Abstract

Learning words is a challenge for children and neural networks alike. However, what they struggle with can differ. When prompted by novel words, children have been shown to tend to associate them with unfamiliar referents. This has been taken to reflect a propensity toward mutual exclusivity. In this study, we investigate whether and under which circumstances neural models can exhibit analogous behavior. To this end, we evaluate cross-situational neural models on novel items with distractors, contrasting the interaction between different word learning and referent selection strategies. We find that, as long as they bring about competition between words, constraints in both learning and referent selection can improve success in tasks with novel words and referents. For neural network research, our findings clarify the role of available options for enhanced performance in tasks where mutual exclusivity is advantageous. For cognitive research, they highlight latent interactions between word learning, referent selection mechanisms, and the structure of stimuli.

1 Introduction

A puzzle in vocabulary acquisition is how children deal with what Quine (1960) termed the inscrutability of reference: the fact there are always multiple candidate referents for a novel word. Prima facie, a learner that encounters, say, the word rabbit for the first time can entertain that it refers to any candidate meaning in the current context of utterance; both with respect to a single referent, e.g. RABBIT, PAW, or CUDDLY BEAST, as well to others that might be present in the scene, e.g., TABLE, BOY, or FEED. Notwithstanding, children do ultimately overcome this and other challenges faced during acquisition (Carey and Bartlett, 1978; Landau and Gleitman, 1985; Bloom, 2000).

What is perhaps more surprising is that children often seem to grasp novel word meaning after a single exposure. For instance, children as young as 15 months old perform well at selecting an unfamiliar referent – a strange object the child has not seen before – from an array of otherwise familiar objects when prompted with an unknown word, e.g., “show me the dax” (Halberda, 2003; Markman et al., 2003). By contrast, recent work suggests that standard neural network (NN) models tend to associate the novel with the frequent and familiar, although child-like tendencies are advantageous for some tasks (Gandhi and Lake, 2019).

In the following, we test NN models optimizing similarity between lexical and both symbolic and visual representations on novel word comprehension, using tasks inspired by the ones children have been tested in (e.g. Horst and Samuelson, 2008). Our main contributions are: (1) models that allow for a systematic evaluation of how a NN’s tendency to associate novel words with novel referents is impacted by interactions between (1a) learning biases and (1b) decision criteria (concretely, comparing effects of (1a) word learning vs. (1b) referent selection); (2) a formalization of this tendency as referent selection in terms of Bayesian inference, highlighting ties to probabilistic pragmatic models (e.g., Goodman and Frank, 2016); and (3) evaluation on symbolic and visual datasets that showcase how this tendency, as well as (1a) and (1b) more broadly, interact with the structure of stimuli.

Our results show that an increased propensity to associate novel words with novel referents can be effected both in training, through a constraining loss function, or by referent selection mechanisms in testing, e.g., by equipping models with pragmatic-like reasoning. The core requirement is that there be a bias against synonymy in either – or both – realms, making new words less likely to be associated with familiar referents seen in training.
2 Background

Children’s tendency to select unfamiliar objects when prompted with unknown words has often been attributed to mutual exclusivity (ME; see, e.g., Markman and Wachtel 1988; Halberda 2003; Markman et al. 2003; Halberda 2006). Pre-theoretically, ME can be characterized as resulting in a propensity to associate novel words with objects for which no label is previously known. It can be construed in different ways. First, it could be effected by a referent selection strategy (e.g. Clark and Clark, 1979; Clark, 1988; Halberda, 2006) akin to Gricean reasoning (Grice, 1975). Intuitively, if an object has a known label, then a speaker should use this label to refer to it, rather than a novel word. Consequently, a novel word can be reasoned to map, or at least circumstantially refer to, an unknown object. Second, it could be a learning bias, linked more closely to meaning acquisition and retention (e.g., Markman and Wachtel 1988; Markman et al. 2003; Frank et al. 2009; Nematzadeh et al. 2016; but see also Carey and Bartlett 1978; Horst and Samuelson 2008; McMurray et al. 2012 on meaning retention over time in ME tasks). For instance, it may be that already established word-meaning associations inhibit linkage of new words to a meaning.

