

A large-scale comparison of cross-situational word learning models

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Abstract

One problem faced by language learners is how to extract word meanings from situations that often present many possible referents. While a word's meaning may be ambiguous given any one scene, a large body of empirical work has found that people are able to learn cross-situationally across multiple occurrences of a given word under many experimental manipulations. There has been correspondingly much interest in modeling such learning, and yet there is little consensus on the main mechanisms underpinning cross-situational word learning. The lack of consensus is in part due to the large number of disparate studies and models, and lack of systematic model comparisons across a wide range of studies. This study seeks to remedy this, comparing the performance of several extant cross-situational word learning models on a dataset consisting of 1,696 participants spread across 44 experimental conditions. Using cross-validated parameters, we fit multiple models representing theories of both associative learning and hypothesis-testing theories of word learning, find two best-fitting models, and discuss issues of model and mechanism identifiability. Finally, we test the models' best-fitting parameters ability to generalize to a set of additional experiments, including developmental data.

Keywords: cross-situational word learning; model comparison; language learning

Introduction

Learning word meanings is a crucial aspect of the process of language acquisition. If a learner's task is to connect the words they hear to the potential referents and eventually to generalizable meanings, the challenge appears formidable (Quine, 1960): words are heard in rich and cluttered contexts. Yet children learn words very quickly. How do they do this?

An array of social (Yurovsky & Frank, 2017), pragmatic (Clark, 1987; Markman, 1992), and linguistic (Gleitman, 1990) cues are often available to reduce a learner's uncertainty. Yet at its heart, these information sources can be seen as reducing the uncertainty inherent in the task of *cross-situational mapping* (Frank, Goodman, & Tenenbaum, 2009): that is, cross-referencing which referents a word has consistently appeared with across multiple uses (Carey & Bartlett, 1978; Gleitman, 1990). If learners are able to learn cross-situationally, then they might be able to pool information about reference (and hence about word meaning) over time and learn even in the absence of perfectly disambiguated input in any particular situation. Can children (or even adults) learn in this way?

The general idea of cross-situational word learning has been adopted into a variety of experimental paradigms for

testing the word learning ability of infants (e.g., Smith & Yu, 2008; Vlach & Johnson, 2013), children (e.g., Akhtar & Montague, 1999; Suanda & Namy, 2012; Vlach & Sandhofer, 2012), and adults (e.g., Yu & Smith, 2007; Smith, Smith, & Blythe, 2011). In such experiments, participants are typically presented with a series of training trials comprised of multiple possible referents (e.g., an array of 2-4 novel objects) and one or more spoken nonce words, and (when possible) instructed to learn the meaning(s) of the presented words. These training trials typically present 10–20 distinct word-referent pairs to be learned across 10–50 trials, presenting each word/referent 3–10 times across a total span of < 10 minutes. Learning is then typically assessed by presenting each word and asking learners to make a forced choice of the best referent, either from the entire set or from a small subset of referents.

People of all ages are able to learn word-object mappings in such paradigms at a level significantly above chance, but their performance is typically far from perfect in all but the most trivial versions of the task (Yurovsky & Frank, 2017). Numerous training manipulations have been found to influence performance. How often mappings are presented (Kachergis, Yu, & Shiffrin, 2016; Suanda & Namy, 2012), the interval between appearances of a mapping (Vlach & Johnson, 2013; Vlach & Sandhofer, 2012), and the number of mappings presented per trial (Yu, 2008) all have been shown to affect learning performance. In sum, the evidence is strong that people can learn word cross-situationally: we are somehow able to integrate evidence (co-occurrence of words and objects) across trials and use that evidence to learn and remember new word meanings in cross-situational learning experiments. But what are the psychological mechanisms supporting this process? And critically, do these mechanisms support naturalistic word learning?

