A principled approach to feature selection in models of sentence processing

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Keywords: cue-based retrieval; plausibility; word embeddings; linguistic features

Abstract

Among theories of human language comprehension, cue-based memory retrieval has proven to be a useful framework for understanding when and how processing difficulty arises in the resolution of long-distance dependencies. Most previous work in this area has assumed that very general retrieval cues like [+subject] or [+singular] do the work of identifying (and sometimes misidentifying) a retrieval target in order to establish a dependency between words. However, recent work suggests that general, hand-picked retrieval cues like these may not be enough to explain illusions of plausibility (Cunnings & Sturt, 2018), which can arise in sentences like *The letter next to the porcelain plate shattered.* Capturing such retrieval interference effects requires lexically specific features and retrieval cues, but hand-picking the features is hard to do in a principled way and greatly increases modeler degrees of freedom. To remedy this, we use well-established word embedding methods for creating distributed lexical feature representations that encode information relevant for retrievial using distributed retrieval cue vectors. We show that the similarity between the feature and cue vectors (a measure of plausibility) predicts total reading times in Cunnings and Sturt's eye-tracking data. The features can easily be plugged into existing parsing models (including cue-based retrieval and self-organized parsing), putting very different models on more equal footing and facilitating future quantitative comparisons.

Keywords: cue-based retrieval; plausibility; word embeddings; linguistic features

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1 Introduction

Research in human sentence comprehension and production increasingly relies on computational models that implement competing psycholinguistic theories to generate testable predictions about human behavior. These models take a variety of forms, including models based on cue-based memory retrieval (Engelmann et al., 2019; Lewis & Vasishth, 2005; Vasishth et al., 2019), self-organization (Smith et al., 2018; Smith & Tabor, 2018; Tabor & Hutchins, 2004), and expectation-based parsing (Futrell & Levy, 2017; Hale, 2001; R. Levy, 2008). They aim to explain well-established sources of processing difficulty like garden paths (Bever, 1970), local coherence effects (where a string of words is locally well-formed but ungrammatical in the context of the rest of the sentence; Tabor et al., 2004), and similarity-based interference (where the presence of words with similar features in a sentence affects processing; Jäger et al., 2017).

Many of these models rely on linguistic features to make quantitative predictions about processing difficulty. Typical features include number, gender, animacy, or structural position. However, there is no universally agreed upon set of features to include in a model. The choice of features is left up to the modeler. An example of this comes from research on subject-verb number agreement. In many languages (such as English), only the grammatical subject determines the number marking on the main verb of the sentence, e.g., *the bird is on the balcony* or *the birds are on the balcony*; we refer to this as subject-verb agreement. In such languages, subject-verb agreement holds even when a non-subject noun has a number marking that mismatches the verb's number marking: compare *the bird eating bread crumbs is on the balcony*, vs. *the birds eating bread crumbs are on the balcony.* One account of how the subject-verb agreement dependency is established is the Marking and Morphing theory (Bock et al., 2001; Eberhard et al., 2005). In this theory, both a syntactic feature (number marking on the subject) and a semantic feature (encoding whether a word refers to one thing or more than one thing) are combined to produce a probability of producing a singular or plural verb. The self-organizing theory in Smith et al. (2018), on the other hand, relies solely on semantic features to bias the competition for which noun controls the verb number. Finally, the cue-based retrieval model of Lewis and Vasishth (2005), recently extended in Engelmann et al. (2019), typically uses a structural feature which refers to a tree-configurational property (such as +subject or +c-command) in combination with another morphological or semantic feature (such as +singular or +animate) to determine the speed and probability of retrieving a noun to set the verb number (see below for more detail).

How the researchers arrived at these features is often unclear from their published papers and is (in our experience) based on extensive exploratory simulations where the goal is to find the model configuration (including features) that "works" best. The temptation to favor one's own model and the lack of transparency undermine models built in this way because there is a large number of hidden degrees of freedom that go into the models. Too much flexibility and poorly constrained parameters (including feature choices) weaken models as predictive and explanatory theories of cognitive processing (Roberts & Pashler, 2000). This is because the more flexible a model is, the wider the range of effect sizes it can predict, and a model that can predict any effect does not tell us much about how the mind works.

Moreover, in the case of subject-verb agreement, the three theories discussed above purport to be general theories of subject-verb number agreement. No matter how the authors arrive at their features, the fact that the features differ makes direct comparisons between models difficult. Any differences in what the models predict could be due to substantive differences in the theories, or they might simply due to the authors' having made different modeling choices. Without settling on a common set of features to use, we cannot place models on equal footing for a fair comparison.

Occasionally, features are chosen (partially) at random to try to avoid this problem (e.g. Rasmussen & Schuler, 2017; Villata et al., 2019). Features in this case are represented as vectors of random numbers. This seems to remove some of the modeler's flexibility, as feature settings are chosen by a random number generator, but it does not actually mitigate the problem. One still has to choose the dimensionality of the feature vectors, the type of feature representation (e.g., discrete or continuous-valued), and the probability distribution from which the random numbers are drawn and its parameters. All of these affect the model's predictions. The meaning of individual feature dimensions is also lost in this approach.

The issue of excessive flexibility in model development is a methodological one, but it has important theoretical implications. As mentioned above, too much flexibility in a model can lead to predictions that can cover all possible outcomes, making the model not particularly useful in understanding the empirical phenomenon of interest (Roberts & Pashler, 2000). A further complication is that numerous sentence processing findings seem to require features that are different for each word. So, not only do modelers face the choice of features for classes of phenomena, they also have to make those choices for every lexical item in each sentence tested in order to fully explain the data reviewed below. Clearly, a more uniform and principled approach to choosing features is need.

We present one solution to these issues below, but first, we motivate the need for lexically specific features by discussing a recent study that exemplifies the problem: the Cunnings and Sturt (2018) "illusions of plausibility" experiments. These experiments involve semantic interference, where choosing features by hand is much more challenging than for morphosyntactic interference based on easily identified features like +singular. In this paper, we focus on semantic interference because of the difficulty it poses for hand-picking, which we discuss presently. In the General Discussion, we speculate about whether the feature selection method we describe here can be extended to morphosyntactic interference as well.

2 Lexically specific features and cue-based retrieval: The Cunnings and Sturt 2018 study

The illusions of plausibility experiment design reported in Cunnings and Sturt (2018) is an excellent example of the need for a principled approach to defining lexically specific features. In order to ground the discussion in theory, we cast the explanation for the observed effects in Cunnings and Sturt (2018) in terms of the cue-based retrieval theory of Engelmann et al. (2019).

Cunnings and Sturt employed eye tracking while reading to measure reading times in sentences like the following:

(1) a. Sue remembered the plate that the butler with the <u>tie</u> accidentally shattered today in the dining room.

b. Sue remembered the plate that the butler with the <u>cup</u> accidentally shattered today in the dining room.

c. Sue remembered the letter that the butler with the <u>tie</u> accidentally shattered today in the dining room.

d. Sue remembered the letter that the butler with the <u>cup</u> accidentally shattered today in the dining room.

