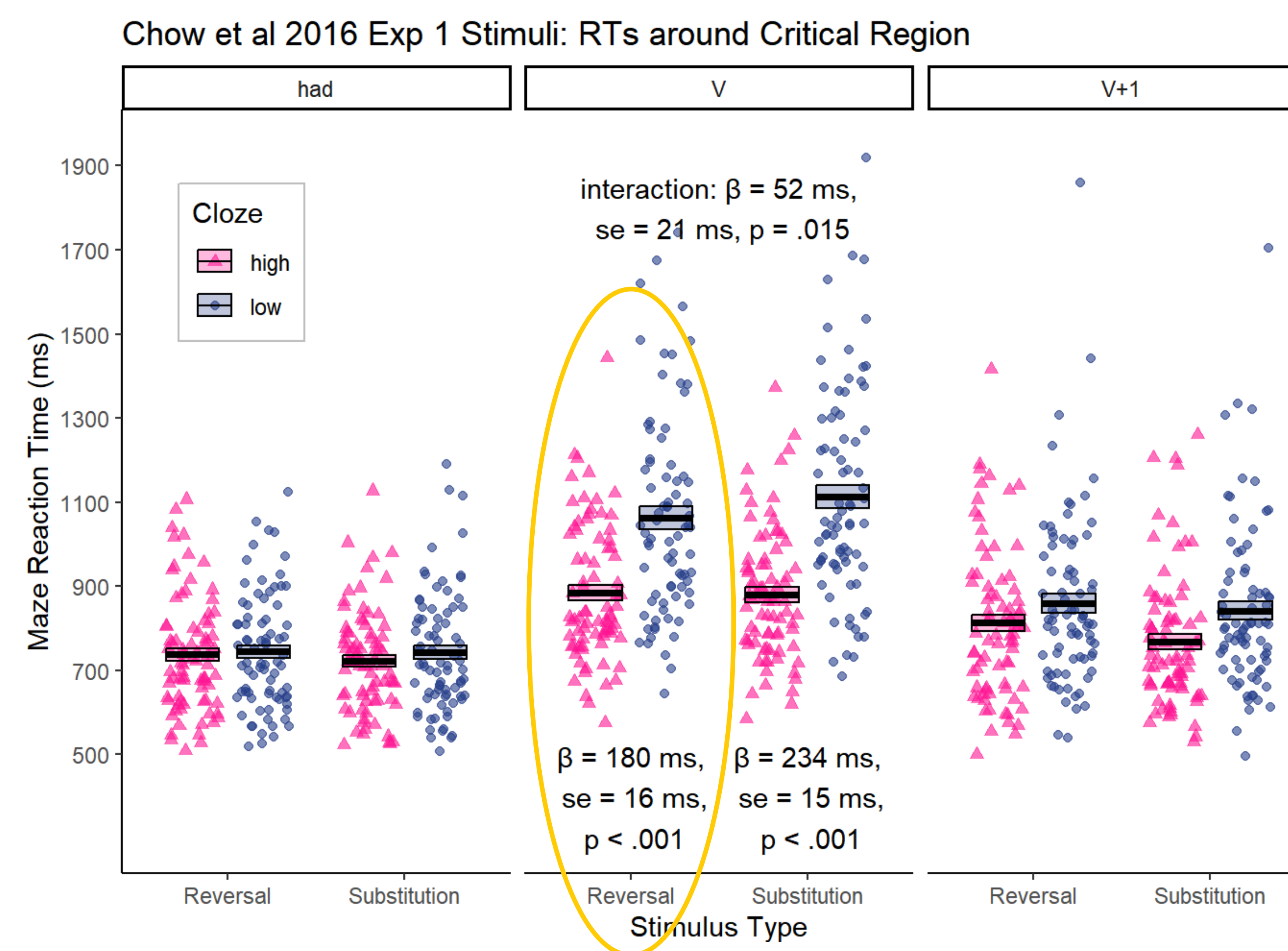


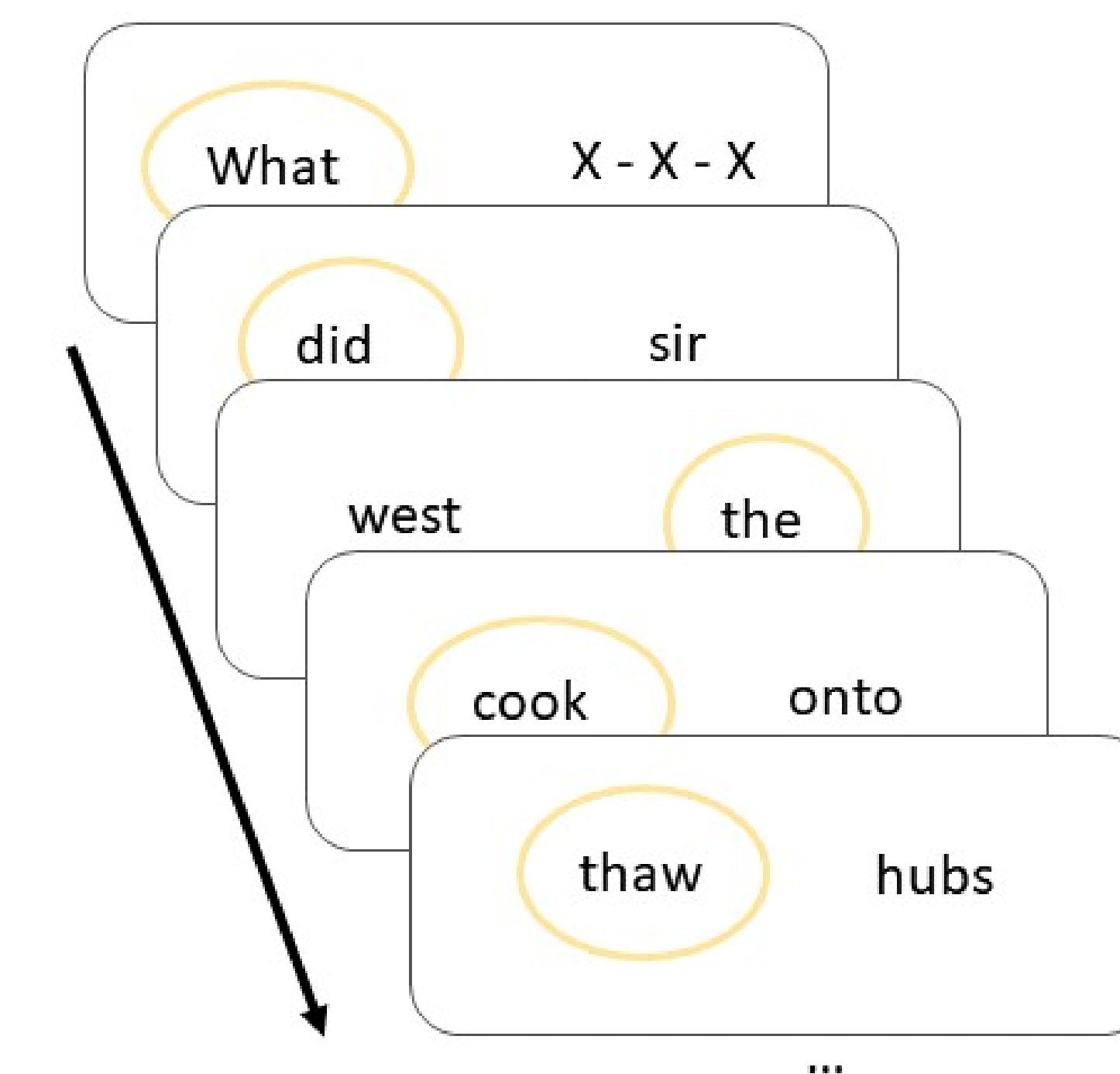
Figure 2: Points represent participant means. Crossbars represent mean and standard error. For interaction: $\text{Imer}(\log(\text{rt}) \sim \text{cloze} * \text{type} + (1 + \text{cloze} | \text{participant}) + (1|\text{item}))$

LME models fit with maximal converging random slopes. Estimates in figures from inferentially-equivalent models of non-logged RTs for ease of interpretation.



https://umwordlab.github.io/output/HSP2023_maze_slow_prediction/

Maze Task and Methods



Highly **incremental**, **focalized** task. Long RTs, no spillover. (Forster, Guerrera, and Elliot 2009)

SOA from last argument to critical verb > 1600ms (compare 1050 ms in Chow et al. (2016), 1800 ms in Chow et al. (2018)).

Husband (2022): slower SOAs in maze reveal stronger effects of morphosyntactic pre-activation.

79 US-based English-reading participants recruited with Prolific completed an online Ibx- and PClbx-based Zehr and Schwarz (2018) A-maze (Boyce, Futrell, and Levy 2020) task. The experimental (120 pairs, 60 each stimulus type) and control comparison (60 pairs) stimuli were split into 4 counterbalanced lists.

Discussion & Conclusion

Slower RTs in the argument reversal condition, where N400s are absent, are **consistent with the slow prediction hypothesis**.