Computational models provide one strategy for instantiating proposals about mechanism. Such models can then be applied to naturalistic data to make a first assessment of whether cross-situational learning could be a viable strategy for word learning “in the wild”. Accordingly, there has been great interest in creating and testing computational models of this task. These models often represent distinct intuitions of how learning operates, variously representing the learning problem as logical inferencing (e.g., Siskind, 1996), proposing and testing hypotheses (e.g., Trueswell, Medina, Hafri, & Gleitman, 2013), or accumulating graded associa-

tions (e.g., Fazly, Alishahi, & Stevenson, 2010; Kachergis, Yu, & Shiffrin, 2012; Tilles & Fontanari, 2012). Extant cross-situational word learning models are too numerous to review exhaustively here.

It is unknown which of these models – or even which broad class of models – best fits the breadth of experimental data. While most models of cross-situational learning have typically been tested against at least a few datasets, to our knowledge there has been no systematic comparison of models across a wide variety of experimental conditions. Identifying the model or models that best predict human performance is thus an important goal for consolidating this broad literature. More broadly, identifying such models could be an important step in assessing the contribution of cross-situational learning to word learning more generally.

Thus, the goal of our current study is to test the ability of a range of cross-situational word learning models in accounting for a wide range of experimental data. Our goal is to scale up both the number of models evaluated and the number of experiment designs (and participants) being used for evaluation. Different models often contain a range of parameters that must be fit to data, an issue that has hindered previous comparison work, either because the parameters have been allowed to vary freely across multiple conditions, or because models’ performance is compared on different datasets. Thus, we focus on out-of-sample prediction of human data using cross-validated parameter fits. We end by examining qualitative results from true out of sample generalization of models to experiments not included in the initial evaluation and parameter fitting.

Method

Procedure

In a nutshell, our goal is to fit a set of models to a set of datasets; members of each of these sets are listed below. Each model typically is defined as a function that takes input data and a group of parameter values (often between 2–4) and then can be evaluated on test trials (typically multi-alternative forced choice test). Each model then returns predictions on each test trial, which can be scored against the “correct” (intended by the design) answer and averaged to produce an analogue to human performance. Our primary outcome measure is the correlation between each model’s performance for each item in a specific experimental condition and item-level human performance on that same experimental condition.

Although input data and test trials are features of specific experimental tests, each model has parameters that must be specified. Typically the settings of these parameters are critical to the predictive performance of the model. Hence, to ensure a fair comparison between models, these parameters must be fit to data. In all cases, we optimize parameter values to minimize the sum of squared error (SSE) between model and human performance, weighting the contribution of each condition’s SSE by the number of participants in that condition. We optimize parameters using differential evolution via the DEoptim R package (Mullen, Ardia, Gil, Windover, &

Cline, 2011). For the stochastic models, each parameter setting was evaluated using a simulated sample of 200 learners.

We conducted two evaluations of models. First, we use cross-validation across conditions to reduce overfitting. We optimize each model’s parameters by leaving out data from 20% of conditions to test generalization via optimization on the initial 80% (5-fold cross-validation). Second, in the *group fit* regime we fit each model to all conditions and datasets to produce a single best-fitting parameter set per model. We then evaluated the correlation between these fitted models and the same data they were fit to. This evaluation thus makes maximal use of our data but incorporates some amount of overfitting. However, it allows us to make the best test of generalization to a selection of other experiments from the literature for which we do not have item-level accuracy.

Models

We fit a baseline co-occurrence model along with six associative models, two hypothesis-testing models, and two hybrid models that store multiple, graded hypotheses—but only a subset of all possible associations. These models and their free parameters are briefly described below.

Baseline Co-occurrence Model The baseline model simply tallies the co-occurrences of any words and objects appearing together on each trial, accumulating the counts in a word \times object matrix M . At test, for word w_1 this model selects the correct referent o_1 according to Luce choice from the co-occurrences of w_1 with all referents: $P(o_1|w_1) = M_{w_1,o_1} / \sum M_{w_1,\cdot}$. The model’s probability of correctly choosing each word per condition is what is scored against people’s average probability of choosing the correct item.