Consider 1a and 1b first. Here, the dependency completion process of interest is between *plate* and the verb *shattered*. As shown schematically in the upper part of Figure 1, the verb triggers a search for a noun, stored as a chunk of information in memory, that is shatterable and is a grammatical direct object of the sentence. These two retrieval cues match *plate* in both sentences 1a and 1b; however, in 1b, there is a second distractor noun inside a prepositional phrase, *cup*, that also has the shatterable property but cannot be a grammatical direct object of the sentence. This so-called partial match with one of the two retrieval cues [+shatterable, +direct-object] leads to a situation referred to as cue overload: in 1b, the fact that two items in memory (*plate* and *cup*) match the shatterable cue leads to increased difficulty in distinguishing the correct target of retrieval. The end result of cue overload is increased retrieval time in 1b vs 1a. For a more detailed exposition of the underlying mechanism that leads to cue overload, see Engelmann et al. (2019) and Vasishth et al. (2019).

The lower part of Figure 1 illustrates the retrieval process in the sentences 1c and 1d. In these sentences, when the retrieval cues [+shatterable, +direct-object] are used at the verb to access the direct object, only the direct object cue matches the target noun *letter*: there is only a partial match of the retrieval cues with the features of the target noun. Now, in 1d, there is also a partial match with the distractor noun *cup* inside the prepositional phrase: the distractor noun matches the cue [+shatterable]. The sentence 1d thus illustrates a situation where there is a partial match with both the target and the distractor noun. In this kind of partial match situation, the cue-based retrieval model predicts a speedup at the verb in 1d compared to the baseline condition 1c. The speedup in 1d is predicted because of a so-called race process (Nicenboim & Vasishth, 2018; Raab, 1962; van Gompel et al., 2000). In a race situation, the parsing system attempts to retrieve the target noun, but in each trial either the target or the distractor noun is probabilistically retrieved depending on which of the two is retrieved faster (this so-called self-terminating parallel search is a property of the cue-based retrieval model; Colonius & Vorberg, 1994; Logačev & Vasishth, 2015; Vasishth et al., 2019). Because the winner of the race is always the chunk that is retrieved fastest, the average retrieval time in a race condition like 1d will be faster than the average retrieval time in a condition like 1c, which does not involve a race. With these predictions of the cue-based retrieval theory in mind, we now reanalyze Cunnings and Sturt (2018)'s data.

The materials in Cunnings and Sturt (2018)'s second experiment differed from those given in 1 only in that the direct object was in pseudo-clefted, e.g., *What Sue remembered was the plate that the butler with the cup accidently shattered today in the dining room.* The direct object of *shattered*, *plate*, is now focused, which might lead to less interference (Engelmann et al., 2019).

2.1 Re-analysis of the Cunnings and Sturt 2018 experiments

Cunnings and Sturt (2018) had 48 participants in each of their two experiments (96 total). There were 32 test items like (1) and 96 fillers in each experiment. Below, we re-analyze their data using Bayesian linear mixed models using Stan and `brms` (Bürkner, 2017; Carpenter et al., 2017). Bayesian models have several important advantages: the so-called maximal model (Barr et al., 2013) can always be fit using regularizing priors (Sorensen et al., 2016); and the plausible values of the effect of interest (given the data and model) can be used directly for inference.

We fit two models on log total reading times, with the verb *shattered* as the critical region. We chose this region as the dependent measure because the original study reported

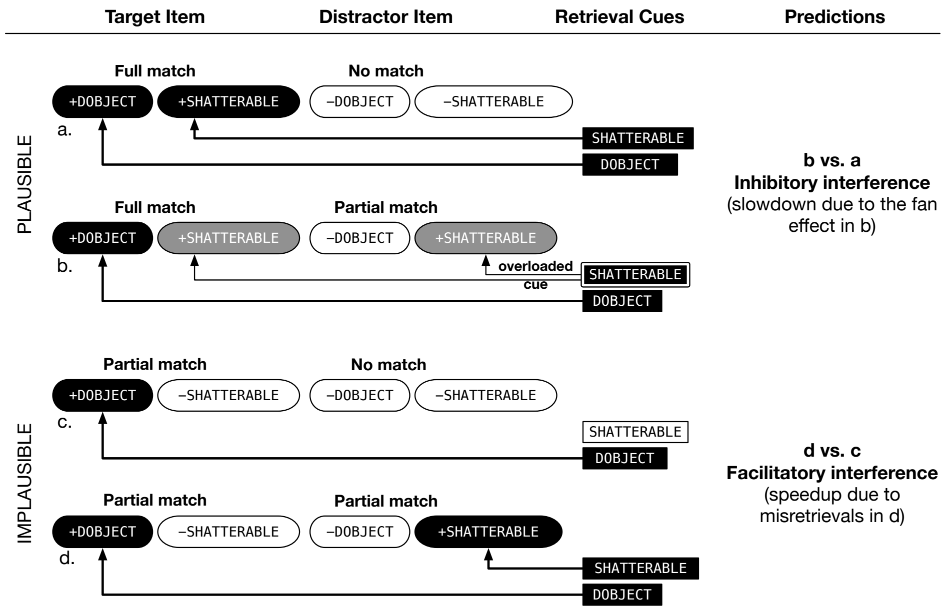

Figure 1. Visualization of the Cunnings and Sturt (2018) experiment and the predictions of the cue-based retrieval model of Lewis and Vasishth (2005), Engelmann et al. (2019). The figure is by Vasishth and Engelmann (2019), available from https://doi.org/10.6084/m9.figshare.10303760.v3 under a CC-BY4.0 license.

an effect here and cue-based retrieval makes its clearest predictions at the verb, where the retrieval is hypothesized to take place. The first model investigated the main effects of target and distractor plausibility, along with the main effect of the between-participant factor experiment (Experiment 1 vs 2). All interactions were also included in the model. The second model included predictors for experiment, target plausibility, and the simple main effect of distractor plausiblity (a nested contrast). The data and a full report of the analysis, including code, are available from https://osf.io/395xb/. Plausible and implausible targets and distractors were sum-coded as +1 and -1, respectively (Schad, Vasishth, et al., 2019). Experiment was coded +1 for Experiment 1, and -1 for Experiment 2. Experiment was included in the by-item random slopes, just as Cunnings and Sturt (2018) did in the analysis in their discussion. Items for which we could not estimate a plausibility rating using the method described in Section 3 were excluded from these models. See below for details.

For the parameters, we chose the following mildly informative priors (Schad, Betancourt, et al., 2019):

1. Intercept: $Normal(\mu = 6, \sigma = 1)$. This corresponds to average total reading times of about 400ms.

2. All fixed effects coefficients: $Normal(\mu = 0, \sigma = 0.5)$. This corresponds to likely

reading time effect sizes of up to 420ms.

3. All standard deviations in random effects, and the standard deviation of the residuals: $Normal(\mu = 0, \sigma = 0.5)$ truncated at 0.

