naturalistic story

reading

Shannon McKnight & Albert Kim Adapted from a talk presented at CUNY 2019

INTRO

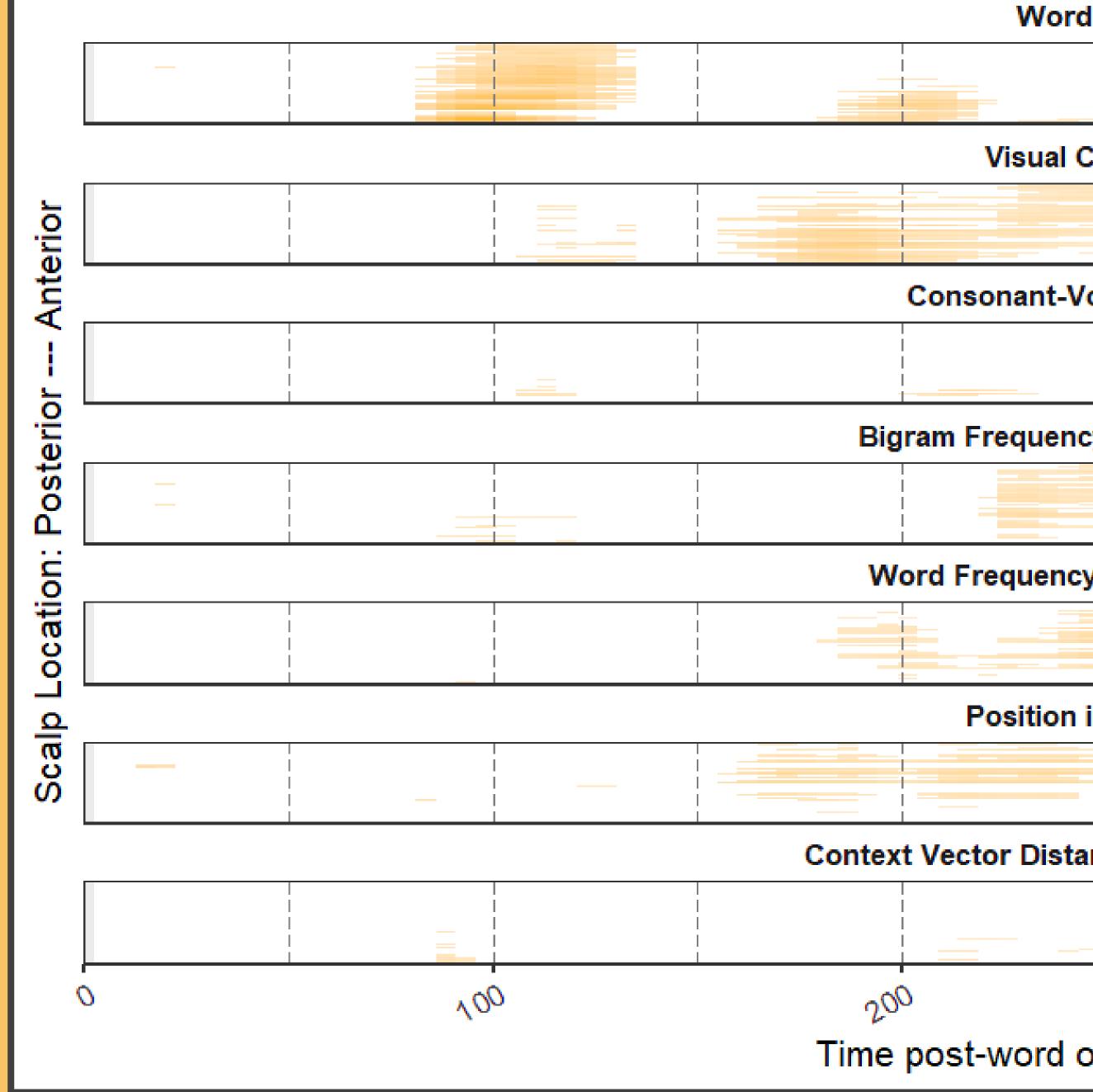
- ERP research often focuses on the response to a single "target word" within a sentence that has been designed to violate our expectations based on contextual information.
- Not only does this experimental paradigm limit the amount of data we're able to collect in one session, it does not capture a complete picture of language processing "in the wild"
- Here we employed a self-paced story reading paradigm to capture the processing of rich context and how it may interact with established components of the visual word recognition system.