Probabilistic Associative Model (PA) The probabilistic associative model (Fazly et al., 2010) represents the meaning of each word w as a probability distribution $p(\cdot|w)$ over the objects appearing across the trials, and incrementally learns these distributions trial-by-trial. The association between a given w and o grows more quickly if $p(w|o)$ is already high (a familiarity bias), unless some other word has a strong association with o ; thus, associations are competitive. A parameter λ is a small smoothing constant added to both the numerator and denominator of each $p(w|o)$, further adjusted in the denominator by a β parameter representing the upper bound on the number of symbol types. At test, the correct referent for each word w is chosen according to Luce choice from the probability distribution over the objects that appeared with that word $p(\cdot|w)$.¹

Familiarity- and Uncertainty- Biased Model (FU) The familiarity- and uncertainty-biased associative model (Kachergis et al., 2012) assumes that learners associate all presented words with all visible objects to some extent, but that they selectively attend more to some of the presented

¹The original model implemented a θ -thresholded lexicon that discretized the probability matrix, but we found that including this mechanism (and additional parameter) resulted in a worse fit to the data.

word-object pairings. Specifically, greater attention is directed to pairings that have previously co-occurred (a familiarity bias), but is also directed to stimuli that have no strong associates, tracked via the entropy (H) of their association strengths (e.g., novel stimuli, or stimuli that have diffuse associations with several stimuli). Thus, the model grows its association matrix as it experiences each trial, dynamically apportioning a fixed amount of associative weight (learning rate χ) among the possible word-object associations, with the relative weight of the familiarity bias and the uncertainty bias determined by parameter λ . Finally, all association strengths decay from trial to trial at a rate controlled by parameter α .

The update rule for adjusting the association $M_{w,o}$ between a given word w and object o on a given trial is:

$$M_{w,o} = \alpha M_{w,o} + \frac{\chi \cdot e^{\lambda \cdot (H(w) + H(o))} \cdot M_{w,o}}{\sum_{w \in W} \sum_{o \in O} e^{\lambda \cdot (H(w) + H(o))} \cdot M_{w,o}} \quad (1)$$

At test, given word w learners use Luce choice, choosing referent o from the m given alternatives in proportion to associative strength $M_{w,o}$.

We also fit a stochastic *sampling* version of this model (see Kachergis & Yu, 2017), which uses the same update equation, but instead of updating all possible word-object associations samples only a single presented object for each word on a trial. This sampling version of the Kachergis model can still build multiple graded associations for each word (or object), but on any given run will accumulate only a sparse, randomized version of what the full associative model would build.

Strength- (S), Uncertainty- (U), and Novelty-Biased (N) Models We also test three variations on the Kachergis et al. model that use only a subset of the mechanisms of the full model in order to understand the contributions of each mechanism. The *strength model* lacks the uncertainty bias term, and thus only implements a bias for familiar (i.e., already-strong) associations, with learning rate (χ) and decay α parameters.

The *uncertainty model* lacks the strength bias term, and thus only implements a bias for stimuli with uncertain (high-entropy) associations. The *novelty model* lacks the strength bias term, and substitutes novelty for the entropy terms (e.g., $1/(\text{frequency}(w)+1)$ instead of $H(w)$). These models still have all three parameters of the original Kachergis model, and at test operate in the same way as the original model.

Bayesian Decay Model (BD) This previously-unpublished model updates the $p(w|o)$ and the joint probability $p(w,o)$ from trial to trial according to a likelihood function that reinforces the association between w and o when they co-occur (scaled by parameter δ), and penalizes all associations that are not occurring on the trial (scaled by parameter α). Thus, in contrast to other incremental associative learning models considered here (e.g., Fazly and the Kachergis class of models), this model globally updates the entire association matrix on each trial – both co-occurring pairs and non-co-occurring pairs, and re-normalizes the tracked probabilities at each time step. At test, this model uses a softmax choice rule with pa-

rameter τ to select the best referent for each word from the presented alternatives.