4. All correlations between varying intercepts and varying slopes: $LKJ(2)$[1]

The end-result of a Bayesian analysis is a posterior distribution of each parameter; this distribution represents plausible values of the parameter given the data and model. In our case, the parameters of interest in the models are those representing the interference effect in plausible and implausible conditions. We report the means of these posterior distributions and 95% credible intervals, which contains parameter values most compatible with the statistical model and data.

2.2 Re-analysis results and discussion

As shown in Figure 2, we can conclude the following: (i) the critical region (the verb *shattered*) is read faster in plausible sentences compared to implausible sentences, as the plausible minus implausible difference is clearly less than zero (-56, 95% credible interval: [-74, -38]) (panel A); (ii) overall, when the distractor is plausible, reading time is faster (the plausible distractor minus implausible condition is less than zero (-26 [-42, -10]), panel B); (iii) the nested analysis shows that the facilitation due to the distractor being plausible is driven by the implausible-target conditions (the posterior that is close to centered on zero in panel C (-9 [-29, 11]) and the clearly negative posterior in panel D (-44 [-71, -19])). See the supplementary material for additional details.

How do these observed effects relate to theoretical predictions? In the plausible-target conditions, the absence of an inhibitory interference effect is problematic for the cue-based retrieval model (panel C). There are also other published experiments that show effects inconsistent with the predicted inhibitory interference effect; see Jäger et al. (2017) for a review and meta-analysis. This failure to find inhibitory interference effects either falsifies a key prediction of the cue-based retrieval model, suggests it is very context specific as suggested by (Van Dyke & McElree, 2011), or is a consequence of the generally low statistical power of published studies on this topic (Nicenboim et al., 2018). In any case, these questions are incidental to the present investigation. What is more interesting here is the central finding of Cunnings and Sturt: facilitatory interference effect in the implausible-target conditions (panel D).

[1] This prior ensures that extreme values like ± 1 are unlikely; for details, see Sorensen et al. (2016).

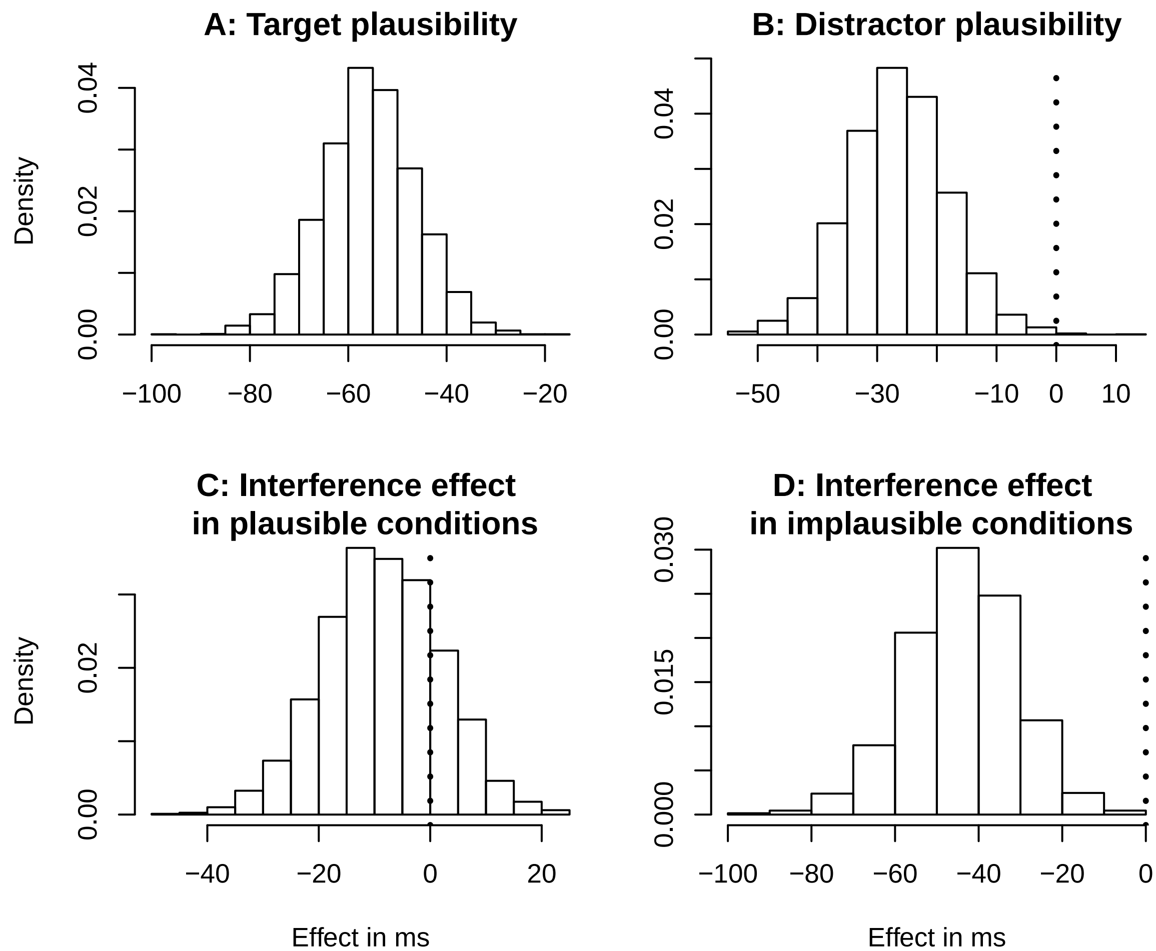

Figure 2. Posterior distributions of the effects of target and distractor plausibility (plots A, B), and of the interference effect in plausible and implausible conditions (C, D). The data are pooled from the two experiments reported in Cunnings and Sturt (2018) and back-transformed from the log-millisecond scale.

There is, however, a really big oversimplification in the cue-based retrieval model that leads to the prediction of facilitatory interference in the implausible-target conditions. Assuming (as Cunnings & Sturt, 2018, also do) that the distractor noun has the feature [+shatterable] skirts around the question of what the lexical features are that make something shatterable. Cunnings and Sturt do not specify them, although they explicitly note that specifying the lexical features will be necessary in order to implement a model of this phenomenon.

In the above discussion, we followed Cunnings and Sturt's approach of using a single ±shatterable feature. However, the question arises: should there be ±rigid, ±breakable, and ±breaks-into-small-irregular-pieces features? Cunnings and Sturt note that a huge number of discrete features would be required to explain the plausibility effects in their various items

(±shatterable, ±choppable, ±bakable, etc.). Each additional feature would require theoretical and empirical justification, introducing a huge amount of flexibility in model development. Illusions of plausibility clearly require features and retrieval cues that are specific to particular lexical items, but discrete, hand-picked features do not seem like a viable path to an implemented model.