Disentangling potential causes of an observed ME bias is not straightforward. Referent selection presupposes learning; and, inversely, latent learning biases cannot simply be read off from how children select referents. Ultimately, the interaction between these systems needs to be considered (Clark, 1988; McMurray et al., 2012). In the following, we use ME as an umbrella term that is agnostic to causes, focusing on causes and their interaction in neural network models only.

Previous models of cross-situational learning that evaluate novel word comprehension include probabilistic and connectionist approaches (e.g., Ichinco et al. 2008; Frank et al. 2009; Alishahi et al. 2008; Fazly et al. 2010; McMurray et al. 2012; see Yang 2019 for a recent overview on cross-situational models). However, these models are not easily scalable to large lexicons, nor can they directly ground word learning on more naturalistic data, e.g., images. By contrast, several scalable NN models that can learn word representations from aligned language-image data in cross-situational settings have been proposed (e.g., Synnaeve et al., 2014; Kádár et al., 2015; Lazaridou et al., 2016; Chrupala et al., 2015; Harwath et al., 2018). None of these studies, however, evaluates models on novel word reference with distractors: the classic setup in which children were put to the test. Similarly, little attention has been paid to the disentanglement of word learning and referent selection in NNs when it comes to mutual exclusivity. That is, to the evaluation of consequences and desirability of mutual exclusivity as part of a network’s training; as a part of its referent selection criterion; or as a combination thereof.

Closer to our present efforts, Gandhi and Lake (2019) evaluate NN models on training-induced tendencies toward one-to-one mappings. Their findings suggest that common deep learning algorithms exhibit a learning behavior contrary to ME, tending to associate novel input to frequent and familiar output. They argue this to be an ill fit to machine learning tasks, such as translation or classification, where instead a tendency toward ME is desirable. While largely sharing Gandhi and Lake’s (2019) motivations, the present study instead aims to provide a differentiated analysis of ME and how it can be brought about by interactions of training and referent selection criteria. In a complementary fashion, recent work by Zarrieß and Schlangen (2019) is similar to ours in that it uses Bayesian pragmatics in the context of novel reference selection in complex scenes with natural images. By contrast, however, they focus on the generation of referring expressions for unseen objects; modeling speakers’ probabilities using listeners’ beliefs. Their investigation also does not hone in on the consequences that particular learning processes can have on pragmatic refinements operating on what is learned, as we do.

3 Models

Our goal is to study referent selection when prompted by a novel word as a function of learning and selection mechanisms. We now introduce these components.

3.1 Word learning

For our models, an input data point is a set of (potentially referring) words, \( W \), and a set of objects in a scene, \( S \). We follow a common approach to train neural similarity models to simplify the optimization problem in cross-situational setups: we align all possible pairs of words and objects in the scene independently (as, e.g., in Lazaridou et al., 2016). The training input is then a set of all word-
object pairs, \(\{\langle w, o \rangle \mid w \in W, o \in S\}\). This is a simplification in the sense that the model does not take into account the relation between objects in a shared scene.

Similarities between objects and words – their learned association – are computed from their encodings into a shared hidden space:

\[
\begin{align*}
  w &= E(w), \\
  o &= V(o), \\
  sim &= \cos(w, o),
\end{align*}
\]

where \(E\) is an embedding of word \(w\) and \(V\) is a visual encoder of object \(o\).

A similarity model like (1) can be optimized in various ways. In particular, the values of \(\cos(w, o)\) will depend on a model’s loss function objective. We implement three classes of objectives using max-margin loss.\(^1\) They correspond to three major categories of learning constraints found in cross-situational word learning models. They either induce (a) competition among words, imposing a soft “an object maps only to one word”-constraint (e.g., Frank et al., 2009; Nematzadeh et al., 2016); or (b) competition among referents, i.e., an “a word maps only to one object”-constraint (e.g., Lazari-dou et al., 2016; Fazly et al., 2010; Nematzadeh et al., 2016); or they (c) induce competition over words and referents, equivalent to favoring one-to-one word-object mappings (e.g., McMurray et al., 2012; Synnaeve et al., 2014). Intuitively framed, (a) is an anti-synonymy bias, (b) is an anti-polysemy bias, and (c) is a combination of both. We implement these constraints as:

**Anti-synonymy: Max-margin over words**

\[
L_w = \sum_i \max(0, 1 - \cos(w, o) + \cos(w_i, o)),
\]

where word \(w_i\) is a negative example, sampled randomly. While similarity between the target word and the object is increased, the similarity between negative example words and the object is decreased. For example, a positive example of word *puppy* used to name referent *DOG* will increase their association. All the while, the association ofDOG with, say, negative example words *kitty* and *kite* decreases. In the limit, this leads to competition among all words. In our example: *puppy*, *kitty* and *kite* stand in competition for being associated with a referent (here: DOG). Probabilistic models that learn \(p(w \mid o)\) similarly enforce competition over words: An increase in the probability of word *puppy* given referent *DOG* decreases the probability of other words “competing” for this referent.

