Unpacking additivity biases reveal the class of sampling algorithm for word predictability

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Introduction. It is now well-established that language comprehension makes use of predictive mechanisms that anticipate upcoming lexical items. Much of the theorizing about these predictive mechanisms is stated at Marr's (1982) computational-level analysis, proposing that these predictions reflect Bayesian updating of a prior probability distribution over lexical items, raising or lowering the probability of any lexical item given input (Kuperburg & Jaeger, 2016). While these models have been widely adopted, it is unclear how they overcome the computational complexity involved in updating potentially very large prior distributions. Algorithmic-level accounts for these computational-level models may help address these concerns and reveal new insights. One algorithmic approach involves *sampling*, proposing that comprehenders iteratively and stochastically sample from the space of possible lexical items (Levy, et al., 2008; Hoover, et al, 2023; and see Sanborn & Chater, 2016). Nevertheless, the specific sampling algorithm deployed by comprehenders remains to be determined.

We investigated which class of sampling algorithms is deployed by comprehenders by investigating the biases comprehenders have when processing in real-time. Constraints on cognitive resources and time pressure limit the number of samples that humans can generate. These limits give rise to different systematic biases, which can distinguish between different classes of Monte Carlo (MC) sampling algorithms (Dasgupta, et al., 2017). Both simple MC methods, like Importance Sampling, and Markov Chain MC (MCMC), display *subadditivity* bias (Fox & Tversky, 1998), where the perceived predictability of a word is higher when the context is unpacked to typical examples. MCMC also displays *superadditive* bias (Sloman, et al., 2004), where the perceived predictability of a word is lower when the context is unpacked to atypical examples. If human language comprehension deploys MC sampling algorithms, we expect to see subadditivity bias, and if it deploys MCMC we also expect to see superadditivity bias.

Method. In a self-paced reading study in English (60 Participants, 120 Items), we manipulated the typicality of unpacked sentence contexts. We measured reading times (RTs) to target words in packed and unpacked conditions, as RTs are inversely related to word predictability (Staub, 2015). If comprehenders are subadditively biased, unpacking to a typical example is expected to increase the probability of the target word, resulting in faster RTs compared to a packed baseline. Moreover, if they are also superadditively biased, unpacking to an atypical example is expected to decrease the probability of the target word, leading to slower RTs compared to a packed baseline.

Sentence contexts and target words were pulled from Peelle, et al. (2020), such that the cloze probability of target words in packed sentence contexts ranged from 0.30 to 0.70. Each sentence context was then unpacked with a typical or atypical example and coordinated before the target word. Typicality was approximated by cloze probability (avg. typical: 0.15; avg. atypical: 0.01). Packing was sum-coded into two contrasts examining Typical Unpacked and Atypical Unpacked conditions against a Packed baseline.

Results. Accuracy on comprehension questions, asked after a third of items, was high (>75% for all participants, avg. >95% for all conditions). Compared to the Packed baseline, RTs on target words were significantly faster in the Typical Unpacked condition (Est=-7.98; t=-2.52; p=.014), reflecting subadditive bias, and significantly slower in the Atypical Unpacked condition (Est=8.80; t=2.70; p=.008), reflecting superadditive bias.

Discussion. These results suggest that comprehenders display both subadditive and superadditive biases for word predictability while reading sentences, consistent with the hypothesis that comprehenders deploy a MCMC-class sampling algorithm when predicting upcoming lexical items in sentence contexts under resource and time constraints. Such an algorithmic-level account helps 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		✓

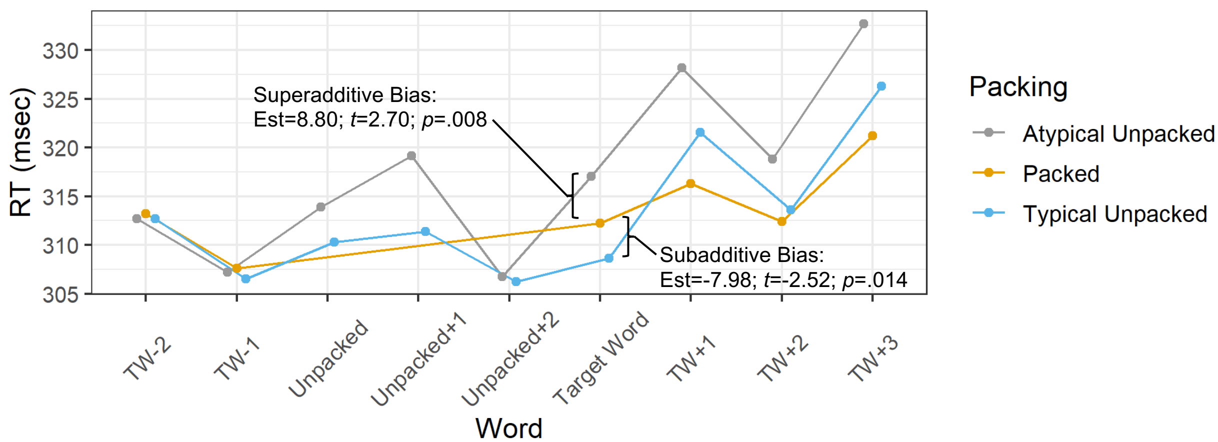
Example Item (target word underlined, typical/atypical unpacking in italics)

<u>Packed</u>: Jordan learned a lot about cars from his <u>dad</u> during the last summer vacation. (target word: 0.45 cloze)

<u>Typical Unpacked</u>: Jordan learned a lot about cars from his *uncle* and his <u>dad</u> during the last summer vacation. (typical unpacking: 0.08 cloze)

<u>Atypical Unpacked</u>: Jordan learned a lot about cars from his *magazines* and his <u>dad</u> during the last summer vacation. (atypical unpacking: 0.01 cloze)

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



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