Additional evidence that lexically specific features are needed in sentence comprehension comes from garden-path effects, which can often be reduced in magnitude or eliminated when plausibility favors the correct parse during a temporary ambiguity (Trueswell et al., 1994; Trueswell et al., 1993). Similarly, encoding interference effects, where similarity-based interference arises due to features that are not relevant for retrieval (Gordon et al., 2001; Hofmeister & Vasishth, 2014; Smith et al., under review; Villata et al., 2018), also call for lexically specific features in order to explain processing difficulties. Finally, Van Dyke and McElree (2006) also argue for lexically specific features. There, participants read sentences like *It was the boat that the guy who lived by the sea sailed/fixed on two sunny days* while holding a list of words (e.g., *table, sink, truck*) in memory. At the verb *sailed* or *fixed*, the clefted noun *boat* has to be retrieved from memory. Van Dyke and McElree found slowed reading times in the *fixed* condition, because the items in the memorized list were also things that could be plausibly fixed but do not otherwise have features that might be used as retrieval cues, like syntactic position in the sentence.

Thus, there is good reason for cognitive models of sentence processing to incorporate lexical-item specific features, especially in cases of semantic or other features that cannot easily be identified with an overt morpheme. No existing model that we are aware of uses lexically specific features that are derived in a principled manner. A possible exception is the self-organizing model in Smith et al. (2018), which uses distinct feature vectors for different classes of nouns; however, even this model does not go to the level of individual lexical items. This paper takes that step and presents a method for transparently generating lexical features and retrieval cues that can be used as a common baseline when comparing models of sentence processing.

3 Using word embeddings to predict illusions of plausibility

We use methods for creating *word embeddings* to make lexical features and retrieval cues from them. Word embeddings are distributed, real-valued vector representations of word meanings derived from large language corpora. Many current word embeddings are derived iteratively using neural network techniques (Bengio et al., 2003; Mikolov, Chen, et al., 2013; Mikolov, Sutskever, et al., 2013), but good performance on various tasks is often found with older techniques based on co-occurrence statistics (Bullinaria & Levy, 2007;

Church & Hanks, 1990; Landauer & Dumais, 1997; O. Levy et al., 2015; Niwa & Nitta, 1994). Our goal here is not to reach state-of-the-art performance on natural language processing or machine learning tasks. Rather, we simply want to constrain part of the cognitive modeling pipeline to facilitate better comparisons between models. We derive two sets of embeddings from the same co-occurrence statistics: *lexical feature* vectors as a representation of a word's meaning and features as well as *retrieval cue* vectors. We test whether these representations reflect relevant differences between conditions that would predict the observed differences in reading times in Cunnings and Sturt (2018).

We now describe the method we used to construct the feature and cue vectors and derive plausibility ratings from them for Cunnings and Sturt's materials. We then test the cue-based retrieval model's prediction of facilitatory interference in implausible sentences using the new plausibility ratings.

3.1 Method

To create lexical feature and retrieval cue vectors, we first parsed the British National Corpus (BNC; "The British National Corpus," n.d.; Burnard, 2007).[2]We used the scripts included with the BNC download to strip the XML meta-information, leaving only the raw text. We then passed the text to the Python implementation of the Stanford dependency parser (Qi et al., 2018) to obtain dependency parses of the sentences in the BNC. The parser takes the raw text and returns dependency-parsed output, from which we extracted dependency triples—e.g. "nsubj(eats, dog)" and "obj(eats, kibble)" from *The dog eats kibble*—which we used to create the word embeddings. All of the Universal Dependency relations (e.g., "nsubj" for subject, "obj" for direct object de Marneffe et al., 2014) that appeared in the parsed corpus were included (48 in total).

To create the lexical feature and retrieval cue vectors, we first created a co-occurrence matrix with a row for each word in the corpus and a column for each dependency relation-governor pair, e.g., "nsubj-eats" or "obj-eats."[3] A word or relation-governor context

[2] The corpus data cited herein have been extracted from the British National Corpus Online service, managed by Oxford University Computing Services on behalf of the BNC Consortium. All rights in the texts cited are reserved.

[3] We initially tried a different method where, instead of dependency relation-verb contexts, we just used the dependency relations as contexts. This led to much shorter lexical feature vectors for nouns, which we then compared with the average of the lexical feature vectors for all nouns that appeared as a verb's direct object. This method perfomed poorly in the analysis of the Cunnings and Sturt data, only predicting the expected reading time effects in Experiment 1 but not Experiment 2. We suspect that the more fine-grained method we present here is better able to account for the reading time data because of the governor-specific nature of the lexial features and retrieval cues. Code for this older method is available at https://github.com/garrett-m-smith/dependency_embeddings

had to appear at least 100 times in the parsed corpus in order to be included in the counts. This resulted in a 48,571-word vocabulary and 91,226 dependency relation-governor pairs. Then, we converted the co-occurrence counts to the point-wise mutual information (PMI, Eq. 1) as a measure of the association between a word and each dependency relation-governor pair (Bullinaria & Levy, 2007; Church & Hanks, 1990; O. Levy et al., 2015; Niwa & Nitta, 1994; Padó & Lapata, 2007; Rei & Briscoe, 2014). The PMI between two random variables w (words) and d (dependency relation-governor pairs) is given in Eq. 1. It measures the extent to which w and d actually co-occur—their joint probability $P(w, d)$—relative to how often they would be expected to co-occur merely by chance—the unigram probabilities $P(w)$ and $P(d)$.

$$PMI(w, d) = \log_2 \frac{P(w, d)}{P(w)P(d)} \tag{1}$$

$$PPMI(w, d) = \max(0, PMI(w, d)) \tag{2}$$

Negative PMI values can be indicative of poor coverage of rare co-occurrences in the corpus, making the estimates less reliable. Therefore, the positive point-wise mutual information (PPMI, Eq. 2) is commonly used instead, a convention which we follow here.

To reduce the dimensionality of the PPMI matrix and improve generalization to non-observed triples (Deerwester et al., 1990), we applied truncated singular value decomposition (SVD) to the PPMI matrix, keeping 300 dimensions (results were similar for 100 dimensions). SVD decomposes the PPMI matrix into three matrices: an $n_{\text{words}} \times 300$ matrix of word embeddings, a 300×300 diagonal matrix of singular values, and a $n_{\text{dependency pairs}} \times 300$ matrix of dependency relation-governor pair embeddings. As recommended by O. Levy et al. (2015), we multiply the word and dependency relation-governor pair embeddings by the square root of the singular value matrix and use the resulting matrices as our lexical feature and retrieval cue matrices, respectively. Specifically, we used the lexical feature vectors for the nouns and the retrieval cue vectors from the direct object-verb pairs in calculating feature cue match values as discussed below.