**Anti-polysemy: Max-margin over objects**

\[
L_o = \sum_i \max(0, 1 - \cos(w, o) + \cos(w, o_i)),
\]

where object \(o_i\) is a negative example, sampled randomly. In analogy to anti-synonymy, this leads to competition between objects. In the case of a positive example of *puppy* and referent *DOG*, it effects an increased association between them; whereas that of *puppy* and, e.g., negative referent examples *CAT* and *KITE* decreases.

**One-to-one: Joint loss**

\[
L = L_w + L_o.
\]

The combination of both losses implies competition over both words and objects, encouraging one-to-one-mappings. For instance, the connectionist model of McMurray et al. (2012) applies such a constraint via a sparse representation of a shared hidden space, where each hidden unit competes with other units through lateral inhibition. This model thereby learns one-to-one mappings between word types and hidden units, and between referents and hidden units.

### 3.2 Negative sampling

Negative sampling plays a crucial role for our models: both in the acquisition of their word-referent associations and, consequently, for how they select novel referents. Our motivations are two-fold. First, a well-defined learning objective not only requires that a correct answer has a low loss value but also that incorrect answers have high(er) loss values. Second, although alignments between novel referents and novel words are, by definition, never observed during training, we nevertheless allow for novel items – words or objects, depending on the loss objective – to appear as negative examples. This is important as, otherwise, their relation to

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\(^1\)One common alternative to max-margin loss for discrete spaces is cross-entropy over softmax classification. We focus on max-margin loss because it is more generally applicable. It is a common choice for non-discrete spaces, such as images and speech, because it does not require a discrete vocabulary or set of objects (e.g., Harwath et al., 2016). Exploratory experiments using softmax for the symbolic dataset, introduced below, yielded the same qualitative trends as those obtained from max-margin optimization.
other items would solely be determined by their (typically random) initialization. Accuracy on referent selection, novel or not, presupposes a minimal degree of discriminatibility, both between words and between objects. Using negative examples is one way to encourage models to discriminate items, even when not learning a particular association for them (as is the case for novel ones). We return to this issue and discuss alternatives in Section 5.

3.3 Referent selection

Once similarity values are learned the models can be put to the test. To better trace independent and joint effects that learning and referent selection criteria can have on novel word comprehension, we consider two selection mechanisms: matching by only similarity and Bayesian inference.

Referent selection as similarity match. A straightforward strategy to pick a referent is to always choose the one that most closely resembles the representation of the word $w$ received. In other words, choosing the object with the highest similarity to the word out of all objects in scene $S$:

$$o^* = \arg\max_{o \in S} \cos(w, o).$$

In probabilistic terms this is equivalent to choosing the object in the scene that maximizes $p(o \mid w)$. Note that for novel words to be most similar to novel objects, as success in ME-tasks with novel words would have it, the similarity between a novel word and familiar objects should be lower(er). In other words, this selection strategy’s success hinges on how (dis)similar a model perceives a known object to be to a novel word, relative to a novel object. We therefore expect performance when matching by highest similarity to be sensitive to the object in the scene that maximizes $p(o \mid w)$.

Referent selection as Bayesian inference. The second criterion we consider is in the spirit of (probabilistic) pragmatic reasoning (Grice, 1975, 1989; Halberda, 2006; Frank and Goodman, 2012; Franke and Jäger, 2014). Intuitively, the models “reason” that, if the speaker intended to refer to an object with a known name, she would have used that name. Since she did not, but instead used a novel label, she must mean the unfamiliar object.