Rescorla-Wagner Model (RW) This associative model is inspired by the prediction-error-based learning model of Rescorla & Wagner (1972). Objects on each trial serve as cues to predict which words will be heard. When a given word is heard, the associations between that word and each object on the trial are scaled at a learning rate β in proportion to the magnitude of the difference between the prediction and the maximum association value (λ). Each trial, the association matrix is subject to decay (parameter α). At test, this model uses Luce choice to select the best referent for each word from the presented alternatives.

Propose-but-Verify Model (PV) In the propose-but-verify hypothesis testing model (Trueswell et al., 2013), one of the presented referents is selected at random for any word heard that has no remembered referent. The next time that word occurs, the previously-proposed referent is remembered with probability α , a free parameter. If the remembered referent is verified to be present, the future probability of recalling the word is increased by ϵ (another free parameter). If the remembered referent is not present, the old hypothesis is assumed to be forgotten and a new proposal is selected from the available referents. This model implements trial-level mutual exclusivity by selecting new proposals only from among the referents that are not yet part of a hypothesis.

Guess-and-Test Model (GT) The guess-and-test hypothesis testing model is based on the description given by Medina, Snedeker, Trueswell, & Gleitman (2011) of a one-shot (i.e. “fast mapping”) learning, which posits that “i) learners hypothesize a single meaning based on their first encounter with a word, ii) learners neither weight nor even store back-up alternative meanings, and iii) on later encounters, learners attempt to retrieve this hypothesis from memory and test it against a new context, updating it only if it is disconfirmed.” We give this model two free parameters: a probability of successful encoding (s , hypothesis formation), and a probability f of forgetting a hypothesis at retrieval. At test, for each word the model chooses the currently hypothesized referent for that word.

Pursuit Model (P) The pursuit model (Stevens, Gleitman, Trueswell, & Yang, 2017) represents a hybrid approach, potentially storing graded associations involving a given word and multiple referents (or vice-versa), while on a given trial greedily pursuing the single strongest association for each presented word. If the strongest associated referent for a given word w is present on the trial, the association is strengthened at a rate determined by γ . If the strongest referent for w is not present, the association is weakened (scaled down by $(1 - \gamma)$) and the association with a random other available referent is strengthened. Novel words are given an initial association of strength γ with the available referent whose strongest association is the smallest, implement-

ing an uncertainty bias in forming associations for novel words. A given word-object association only enters the lexicon if $p(o|w) > \theta$, a threshold parameter. At test, this model chooses the best referent for each word by Luce choice from the lexicon, which may or may not have multiple referents associated with each word.

Data

The modeled data are average accuracies from 726 word-object pairs in 44 experimental conditions, in which a total of 1696 subjects participated. Table 3 shows a variety of characteristics of each experimental condition, including the number of trials (range: 18-108), the number of words and referents presented per training trial (1-4), the number of total to-be-learned pairs ($S_m = \$12-24$), the number of participants per condition, and the average accuracy and SD of performance. Most of these data have been previously published: data from 13 of the conditions were reported in Kachergis & Yu (2013), data from 12 conditions are from Kachergis et al. (2012), and data from another nine conditions are from Kachergis et al. (2016). However, data from several conditions are contributed by Chen Yu’s lab at Indiana University, and have never before been published. Each condition consists of an ordered list of training trials consisting of 1-4 words and 2-4 objects per trial. At test, participants heard each word and were asked to select the best referent from either all m presented objects (m -alternative forced choice; AFC), or from a subset (e.g., 4AFC). A table containing details of each condition is available on OSF: <https://osf.io/s2aty/>.

Results

Table 1 shows the sum of squared error (SSE) and correlation (r) for each model’s best-fitting parameters vs. average human performance on the 726 items, both for the CV fits and for the all-condition fits, along with the number of fitted parameters in each model (P). The results of the two fitting procedures yielded fairly similar SSEs and correlations, and a consistent rank-ordering of the models, with the Kachergis sampling model performing best, followed closely by the Fazly et al. model and then the associative Kachergis et al. model. The hypothesis testing models (Propose-but-Verify and Guess-and-Test) and the Pursuit model fit less well than the 0-parameter baseline co-occurrence counting model (not in the table), which had $SSE = 32.0$ and $r = 0.53$. Correlations between data and models are presented in Figure 1.