Pre-trained word embeddings that use different association measures are available (e.g., word2vec and GloVe; Mikolov, Sutskever, et al., 2013; Pennington et al., 2014). So why did we choose to create our own PPMI embeddings? The most popular embeddings, in their widely available forms, are based on linear bag-of-words contexts instead of syntactic dependency contexts. While the similarity between word2vec or GloVe vectors encodes a certain notion of similarity or association, applications to human parsing questions seem to be more naturally addressed by word embeddings that take syntactic structure into account. In Cunnings and Sturt (2018)'s materials, we are not concerned about whether *shattered* often co-occurs within some n words of *plate* or *tie*; we are interested in which of the two nouns is the more plausible direct object. Thus, encoding information about how often a word appears as a direct object of a particular verb is directly relevant to the question of how illusions of plausibility arise. We speculate that word2vec or GloVe bag-of-words-based embeddings would likely produce similar results, but we believe that using syntactically informed embeddings more closely approximates the information people use when processing these sentences. In addition, PPMI is conceptually simple and fast to calculate, so we chose it over the newer alternatives.[4]

There are some existing word embeddings that take dependency structure into account, e.g., Gamallo (2017), O. Levy and Goldberg (2014a), Padó and Lapata (2007), Rei and Briscoe (2014), Zhao et al. (2014). However, these embeddings do not encode the information that we need for use in cognitive models of sentence processing. Typically, they include both the governors of a word and its dependents as syntactic contexts in creating the lexical feature vectors. Thus, they collapse the distinction between lexical features (as we use the term) and retrieval cues. What is needed for lexical features in cognitive models is a representation of the meaning of a word *as a dependent of other words* and not as the governor. Thus we chose to create our own vectors that stucture the information in the parsed corpus in a way that is consistent with implemented models of sentence processing.

We used the cosine similarity between each noun's feature vector v_{noun} and the retrieval cue vector for the direct object-verb pair in that sentence $v_{\text{retrieval}}$ (Eq. 3) as a measure of the plausibility of the retrieval targets and distractors in Cunnings and Sturt (2018).

$$\text{plausibility} = \frac{v_{\text{noun}} \cdot v_{\text{retrieval}}}{|v_{\text{noun}}||v_{\text{retrieval}}|} \tag{3}$$

In Eq. 3, $v_1 \cdot v_2$ is the dot product between two vectors, $|v|$ is the magnitude of a vector. Because we are using PPMI, the plausibility can only range between zero and one. (For PMI, it can range between -1 and 1.) PPMI combined with cosine similarity has been shown to provide good performance in semantic and syntactic clustering (Bullinaria & Levy, 2007). See below for validation experiments using our own method.

Finally, we calculated the difference in plausibility between the target and the distractor. We refer to this as the "distractor advantage": positive values indicate that the distractor was a more plausible fit to the verb than the target, and negative values indicate that the target was more plausible. We mean-centered and standardized (rescaled the

[4] Also, as O. Levy and Goldberg (2014b) note, the neural network-based/predictive models like word2vec are actually equivalent to factorizations of the PPMI matrix under certain circumstances. Thus, the distinction between neural/predictive models and count-based models might be more apparent than real, especially given that they can perform similarly when the hyperparameters are set appropriately (O. Levy et al., 2015).

standard deviation to 1) these differences for the analyses below.

For some verbs, the past-tense form did not appear in the corpus with a direct object, but the present-tense form did (missing verb forms: *chopped, watered, sailed, baked, peeled*). We therefore used the retrieval cue vector for the present-tense form instead. Even after this correction, there were 22 verb-target-distractor combinations for which the distractor advantage could not be calculated due to words being missing from the corpus (total combinations: 128); these are excluded from all further analyses. The code for creating retrieval cue and lexical feature vectors is available at https://github.com/garrett-m-smith/spec_context.

3.2 Validating the lexical feature vectors

To ensure that our method indeed extracts meaningful semantic structure from the parsed corpus, we tested the lexical features and retrieval cues in three ways. The first two tests focus on the lexical features, i.e., the 300-dimensional word embeddings, and use two standard evaluation data sets for word embeddings. The first test used the SimLex-999 data set (Hill et al., 2015), which contains human similarity (not just association or relatedness) ratings for 666 noun pairs, 222 verb pairs, and 111 adjective pairs. Each pair was rated by at least ten participants. We calculated the Spearman rank correlation between the SimLex-999 ratings and the cosine similarity between the lexical feature vectors for each word in the pair. (Note that, while we only used the lexical feature vectors for nouns in the main analyses below, our method also creates lexical feature vectors for verbs, i.e., vectors representing features of verbs when they are dependents of other words, which we use here.) The correlation was 0.362.

For the second validation test, we used the WordSim353 dataset (Agirre et al., 2009; Finkelstein et al., 2002), which contains 353 word pairs split into two subsets, one with human ratings of similarity and the other with ratings of relatedness. For the similarity subset, the Spearman rank correlation (calculated as for the SimLex-999 data set) was 0.693 and 0.41 for the relatedness subset. Thus, while our word and context vectors do not approach the state of the art on these tasks[5], the correlations indicate that our method is extracting useful semantic structure from the parsed dependency corpus.

The final validation test was similar to Cunnings and Sturt's own plausibility norms. They found that the plausible targets and distractors were rated similarly highly plausible

[5] See https://aclweb.org/aclwiki/Similarity_(State_of_the_art). The state of the art for WordSim353 is currently Speer et al. (2017)'s combined knowledge-graph-word embedding approach, which had a Spearman rank correlation of 0.828 on the WordSim353 task. The state of the art for the SimLex-999 task was Recski et al. (2016), which also combined knowledge graphs with word embeddings and achieved Spearman rank correlation of 0.76.

and the implausible targets and distractors similarly implausible. We calculated the cosine similarity between the lexical feature vector of each word (target or distractor) and the retrieval cue vector for each item. We found comparable results: The targets and distractors in the plausible conditions had high cosine similarities with the relevant retrieval cues (0.464, SE = 0.033 and 0.499, SE = 0.029, respectively). Implausible targets and distractors also had approximately equal cosine similarities with their retrieval cues (0.057, SE = 0.013 and 0.051, SE = 0.01, respectively). Thus, our lexical feature and retrieval cue vectors clearly reflect the plausibility manipulation that Cunnings and Sturt used to construct their materials.

3.3 Predictions

Cue-based retrieval makes different processing time predictions depending on whether the target matches the retrieval cues (target match/plausible conditions) or not (target mismatch/implausible conditions). For target match (plausible) conditions, the better the feature match of the distractor, the *slower* processing should be. There is no indication of this effect in Cunnings and Sturt's data. For target mismatch (implausible) conditions, the better the feature match of the distractor, the *faster* processing should be. Thus, in implausible sentences, in terms of the distractor advantage variable we have defined, we predict the following: As the distractor advantage increases (i.e., the distractor becomes more plausible than the target), the faster total reading times at the verb should be.

3.4 Analyses

The data were again analyzed using `brms` (Bürkner, 2017, 2018), which provides a user-friendly interface to the probabilistic programming language Stan for fitting Bayesian models (Carpenter et al., 2017). Once again, the dependent measure was the log-transformed total reading times at the verb. The analysis included binary predictors for target plausibility (`target`) and experiment (`exp`), the centered and standardized distractor advantage nested within plausible (`PlausDistrAdv`) and implausible (`ImplausDistrAdv`) target sentences, and all interactions with the factor experiment (`exp`). The binary factors were coded as in the previous analysis. The random effects structure included by-subject random intercepts and slopes for target plausibility and the distractor advantage variables, as well as by-item random intercepts and slopes for all within-item fixed effects. The R formula was:

```
logrt ~ exp*(target + PlausDistrAdv + ImplausDistrAdv)
        + (1 + target + PlausDistrAdv + ImplausDistrAdv | subject)
        + (1 + exp*(target + PlausDistrAdv + ImplausDistrAdv) | item)
```

The same mildly informative priors were used for all parameters, as discussed earlier.