Suggests that the **maze task allows slower argument-related predictive processes to emerge**.

Is argument reversal effect from P600 (present in EEG)? Small 50ms interaction doesn't seem "to scale" as P600 only for reversal vs P600 + N400 for substitution. Compare effect size in Kutas 1993 stimuli.

Additional analyses of **continuous** variables for cloze, GPT-2 surprisal, and plausibility are in progress to further explore the correlations between stimuli variables and the characteristics of associated maze and EEG responses.

References

Boyce, Veronica, Richard Futrell, and Roger P. Levy. 2020. *JML* 111 (April): 104082. <https://doi.org/10.1016/j.jml.2019.104082>.
 Chow, Wing-Yee, Ellen Lau, Suiping Wang, and Colin Phillips. 2018. *LCN* 33 (7): 803-28. <https://doi.org/10.1080/23273798.2018.1427878>.
 Chow, Wing-Yee, Cybelle Smith, Ellen Lau, and Colin Phillips. 2016. *LCN* 31 (5): 577-96. <https://doi.org/10.1080/23273798.2015.1066832>.
 Drummond, Alex. 2013. *Ibex Farm*. Forster, Kenneth I., Christine Guerrera, and Lisa Elliot. 2009. *Behavior Research Methods* 41 (1): 163-71. <https://doi.org/10.3758/BRM.41.1.163>.
 Husband, Edward Matthew. 2022. *Glossa Psycholinguistics* 1 (1). <https://doi.org/10.5070/G601153>.
 Kutas, Marta. 1993. *LCP* 8 (4): 533-72. <https://doi.org/10.1080/01690969308407587>.
 Zehr, Jeremy, and Florian Schwarz. 2018. "PennController for Internet Based Experiments (IBEX)." <https://osf.io/md832/>.