This idea of modeling interpretation as an inversion of production in goal-oriented language use has received much recent attention at the interface of experimental pragmatics and cognitive modeling. This is due both to these models’ theory-driven foundations as well as to their success in capturing varied linguistic phenomena (e.g., Frank and Goodman, 2012; Franke and Jäger, 2014; see Goodman and Frank, 2016 for an overview of applications). However, they have mainly been applied to small and discrete symbolic domains (though see Monroe and Potts, 2015; Andreas and Klein, 2016; Monroe et al., 2017; Zarrieß and Schlangen, 2019).

In line with the motivations behind this family of pragmatic Bayesian models, we approximate referent choice as pragmatic inference for our neural models. The choice of the most likely referent from all objects in a scene, $o \in S$, given word $w$ can be written as $\arg\max_{o \in S} p(o \mid w, S)$. In models of rational language use, $p(o \mid w, S)$ is construed as capturing listener probabilities: the likelihood of a listener interpreting $w$ as $o$ in $S$. Due to the sparsity of actual observations for all potential scenes $S$, such listener probabilities are hard to model computationally. However, we can calculate them through their inverse, the speaker probability, using Bayes’ rule:

$$p(o \mid w, S) \propto p(w \mid o, S)p(o \mid S)$$

We make two assumptions to approximate the left-hand expression. First, we assume that the label used for an object depends only on itself and not on the other objects present in a scene. This is a simplification: Linguistic choice can certainly vary as a function of other objects present in a scene. For instance, in a scene with two dogs, of which one is a Rottweiler, a speaker may prefer to say Rottweiler instead of dog (Ferreira et al., 2005; Graf et al., 2016). Second, we assume the prior over objects in a scene to be uniform, $p(o \mid S) = 1/|S|$. In naturalistic scenarios, speaker goals and contextual saliency can certainly skew this distribution. However, this assumption minimally holds true for the experimental conditions in which children are often tested in, which is the kind of scenario we restrict ourselves to here (see Brochhagen 2018§3.2 for discussion). With these provisos, the right-hand side of (3) simplifies to $p(w \mid o)$. Referent selec-
We evaluate model performance of all possible pairs with children, we construct test scenes including words that could have been uttered to refer to each word in a scene. Referent selection as Bayesian inference, in (4), additionally factors in alternative words that could have been uttered to refer to each object.

\[ o^* = \arg \max_{o \in S} p(w \mid o). \tag{4} \]

The speaker probability \( p(w \mid o) \) is obtained from the similarity values learned by our neural models, by normalizing \( \cos(w, o) \) over all words in the vocabulary given object \( o \):

\[ p(w \mid o) = \frac{\cos(w, o)}{\sum_i \cos(w_i, o)}. \tag{5} \]

Previous computational approaches, in particular Alishahi et al. 2008 and Fazly et al. 2010, have also exploited \( p(w \mid o) \) to model performance on novel word reference tasks (see also Frank et al., 2009). However, the motivation to do so in the context of novel word reference was not clear. By contrast, we just provided an explicit derivation of mutual exclusivity, construed as a selection criterion, using Bayesian inference. It clarifies how \( p(w \mid o) \) is related to ME and builds on theory-driven probabilistic pragmatic models.

To recapitulate, referent selection as similarity match, in (2), picks the candidate referent that most closely resembles the representation of a given word in a scene. Referent selection as Bayesian inference, in (4), additionally factors in alternative words that could have been uttered to refer to each object.

### 4 Experiments

We evaluate model performance of all possible learning–selection combinations introduced in Section 3. That is, models are trained with max-margin loss over objects, words, or both; and select referents either by similarity or Bayesian inference.\(^2\) In analogy to experiments on novel referent selection with children, we construct test scenes including one novel object and several familiar objects, the latter being observed during training. Task success is defined as selecting the unfamiliar referent when prompted by a novel word.

We employ two datasets. The first is a symbolic dataset of annotated child directed speech (Frank et al., 2009), enabling for a baseline comparison to previous models (Lazaridou et al., 2016) and for a comparison of the models from Section 3 in a well-understood, if artificial, setting. The second is the Flickr30k Entities dataset (Young et al., 2014; Plummer et al., 2015), which comprises images and associated captions. Using images allows us to assess whether the trends that obtain for symbolic data can translate to larger corpora, as well as whether they do so for the, arguably more natural, problem of discriminating and selecting objects found in images.