3.5 Results

The posterior distributions of the parameters of interest are plotted in Fig. 3. Here, we report the results on the original millisecond scale with 95% credible intervals. The 95% credible interval gives a range of values that contains plausible values of a parameter with 95% probability given the data and statistical model. The results were similar to those of Cunnings and Sturt (2018)'s original analyses. Overall, plausible targets induced faster reading times at the verb: -74ms, [-98, -52]. The main effect of experiment was centered on zero: -9ms, -42, 24 The interaction of target plausibility with experiment was also centered on zero (4ms, [-17, 24]), resulting in similar effects in both experiments: Experiment 1, -80ms, [-124, -36]; Experiment 2, -69ms, [-112, -25]. The nested effect of distractor advantage in plausible-target sentences was inconclusive -13ms, [-41, 17]. Again, the interaction of distractor advantage in plausible sentences with experiment showed little effect (3ms, [-24, 32)] and consistent effects in both experiments: Experiment 1, -18ms, [-74, 38]; Experiment 2, -7ms, [-64, 50]. In implausible sentences by contrast, the effect of distractor advantage was clearly negative (-54ms, [-89, -21])indicating a facilitatory interference effect: the more plausible the distractor was compared to the target, the faster reading times were. This effect was similar for both experiments: Experiment 1: -53ms, [-108, -3]; Experiment 2: -56ms, [-107, -5]. Figure 4 shows the posterior total reading time estimates for each target-implausible item along with the overall effect of distractor advantage for those sentences.

To compare the predictive accuracy of the factorial reanalysis of Cunnings & Sturt's design with the analysis based on the distractor advantage, we used approximate leave-one-out cross-validation (Vehtari et al., 2017) as implemented in the R package `loo` (Vehtari et al., 2019). The leave-one-out procedure returns an estimate of how much a statistical model's predictions deviate from the actual data called the expected log point-wise density ($\widehat{elpd}$). The estimation provides a standard error for each $\widehat{elpd}$, which gives a measure of the uncertainty around the $\widehat{elpd}$ values. The factorial model had an expected log point-wise density (*elpd*) of -1654.328 (standard error: 32.038); the distractor advantage model performed somewhat more poorly $elpd$ = -1658.824, SE = 31.861. The difference in $\widehat{elpd}$ values was -4.496 (SE = 3.455). If we use the estimated difference plus or minus two standard errors as an estimate of the 95% confidence interval, we can conclude there was no real difference in predictive performance between the factorial analysis and the analysis using distractor advantage, as the confidence interval contains zero.

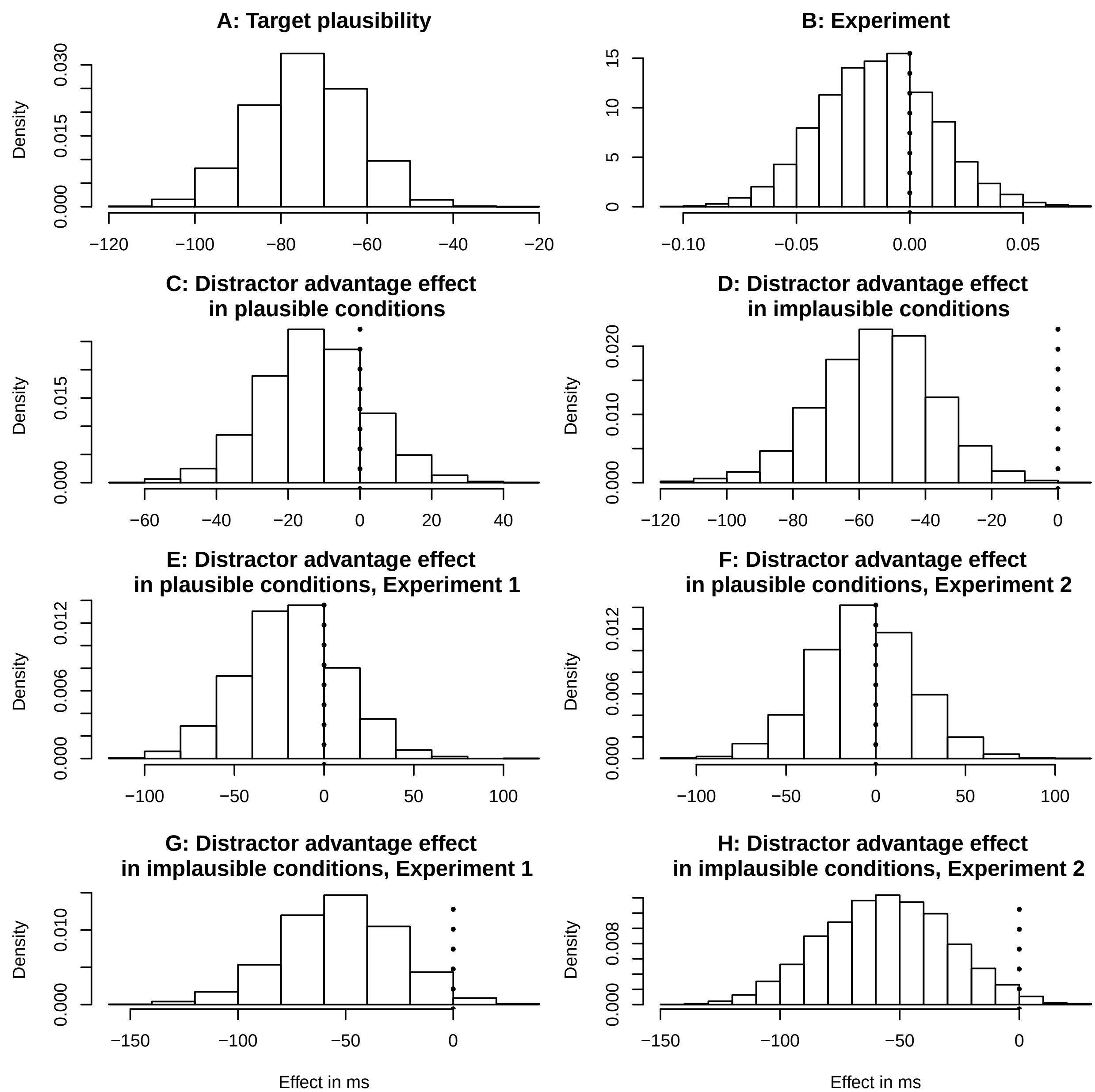

Figure 3. Posterior distributions of effects in the distractor advantage analysis plotted in milliseconds (ms).