How related to each other are these models? Table 2 shows the correlations between model predictions made using the group-optimized parameters. These results are discussed below.

| Model | CV SSE | r | All SSE | r | P |
|-----------------|--------|------|---------|------|---|
| Kachergis samp | 17.74 | 0.74 | 17.76 | 0.74 | 3 |
| Fazly | 18.72 | 0.73 | 18.77 | 0.73 | 2 |
| Kachergis | 18.92 | 0.72 | 19.07 | 0.72 | 3 |
| Novelty | 22.02 | 0.67 | 22.01 | 0.67 | 2 |
| Uncertainty | 23.06 | 0.69 | 23.02 | 0.69 | 3 |
| Bayes decay | 23.95 | 0.62 | 23.71 | 0.63 | 3 |
| Rescorla-Wagner | 31.80 | 0.62 | 31.79 | 0.62 | 3 |
| Strength | 39.05 | 0.46 | 39.07 | 0.46 | 2 |
| Propose-Verify | 42.92 | 0.35 | 31.30 | 0.50 | 2 |
| Guess-Test | 43.01 | 0.32 | 31.92 | 0.48 | 2 |
| Pursuit | 49.33 | 0.31 | 46.75 | 0.35 | 3 |

Table 1: Cross-validated and group model fits.

| | Ks | PA | FU | N | U | BD | RW | S | PV | GT |
|----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| PA | .87 | - | - | - | - | - | - | - | - | - |
| FU | .92 | .84 | - | - | - | - | - | - | - | - |
| N | .87 | .79 | .87 | - | - | - | - | - | - | - |
| U | .82 | .81 | .83 | .74 | - | - | - | - | - | - |
| BD | .75 | .79 | .79 | .82 | .64 | - | - | - | - | - |
| RW | .51 | .58 | .50 | .50 | .47 | .56 | - | - | - | - |
| S | .83 | .84 | .78 | .79 | .80 | .70 | .67 | - | - | - |
| PV | .47 | .54 | .45 | .45 | .44 | .51 | .95 | .64 | - | - |
| GT | .60 | .59 | .60 | .74 | .53 | .67 | .53 | .65 | .45 | - |
| P | .41 | .47 | .39 | .43 | .35 | .52 | .58 | .49 | .53 | .58 |

Generalization Experiment Results

Using the parameters optimized to each model for all of the conditions, we simulate model performance for a selection of published experiments and compare to participants’ group-level performance for these conditions.

Discussion

We set out to conduct a systematic comparison of several models of cross-situational word learning models across a wide variety of experimental conditions. Using a database of 1696 participants in 44 conditions, we found best-fitting parameters for 11 different models under two different regimes: 1) simultaneously fitting all of the data, and 2) 5-fold cross-validation, testing generalization to the final 20% of conditions after training on 80% of them. The results of both fitting regimes were consistent and clear: shown in Table 1, the associative models achieved much better fits (lower SSE and higher correlation) than the hypothesis-testing models (Guess-and-Test; Medina et al. (2011) and Propose-but-Verify; Trueswell et al. (2013)), which made strongly-correlated predictions (see Table 1: .95). The hybrid Pursuit model (Stevens et al., 2017) fared even more poorly, in part because it often outperformed humans ($M_{mod} = 0.58$, $M_{hum} = 0.48$).

Among the associative models, the Fazly et al. (2010) model and the Kachergis et al. (2012) model both fare quite well, and the sampling version of the Kachergis et al. model

