Additivity biases and classes of sampling algorithms for word predictability

It is now well-established that the cost to comprehend a word is related to its contextual predictability. Bayesian updating of a prior probability distribution over lexical items provides a computational-level account of these effects (Kuperburg & Jaeger, 2016); however, the complexity involved in updating potentially very large probability distributions is potentially computationally intractable. Algorithmic-level accounts such as *sampling*, where comprehenders iteratively and stochastically sample from the space of possible lexical items, may help address these complexity concerns and make new predictions (Levy et al., 2008; Hoover et al., 2023).

One prediction concerns the possibility that language comprehension has certain anchoring *biases*. Different sampling algorithm classes predict different biases when resource- and time-limited; therefore, diagnosing which biases are found in comprehension can restrict which sampling algorithm classes could support comprehension (Dasgupta et al., 2017). Both simple Monte Carlo (MC) methods (e.g. Importance Sampling) and Markov Chain MC (MCMC), are *subadditive* biased (Fox & Tversky, 1998), where perceived word predictability is higher when a context is unpacked to typical examples, predicting e.g. faster reading times. MCMC is also *superadditive* biased (Sloman et al., 2004), where perceived word predictability is lower when a context is unpacked to atypical examples, predicting e.g. slower reading times. If language comprehension deploys general MC sampling algorithms, we expect to see subadditivity bias, and if it deploys MCMC, we also expect to see superadditivity bias (see Table).

Method. We investigated potential comprehension biases in a self-paced reading study in English (60 Participants, 120 Items). Typicality of unpacked contexts was manipulated to detect whether comprehenders are subadditive or superadditive biased relative to a packed baseline context. Packed contexts and target words were pulled from Peelle et al. (2020), and unpacked contexts were created by inserting a typical or atypical word before the target word.

Results. Compared to the Packed baseline, target word RTs were significantly faster in the Typical Unpacked condition, reflecting subadditive bias, and significantly slower in the Atypical Unpacked condition, reflecting superadditive bias (see Figure).

Discussion. Comprehenders display both subadditive and superadditive biases for word predictability, consistent with the hypothesis that comprehenders deploy an MCMC-class sampling algorithm when predicting upcoming lexical items in sentence contexts under resource and time constraints. Such algorithmic-level accounts help to explain how comprehenders update their priors and why comprehension can approach the ideal predictions of computational-level Bayesian models.

Table: Summary of biases, RT predictions, and relationship to classes of sampling algorithms

Bias	Description	Reading Time	***Importance Sampling***	***MCMC Sampling***
Subadditivity	Perceived predictability of a word is *higher* when the context is unpacked to *typical* examples.	*Faster* than packed baseline	✓	✓
Superadditivity	Perceived predictability of a word is *lower* when the context is unpacked to *atypical* examples.	*Slower* than packed baseline		✓

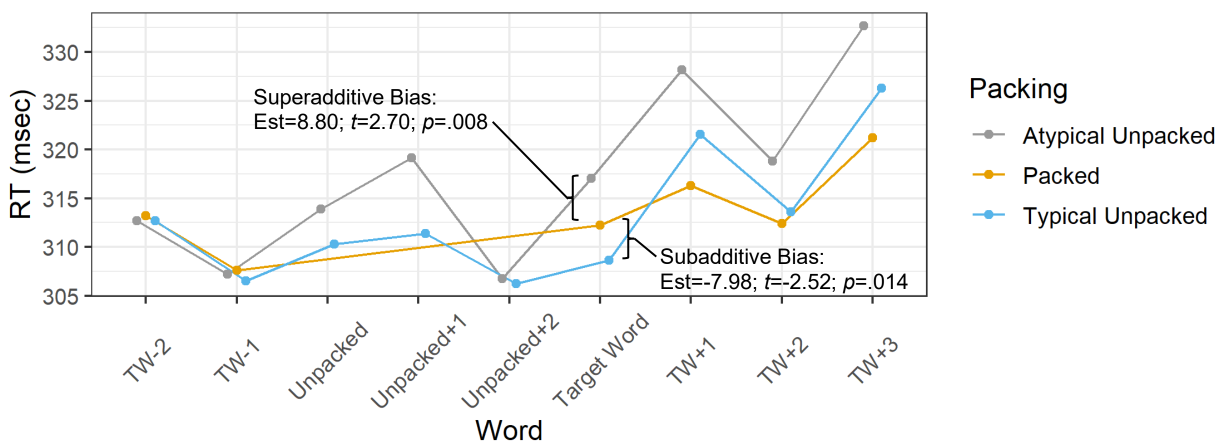
Example Item: (target word underlined, typical/atypical unpacking in italics)

Packed: Jordan learned a lot about cars from his dad during the last summer vacation. (target word: 0.45 cloze) [all items range: 0.30-0.70]

Typical Unpacked: Jordan learned a lot about cars from his *uncle* and his dad during the last summer vacation. (typical unpacking: 0.08 cloze) [all items avg: 0.15]

Atypical Unpacked: Jordan learned a lot about cars from his *magazines* and his dad during the last summer vacation. (atypical unpacking: 0.01 cloze) [all items avg: 0.01]

Figure: Average reading times by word for packed and unpacked conditions.



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