Model hyperparameters were determined using random search over a set of learning rates; a set of initialization ranges for word and object embeddings; and hidden dimension sizes (see Appendix A for details). We evaluate models at their lowest loss after a maximum of 20 epochs, using stochastic descent. One could worry that evaluating models at their least training loss could lead to overfitting. However, note that optimizing the loss function does not imply optimizing model accuracy on referent selection because the objective we use is cross-situational. Moreover, training includes no positive examples of alignments between novel words and objects. Lastly, models evaluated after a single epoch exhibited the same general trends as those reported below.

### 4.1 Symbolic dataset

**Data.** Frank et al.’s (2009) data comes from two transcribed recordings from the Rollins section of CHILDES (MacWhinney, 2000). It comprises 620 utterances with around 3800 tokens. Utterances are annotated with objects present at speech time, e.g., \( W = \{ \text{get}, \text{the}, \text{piggie}, \text{the bunnies} \} \) and \( S = \{ \text{PIG}, \text{COW} \} \), respectively, for words and objects in a scene. A gold lexicon provides the correct alignments between 22 objects and 36 word types, including some “synonyms” (\textit{bunny}, \textit{bunnies}). We report our results on two training setups: on the dataset with all words and on a subset of the corpus consisting only of referring words (as annotated in the gold lexicon). These two training datasets contain a total of 620 and 184 scene data points respectively. There is a mean of 4.1 words (1.05 referring words) and 2.4 objects per scene.

**Evaluation setup.** For familiar word comprehension, we follow previous work (Frank et al., 2009; Lazaridou et al., 2016) and report Best F-scores between the gold lexicon and the one learned by the models, constructed by including all word-object pairs with a similarity score above a threshold, picking the best such threshold. F-scores are computed

\[^2\text{All models were implemented and trained using PyTorch (Paszke et al., 2017). They will be made publicly available upon acceptance.}\]
Table 1: Mean Best F-scores and standard deviations across max-margin objectives in 25 experiments, as well as F-Scores reported in Lazaridou et al. 2016.

| Loss         | Ref. words | All words |
|--------------|------------|-----------|
| over words   | .68 (.02)  | .65 (.02) |
| over objects | .75 (.02)  | .71 (.01) |
| joint        | .69 (.01)  | .68 (.03) |

Lazaridou –visual (shuffled) .65
Lazaridou +visual .70

at type level, we therefore weight the max-margin loss computed for each target token (word or object) by its inverse frequency in the corpus.

In order to test performance on novel items, we added five novel words to the vocabulary (dax1,..., dax5). Accuracy scores come from evaluations of 20 test scenes per novel word. Each such scene includes one novel object and two uniformly sampled familiar objects, drawn from the set of objects that models were trained with. For example, a prompt with novel word dax1 could be evaluated in scene {CAT, COW, DAX1}.

Results. As shown in Table 1, our models achieve very good Best F-scores on both variants of the symbolic dataset. They are around the range of those obtained by Lazaridou et al. (2016) even though our models do not consider relations between words nor rely on visual information. However, as showcased next, F-scores are not indicative of how well models fare on our main task of novel referent selection.

Mean accuracies on referent selection with novel items for both symbolic dataset variants are shown in Figure 1. In a nutshell, Bayesian inference always presents an improvement over picking by similarity only, but this improvement’s magnitude hinges on the loss’ objective. If competition over words is already encouraged during learning (here: with an anti-synonymy bias) then picking by similarity only is a viable, though suboptimal, selection strategy.

A comparison of Bayesian inference when training with max-margin loss over words against one over objects additionally shows that, if competition over words is enforced through a referent selection mechanism, then learning with a complementary bias against polysemy can be as or even more useful than imposing the constraint in both training and selection.

4.2 Visual dataset: Flickr30k Entities

Data. Flickr30k (Young et al., 2014) contains images with crowd-sourced descriptions. Its augmentation, Flickr30k Entities (Plummer et al., 2015), additionally provides annotated bounding boxes that link objects to their referring expressions. We pre-process Flickr30k Entities to extract word-object annotations. For each referring expression in a caption, e.g., a smiling person, we take the last word (person) as the linked object’s label.

The visual features of each object (bounding box) are then pre-computed using a convolutional neural network VGG16 model trained on ImageNet (Simonyan and Zisserman, 2015). We process the bounding box region of the object scaled to 224 × 224 pixels and take the output of the last layer of the model, which is a 1000-dimensional vector.