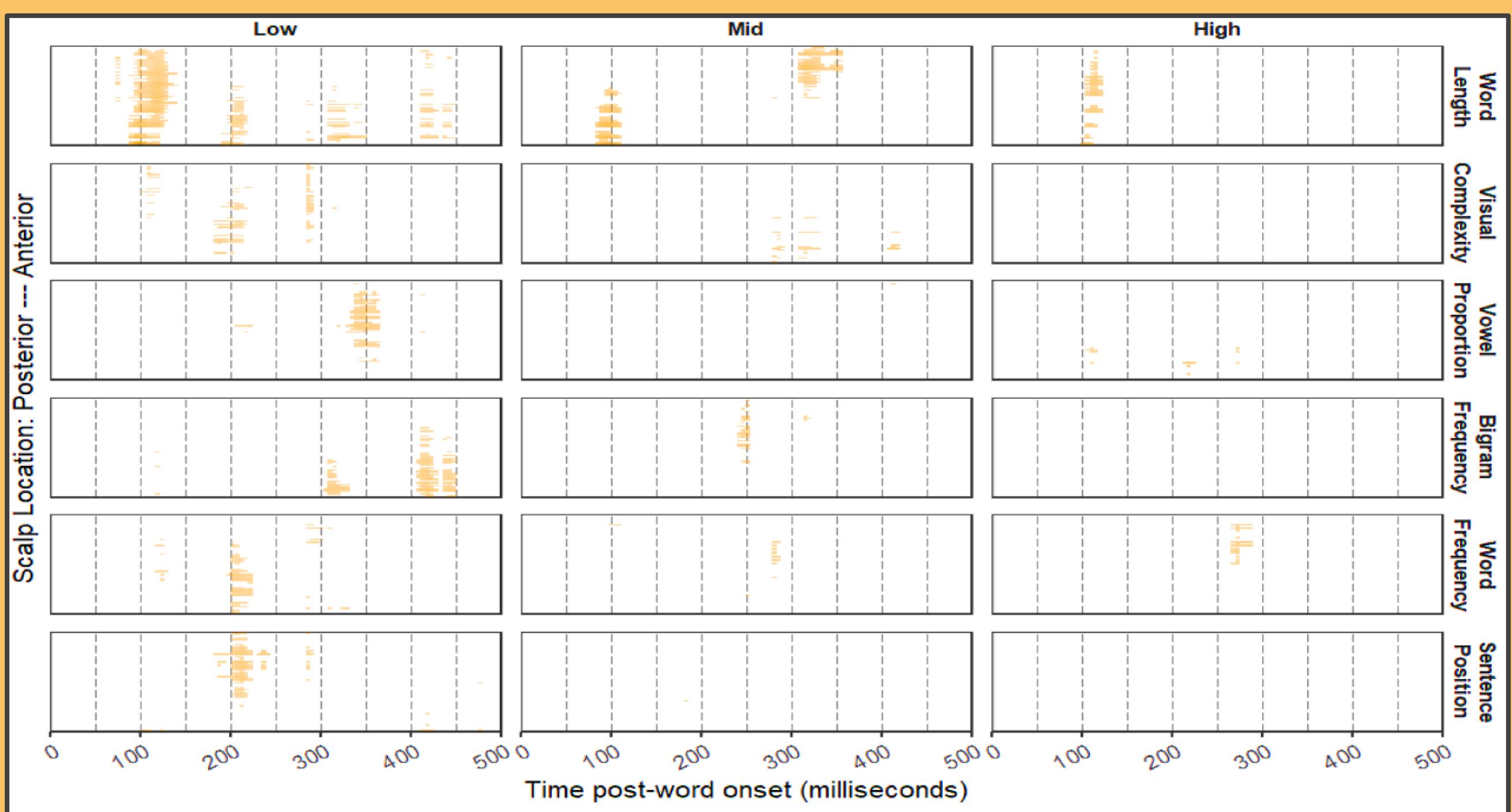
METHOD

- 30 participants read 9 short factual narrative stories during EEG recording
- Stories were presented one word at a time at a self-paced presentation rate
- Participants were instructed to read for comprehension and were probed with a set of multiple-choice questions at the end of each story
- Grand-average ERPs were constructed for each content word (~1400 words total) across all participants between 0-500ms post-word onset, relative to a 200ms preword baseline.

Interactions between Context Similarity (columns) and Lexical Factors (rows): This analysis suggests that contextual similarity has indirect effects before semantic similarity operations that occur at the N400. When contextual similarity is low, lexical factors are more highly correlated with the EEG than when contextual similarity is high. This suggests that physical and lexical information is not used as much during word recognition when a word fits in it's context.

Capturing effects Vector representations of semantic of context during similarity capture facilitation effects of context on the N400.





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MASS-MULTIVARIATE ANALYSIS ERPs were sampled every 5ms across 62 electrode sites • The following model was evaluated at each combination of time x spatial location: Voltage $= \beta_0 + \beta_1 * Length + \beta_2$

* Frequency + β_3 * ContextFit + β_4 * VisualComplexity + β_5 * BigramFrequency + β_6 * SentencePosition + β_7 * VowelProportion

• False-discovery rate multiple comparisons corrections were applied across all time x spatiallocation combinations

CONTEXT BASED SEMANTIC SIMILARITY GloVe vector space representations (Manning et al 2014) were collected for all words presented in the stories. To generate a context similarity measure, the vector representations for the 10prior content words to a given were summed and compared to the current word vector by computing the cosine

angle between the current word vector

and the summed context vector.

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