Contributions of Propositional Content and Syntactic Categories in Sentence Processing

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Expectation-based theories of sentence processing posit that processing difficulty is determined by predictability in context [3, 6]. While predictability quantified via surprisal has gained empirical support, this representation-agnostic measure leaves open the question of how to best approximate the human comprehender's latent probability model. One factor related to memory usage that has received less attention in psycholinguistic modeling is the influence of *propositional content*, or meaning that is being conveyed by the sentence. Early psycholinguistic experiments have demonstrated that the propositional content of utterances tends to be retained in memory, whereas the exact surface form and syntactic structure are forgotten [1, 4]. This suggests that memory costs related to incrementally constructing a representation of propositional content might manifest themselves in behavioral responses during online sentence processing.

This study uses a generative, incremental, and differentially content-sensitive processing model to estimate surprisal predictors that capture the influence of *propositional content* differentially with that of *syntactic categories*, which are devoid of propositional content. The processing model extends a left-corner parser [5, 9] to incorporate propositional content by augmenting each node in a parse tree to consist not only of a syntactic category label but also a *predicate context vector*, which consists of $\langle$*predicate*, *role*$\rangle$ pairs that specify the content constraints on a variable over discourse entities. These predicate context vectors are obtained by reannotating the training corpus using a generalized categorial grammar of English [8], which is sensitive to syntactic valence and non-local dependencies. The parser is implemented as a series of feedforward neural network submodels that make parsing decisions using predicate context vectors and syntactic category labels as features. An advantage of this formulation is that this processing model can be trained to make parsing decisions without conditioning on either predicate context vectors or syntactic categories, which allows a clean ablation of their contribution to the probability model.

In order to evaluate the contribution of propositional content and syntactic categories to predicting behavioral responses, surprisal predictors for the Natural Stories self-paced reading corpus [2] were calculated from the content-sensitive processing model and its two ablated versions, which were trained on sections 02 to 21 of the WSJ corpus [7] using three different random seeds. Subsequently, a series of ablative likelihood ratio tests with nested linear mixed-effects models were conducted to test whether surprisal estimates from the full processing model (*FullSurp*) improve regression model fit over those from a processing model that lacks propositional content information (*NoConSurp*) or syntactic category information (*NoCatSurp*). As there were three variants of each surprisal predictor, a total of nine (3×3) LRTs were performed for each ablated surprisal predictor. The regression models also included baseline predictors for word length, word position, and 5-gram surprisal. All predictors were z-transformed prior to fitting, and all surprisal predictors were spilled over by one position. All regression models included by-subject random slopes for all fixed effects and random intercepts for each word and subject-sentence interaction. The results in Table 1 show that *FullSurp* made a statistically significant contribution to model fit over *NoConSurp* in six out of nine LRTs, which is highly significant according to a binomial test ($p < 0.001$). The significant contribution of *FullSurp* over *NoCatSurp* was observed as well, with six out of nine LRTs indicating significantly improved model fit ($p < 0.001$).

To explore the extent to which integration costs associated with filler-gap constructions could be explained by the influence of propositional content, we replicate the same experiment on filler-gap verbs. The results in Table 2 show that *FullSurp* made a significant contribution to model fit over *NoConSurp* in three out of nine LRTs ($p = .008$). This indicates that the full processing model captures the influence of propositional content and syntactic categories differentially, both of which contribute to predicting self-paced reading times, suggesting their role in sentence processing.

NoConSurp	*FullSurp* 1	2	3
1	*ConvFail*	0.035*	0.018*
2	0.004**	*ConvFail*	0.047*
3	0.003**	0.058	0.036*

NoCatSurp	*FullSurp* 1	2	3
1	*ConvFail*	<0.001***	*ConvFail*
2	<0.001***	<0.001***	<0.001***
3	*ConvFail*	<0.001***	<0.001***

Table 1: p-values from LRTs testing the contribution of *FullSurp* over *NoConSurp* (left) and *NoCatSurp* (right) to regression models predicting self-paced reading times. Any LRT in which either the base or full regression model failed to converge (*ConvFail*) was considered as a null result. $^* : p < 0.05,\ ^{**} : p < 0.01,\ ^{***} : p < 0.001.$

NoConSurp	*FullSurp* 1	2	3
1	0.095	0.046*	0.037*
2	0.119	0.058	0.049*
3	0.186	0.097	0.081

Table 2: p-values from LRTs testing the contribution of *FullSurp* over *NoConSurp* to regression models predicting self-paced reading times of filler-gap verbs. $^* : p < 0.05$.

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