Each image is treated as a scene. This yields a natural co-occurrence distribution of objects to be used for our cross-situational setup. There are a couple of important differences to the previous dataset. First, one word can refer to many instances of the same concept represented as different objects across images. The symbolic dataset did not harbor this kind of ambiguity. Second, object embeddings are initially determined by the pre-processed VGG16 vectors rather than, as previously done, randomly initialized. Third, images can have up to

\[\text{a smiling person with Mohawk hairstyle}\]

are annotated as two separate referring expressions aligned with different image regions.

Figure 1: Mean accuracy on novel referents in 25 experiments per condition, with random baseline (.33) as dashed line. Means, from left to right and top to bottom: [.87, .37, .67] (all words, similarity); [.9, .8, .78] (all words, inference); [.72, .36, .73] (ref. words, similarity); and [.79, .67, .75] (ref. words, inference).
five different descriptions. We treat the resulting word-object alignments as independent data points.

We excluded objects that span more than one bounding box, typically referred to by plurals, as well cases in which one object’s bounding box contained another one’s. This results in 29782 images, a vocabulary of 6165 referring words, and a total of 130327 data-points, with a mean of about 2.22 objects per scene.

Evaluation setup. For experiments on Flickr30k, we restrict our evaluation of both familiar and novel words to accuracy on referent selection since there is no gold lexicon to benchmark against. We exclude scenes containing only one candidate referent to avoid trivial solutions.

We let dogs be a surrogate category for novel items. That is, where children would see unfamiliar objects in an otherwise familiar array and be prompted with an unfamiliar word, our models are trained without encountering positive examples of dogs nor of words used to refer to them (e.g., *dog, dogs, puppy, retriever, shepherd, corgi, pug, collie* or *spaniel*). We then evaluate the models on images containing dogs, such as the one shown in Figure 2.

The particulars of this setup and the choice of any single existing category as a stand in for a novel one certainly affects the results that follow. Our choices are motivated by wanting to retain the integrity of images as natural scenes; and by practical considerations, such as dogs appearing frequently enough in the data to ensure that a variety of different kinds of scenes with different numbers of objects are evaluated.

| Loss       | Similarity | Inference |
|------------|------------|-----------|
| over words | .65        | .65       |
| over objects | .62      | .62       |
| joint      | .64        | .64       |

Table 2: Mean accuracy of 30 experiments per condition on items seen as positive training examples (mean random baseline: .42; SD < .009 for all conditions).

Results. We report performance on both familiar and novel items. Table 2 shows results obtained when evaluating referent selection using only words and objects that appeared as positive cases in training. The low deviation across experiments suggests that all models have comparable endpoints, with models that enforce anti-synonymy slightly outperforming those trained with max-margin loss over objects. Note also that different ways of selecting referents do not impact accuracy when models are sufficiently trained. In other words, acquired word-meaning associations are refined enough after training, leaving no room for Bayesian inference to further improve on them.

As shown in Figure 3, things are different for novel items. In a similar fashion as in the symbolic case, Bayesian inference offers a major advantage over choosing referents by highest similarity to models trained with loss over objects only. When choosing by similarity only, performance is about random for models with only an anti-polysemy learning bias.

There are two main differences from the symbolic case, however. First, Bayesian inference confers no advantage to models that learned with anti-synonymy. By contrast, it did provide some, albeit small, edge to models evaluated on symbolic data. Second, in the visual case, anti-polysemy can be helpful. This is suggested by both the better mean performance of models learning with max-margin loss over objects that use Bayesian inference to that of models learning with only max-margin loss over words; as well as by the stark success of models trained with joint objectives compared to those trained only with max-margin loss over words. More succinctly put, while max-margin loss over objects conferred no clear advantage in our symbolic experiments, it did so for the visual ones.

To understand the positive effect of anti-polysemy for this set of experiments, let us first address another result particular to Flickr30k: the contrast of deviances across max-margin objectives.
This difference can be traced back to the consequences of the refinements they effect. Recall that max-margin loss over objects aligns a positive example of a word-object pair while separating this word from negative object examples. That is, with max-margin over objects, referents seen as positive examples and referents seen as negative ones are pulled apart. This loss objective thus leads to improved object discriminability. Since word discriminability is not directly improved upon, however, the performance of models with only an anti-polysemy bias is sensitive to the random initialization of (novel) word embeddings. This leads to large variations in performance across experiments. By contrast, since visual embeddings were not initialized randomly but pre-trained, no such deviance is observed for losses that improve only word discriminability during learning.