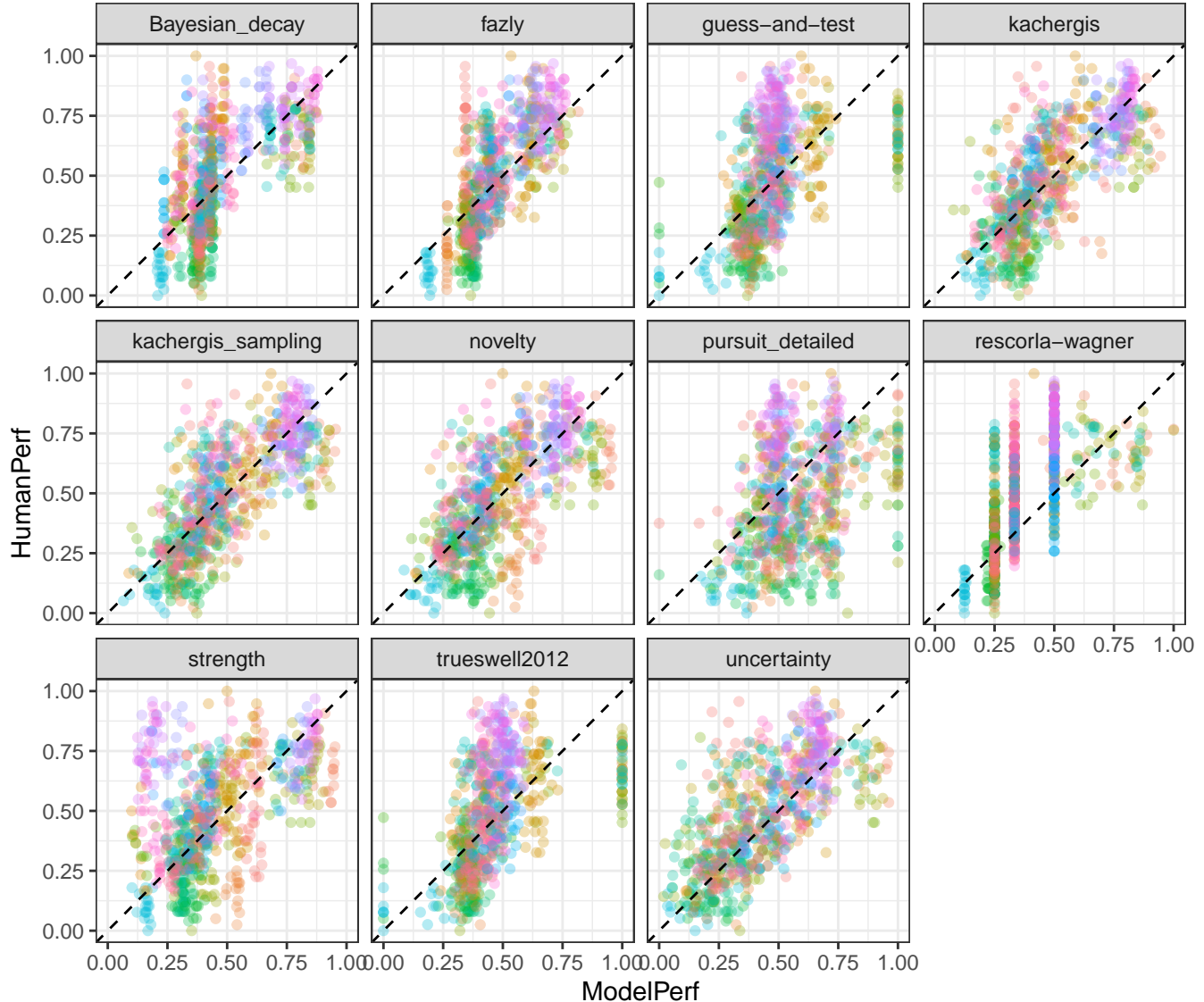


Figure 1: Human vs. model performance with a single best-fitting set of parameters for all conditions.

performs slightly better, albeit with 3 free parameters compared to 2 in the Fazly et al. model. The predictions of the top three models are more correlated with each other than with the human data (see Table 1): Fazly vs. Kachergis sampling: .87, Fazly vs. Kachergis: .84, Kachergis vs. sampling: .92. But the Fazly model also showed a .84 correlation with the Rescorla-Wagner model, and both Kachergis models showed a .87 correlation with the simpler novelty-biased associative model—stronger than for the uncertainty-bias mechanism used by these models.