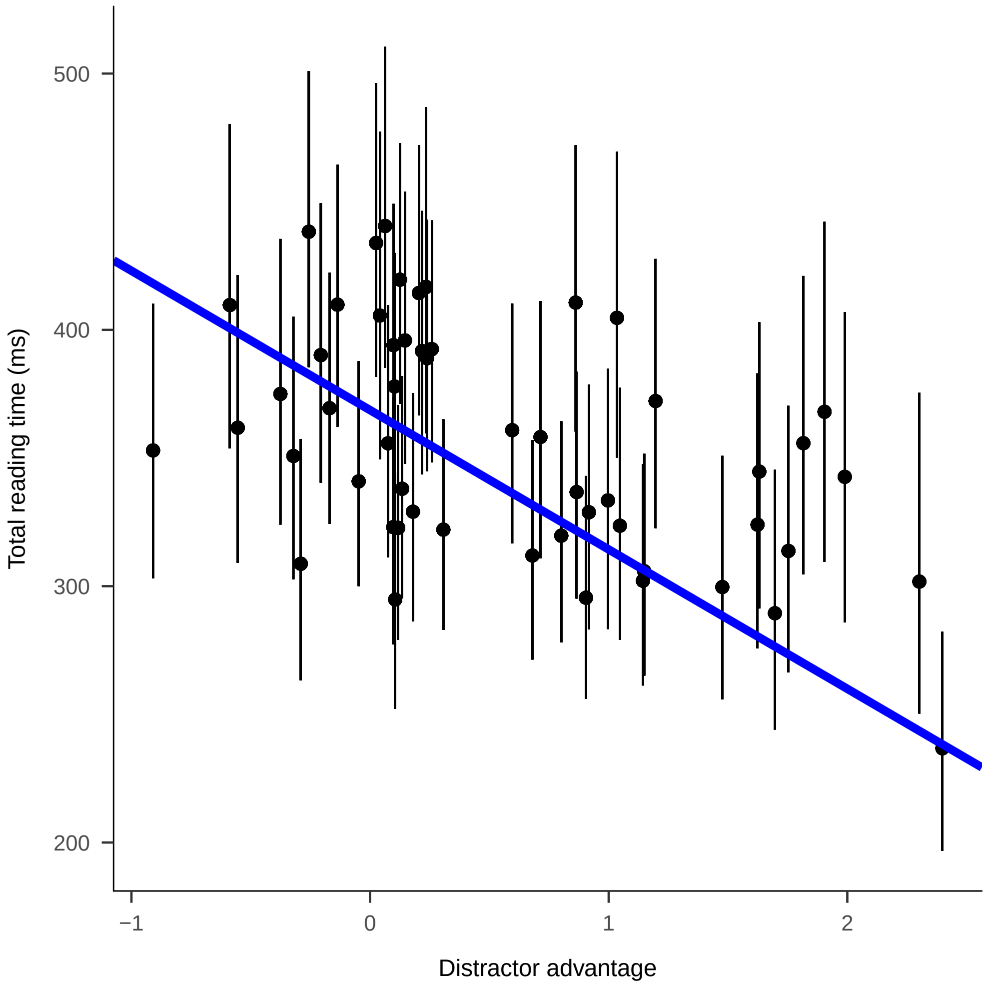

Figure 4. Posterior distributions of total reading times for each item as a function of distractor advantage in the target-implausible conditions. Error bars show 95% credible intervals. The line is the population-level effect of distractor advantage in the target-implausible conditions.

3.6 Discussion

Using well-established methods from computational linguistics and machine learning, we derived lexical features and retrieval cues from a large, dependency-parsed corpus. Using these features, we calculated the distractor advantage, the relative plausibility of the distractor to the target given a verb's retrieval cues. Our reanalysis of Cunnings and Sturt (2018)'s data showed that total reading times at the verb decreased as the distractor advantage increased: The more plausible the distractor was as a direct object of the critical verb compared to the target, the faster participants read the verb. This replicates previous findings and is consistent with the predictions of cue-based retrieval theory (Engelmann et al., 2019; Jäger et al., 2017; Lewis & Vasishth, 2005; Vasishth et al., 2019). Moreover, it demonstrates that our method of deriving lexical features has promise as a relatively objective method of choosing features to use in future computational models of sentence processing. The interference effect considered here is a semantic one; future work will determine the extent to which this method can be applied to purely morphosyntactic interference effects, e.g., in subject-verb number agreement and reflexive binding (Dillon et al., 2013; Jäger et al., 2019).

4 General discussion

In this study, we asked whether corpus-based plausibility measures could be used to predict reading times in grammatical but implausible sentences. We presented a method for extracting distributed lexical features and retrieval cues from the British National Corpus using tried and tested methods from computational linguistics. Using Cunnings and Sturt (2018)'s two eye-tracking experiments on illusions of plausibility as a test case, we showed that the plausibility difference between a distractor and the correct retrieval target (distractor advantage) predicted a decrease in log total reading times at the verb in Cunnings and Sturt's Experiment 1 (but not in Experiment 2). This effect demonstrates the promise of these feature extraction and plausibility estimation methods for predicting human sentence processing data.

4.1 Limitations

While we believe our results demonstrate the promise of this approach to incorporating distributed features into cognitive models of sentence processing, there are some important limitations. First, the lexical features and retrieval cues are based on automatically parsed text. The parser we used showed good performance on a number of standard measures of automatic parsers (Qi et al., 2018). However, we did not check the parses by hand, so we expect that the dependency triples we used to derive features contain errors. This is an issue for all other results that rely on automatic parsers (Boston et al., 2008; Boston et al., 2011; Demberg & Keller, 2008; R. Levy, 2008). But given that the dependency type under consideration here (direct object) is quite common and easily identified in English, we do not believe that this was a significant source of bias in our results.

Relatedly, we did not take ambiguity or polysemy into account when deriving features. However, our results show that even these rather coarse features can predict reading times in Cunnings and Sturt (2018). The Python implementation could be extended in future work to allow more subtle distinctions between word forms. We expect that this would strengthen the pattern we have already observed here.

We also do not yet know how our lexical features and retrieval cues will perform for other types of similarity-based interference. For example, subject-verb number agreement and reflexive binding, as studied in Dillon et al. (2013) and Jäger et al. (2019), seem to rely exclusively on morphosyntactic features and cues (e.g., ±plural, ±c-command) to control the retrieval process. In our method, we have created token-based lexical features, i.e., separate word embeddings for *plate* and *plates* and separate retrieval cue vectors for "obj-shatter" and "obj-shatters", so we suspect that our method might predict number interference effects. Reflexive binding might be more difficult, though, as our method currently relies on binary word-word dependencies and does not consider hierarchical relations like c-command. We leave this futher testing to future research.

There are also some limitations of the data used for model evaluation here. Even with both experiments together, there is just not enough data to obtain reliable estimates of the effect with any degree of precision. This becomes clear when we carry out a prospective power analysis for a hypothetical follow-up study that compares only the plausible and implausible distractors in target-implausible sentences. The best estimates we have of the facilitation effect predicted by the cue-based retrieval model comes from the meta-analysis by Jäger et al. (2017). The meta-analysis showed that the subject-verb agreement attraction effect, which involves the same mechanism as assumed here for the distractor-plausibility manipulation, was -22ms, with a 95% credible interval of $[-36, -9]$ms.[6] Using the lower and upper bounds of these estimates, a sample size of 48 participants and 32 items, and all the other parameters estimated from our reanalysis of the original design (combining both experiments' data together from the Cunnings and Sturt study), we obtain power estimates ranging from as low as 0.16 to 0.89. The consequence of the potentially low power here is that we should be careful in drawing conclusions using this data set. A larger sample study of their plausibility manipulation would be very informative.