The answer to the question of what can make anti-polysemy advantageous is then that it improves object discriminability; the amount of objects and their close resemblance being a major difference between the symbolic dataset and Flickr30k Entities. Nevertheless, learning to discriminate words remains pivotal to our task. As a consequence, the joint objective, profiting from both increased object and increased word discriminability, outperforms either individual loss objective.

5 Conclusion

Our results suggest that novel word comprehension can be achieved with scalable models with continuous representations and conventional learning algorithms. A core requirement for this to happen is to induce competition over words: either during learning, through a constraining loss objective, or during referent selection, through pragmatic-like reasoning. This requirement mirrors broader patterns found in natural language: While the existence of true synonyms is highly contested (e.g., Goodman, 1949; Quine, 1951), there is little doubt in the fact that polysemy abounds (Santana, 2014; Rzymski et al., 2019).

Although, in principle, anti-polysemy is not required for success on ME (contra, e.g., Gandhi and Lake 2019) our results on visual data paint a more nuanced picture. They show that, while anti-synonymy alone can lead to moderate success on this difficult task, a training regime that encourages task-specific discrimination of objects (here: the visual domain) can further improve on it. Plainly put, models profit from better discriminating the objects they will be tasked to keep apart. For ME, this means better discriminating novel objects, appearing as negative examples, from positive word-object associations established during training. Models learning only with an anti-synonymy bias have to make do with what pre-processed visual embeddings give them to work with. More broadly and domain-independently, items need to be recognized as novel; or, conversely framed, not be confused with other items. One way to encourage such discrimination is through negative examples, as done here. A different strategy is to manipulate their initialization as a function of the task and data at hand. This is akin to having special slots for novel items. We hope the specifics of such a manipulation and its comparison with the kind of “acquired discrimination” we investigated here to be addressed in future research.

Taking stock, different learning and selection combinations can yield ME-like behavior. Irrespective of the locus of such mechanism, the association of novel words with novel referents is enabled through competition among words; intuitively framed, a bias against absolute synonymy. Here, this bias took the form of either max-margin loss over words or an approximation of Bayesian inference over word-alternatives for referents present in a scene, inspired by pragmatic reasoning. More broadly, our results highlight the importance of evaluating word learning models on more complex and varied datasets since trends observed on small symbolic data do not necessarily scale up to visual features and large lexica.
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### Table 3: Model hyperparameters.

|            | Symbolic | Visual |
|------------|----------|--------|
| hidden size| 200      | 200    |
| learning rate | 0.5    | 0.5    |
| weight decay | 0.0     | 0.0    |
| word init range | 0.01  | 0.1    |
| object init range | 0.5    |        |

A Hyperparameter search

Hyperparameters were determined using random search over a set of learning rates; a set of initialization ranges for word and object embeddings; and a selection of hidden dimension sizes. An initial, wider, search indicated that some hyperparameters varied across datasets, but not across max-margin objectives. We therefore conducted two separate searches, with values informed by this first search.

For the symbolic dataset, we performed a random search (250 models) over learning rates (sampled uniformly from \([0.001; 0.5]\), weight decays (sampled uniformly from \([0; 0.1]\) with 0 manually added and checked against all other parameters), symmetric word initialization ranges (sampled uniformly from \([0.01; 1]\)) and symmetric object initialization ranges (sampled uniformly from \([0.01; 1.0]\)). All parameter configurations obtained in this manner were evaluated with hidden dimension sizes of either 200 or 300.

For the visual dataset, we performed another random search (250 models) over learning rates (sampled uniformly from \([0.05; 2]\), weight decays (sampled uniformly from \([0; 0.1]\) with 0 manually added and checked against all other parameters), and symmetric word initialization ranges (sampled uniformly from \([0.01; 1]\)). All parameter configurations obtained in this manner were evaluated with hidden dimension sizes of either 200, 300, or 400.

We chose parameters after training for 10 epochs – selected based on stable tendencies relative to training with 1, 5 or 20 epochs – according to least loss. The resulting parameters are shown in Table 3.