4.2 Distributed features and cues in ACT-R

The main predictions for Cunnings and Sturt, 2018 in the current study were derived from Lewis and Vasishth, 2005's cue-based memory retrieval model. This model uses the following equations to determine the activation of chunks in memory, which is used in turn to predict retrieval times and probabilities:

$$A_i = B_i + \sum_j W_j S_{ij} \tag{4}$$

[6] This meta-analysis estimate is consistent with another investigation of subject-verb agreement attraction that had 181 participants (Jäger et al., 2019). There, the estimate of the agreement attraction effect was -22ms $[-46, 3]$ms.

$$S_{ij} = \text{MAS} - \ln(\text{fan}_j) \tag{5}$$

In Eq. 4, the activation of a chunk i, denoted A_i, is the sum of its base activation B_i (a function of how often the chunk has been accessed in the past) and the spreading activation term $\sum_j W_j S_{ij}$. This sum runs over all retrieval cues j, weighting each one by W_j (which is typically set to be equal for all cues j). The activation that spreads to chunk i from cue j, S_{ij}, is given by Eq. 5. Each cue has a maximum amount of activation it can spread to a chunk, the maximum associative strength MAS, but this is reduced by the natural logarithm of the fan of j, the number of other chunks (out of n total chunks) that also match cue j.

However, these equations have only ever been tested with discrete features and retrieval cues (to our knowledge), making activation basically a function of how many cues a chunk matches. We believe this has been more a result of convenience and conceptual simplicity, as there is no fundamental restriction in ACT-R to discreteness in this way. One way of adapting these equations to continuous-valued feature vectors is to replace equations 4 and 5 with the following:

$$A_i = B_i + \cos(f_i, c) - \frac{1}{n-1} \sum_{k \neq i} \cos(f_k, c) \tag{6}$$

Here, the activation of chunk i, A_i, is the sum of its baseline activation B_i (as before) and the cosine similarity between its distributed feature vector f_i and the distributed retrieval cue vector c. This is similar to the idea of activation spreading from each matched feature, except that it is now the continuous overlap on each cue/feature dimension that determines how much activation is affect. A redefined fan term is then subtracted: the average cosine similarity between the feature vectors of the other $n-1$ chunks k and the retrieval cues. This modification of the basic equations of ACT-R would require thorough testing using data from properly powered experimental designs. Such data do not exist yet, so such a large-scale evaluation is not currently possible; however, more and more researchers are attending to the power properties of their studies (Brehm & Goldrick, 2017; Stack et al., 2018; Zormpa et al., 2019), and we expect that such data will become available in the future.

Once large-sample data become available, using the modified ACT-R equation shown above would allow us to use our word-embedding based features and retrieval cues directly to predict reading times for comparison with competing models, for example self-organizing models. Thus, the work presented here prepares the way for large-scale evaluations of competing models of sentence processing, taking us beyond initial attempts (Engelmann et al., 2019; Nicenboim & Vasishth, 2018).

4.3 Implications for self-organizing parsing models

Our approach is intended to apply to multiple parsing models to facilitate quantitative comparisons of how well competing models account for existing data. After ACT-R, the most natural model to test our approach in is the self-organized sentence processing framework (SOSP), for example as implemented in (Smith, 2018; Smith et al., under review; Smith & Tabor, 2018). A number of self-organizing models have been developed (Cho et al., 2018; Cho et al., 2017; Green & Mitchell, 2006; Kempen & Vosse, 1989; McRae et al., 1998; Smith et al., 2018; Stevenson, 1994; Stevenson & Merlo, 1997; Tabor & Hutchins, 2004; Vosse & Kempen, 2000, 2009). Their implementations sometimes differ in theoretically important ways; however, all of them rely on the feature match between words or phrases and attachment sites on other words or phrases for structure formation. Typically, words interact locally with each other by trying to form attachment links to connect them. For example, in Smith et al. (under review)'s SOSP model, the strength of a dependency link grows in proportion to how well the features on the dependent match the features that the governor "expects" in a particular dependent type. Links compete for attachment, with all possible ways of attaching words competing. In the end, the links with the best feature match are most likely to win out against other, less well-formed links, and parsing proceeds more quickly for well-formed links than ill-formed ones.

While self-organizing theories are in principle applicable to any sentence processing phenomenon, a common criticism is that their complexity makes them difficult to "scale up" (e.g., Bicknell & Levy, 2009; Bicknell et al., 2009). Indeed, many self-organizing models can only capture one or two processing effects (Cho et al., 2018; Cho et al., 2017; Cho & Smolensky, 2016; Smith & Tabor, 2018; Stevenson, 1994; Stevenson & Merlo, 1997; Tabor & Hutchins, 2004; Villata et al., 2019). Even models that can account for multiple phenomena simultaneously (Kempen & Vosse, 1989; Vosse & Kempen, 2000, 2009) typically have a large number of free parameters, including the features that are so crucial for structure building. Thus, it is important to constrain these models as much as possible. The word embedding-based features that we have developed can be used immediately to constrain these models.

4.4 Exploratory and confirmatory modeling

A principled way to compare competing models would be to settle on a single, fixed set of features for all models before any simulations are run. This constrains each model by requiring it to have the same starting point as all others and prevents the researcher from building in bias toward their favored model. However, we recognize that open-ended, exploratory model building can and does lead to theoretical breakthroughs or new ways of conceptualizing sentence processing phenomena. Close engagement with experimental and modeling data can draw our attention to previously unnoticed patterns that require further exploration or testing (MacEachern & Van Zandt, 2019). It is also important to determine the full range of a model's predictions by varying all parameters through their full range (Roberts & Pashler, 2000). Only once the predictions are known does it make sense to start imposing additional constraints. However, for more well-established parsing models like cue-based retrival and self-organization, quantitative comparisons of implemented models are crucial for improving empirical predictions and clarifying where and how theories differ. The constraint of a single, fixed set of features is indispensable for making a fair comparison between models and the theories they embody and makes preregistering model comparisons (as Lee et al., 2019, advocate for) more straightforward. Thus, we recommend both approaches in different contexts: freely explore new models, but also make sure that well-established models are put on equal footing for comparison.

4.5 Conclusion

In recent years, computational implementations of psycholinguistic theories have become increasingly common (e.g. Hammerly et al., 2019; Nicenboim & Vasishth, 2018; Parker, 2019; Smith et al., 2018). This is a welcome development, but it raises the important question of how to conduct fair, quantitative model comparisons against human data; such model comparisons are vital if we want to understand the relative strengths and weaknesses of the different models. For such comparisons to be meaningful, the models should differ only in theoretically important ways; ancillary modeling choices, such as which features to use, should be held constant between models. We have provided a method for reducing modeler degrees of freedom by more objectively choosing lexical features and retrieval cues and demonstrated their utility using eye-tracking data from a semantic interference task. Our hope is that this work will stimulate theory development in human sentence processing through principled and informative model comparisons.

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