The Kachergis and Fazly models make maximally divergent predictions in the conditions with fewer words than objects per trial (esp. 1x3, 1x3 6/18 4AFC, and 1x4), which hints at a difference in mechanism for these models and may guide the design of a new experiment to diagnose which is better able to account for human behavior.

Although we have aimed for broad coverage of models and

experimental conditions, this study is far from complete in both respects. First, there are many other models that we have not yet implemented (e.g., Tilles & Fontanari, 2012; McMurray, Horst, & Samuelson, 2012), or that we have not finished fitting to the data (e.g., Yurovsky & Frank, 2015). Moreover, this dataset represents performance from a fairly homogeneous sample: English-speaking US college students, mostly from a single midwestern university. Future work should aim to include not only more models, but a more broadly diverse sample, both in terms of language background and age. We enthusiastically invite other researchers to contribute datasets and model implementations for future, larger-scale comparisons.

In summary, we have shown not only how a large model comparison can help rank models from most to least able to account for human data, but also how such comparisons can identify models that mimic each other, as well as iden-

tifying experimental designs that might aid in distinguishing models. Future work should extend this comparison to cross-situational word learning models and extant datasets beyond those tested here, and design novel experiments designed to distinguish these models. Finally, assuming that cross-situational learning is an important tool in the language learner's toolbox, it is important to consider how these models can be extended to incorporate other information sources at the learner's disposal, such as social cues, pragmatics, and syntactic constraints on meaning (Hirsh-Pasek, Golinkoff, & Hollich, 2000; Markman, 1990; Yurovsky & Frank, 2017). While many of these models have mechanisms for preferentially selecting and storing particular associations, most have yet to formally incorporate relevant cues from social partners—linguistic and nonlinguistic (though see Yurovsky & Frank, 2017).

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References

- Akhtar, N., & Montague, L. (1999). Early lexical acquisition: The role of cross-situational learning. *First Language*, 19, 34–358.
- Carey, S., & Bartlett, E. (1978). Acquiring a single new word. *Papers and Report on Child Language Development*, 15, 17–29.
- Clark, E. V. (1987). The principle of contrast: A constraint on language acquisition. In B. MacWhinney (Ed.), *Mechanisms of language acquisition*. Hillsdale, NJ: Erlbaum.
- Fazly, A., Alishahi, A., & Stevenson, S. (2010). A Probabilistic Computational Model of Cross-Situational Word Learning. *Cognitive Science*, 34(6), 1017–1063.
- Frank, M. C., Goodman, N. D., & Tenenbaum, J. B. (2009). Using speakers' referential intentions to model early cross-situational word learning. *Psych. Science*, 20(5), 578–585.
- Gleitman, L. (1990). The structural sources of word meaning. *Language Acquisition*, 1, 3–55.
- Hirsh-Pasek, K., Golinkoff, R. M., & Hollich, G. (2000). An emergentist coalition model for word learning: Mapping words to objects is a product of multiple cues. In R. M. Golinkoff, K. Hirsh-Pasek, L. Bloom, L. B. Smith, Woodward A. L., N. Akhtar, & G. Hollich (Eds.), *Becoming a word learner: A debate on lexical acquisition*. New York, NY: Oxford University Press.
- Kachergis, G., & Yu, C. (2013). More naturalistic cross-situational word learning. In M. Knauff, M. Pauen, N. Sebanz, & I. Wachsmuth (Eds.), *Proceedings of the 35th annual conference of the cognitive science society*. Austin, TX.
- Kachergis, G., & Yu, C. (2017). Observing and modeling developing knowledge and uncertainty during cross-situational word learning. *IEEE Transactions on Cognitive and Developmental Systems*.
- Kachergis, G., Yu, C., & Shiffrin, R. M. (2012). An associative model of adaptive inference for learning word-referent mappings. *Psychonomic Bulletin and Review*, 19(2), 317–324.
- Kachergis, G., Yu, C., & Shiffrin, R. M. (2016). A bootstrapping model of frequency and contextual diversity effects in word learning. *Cognitive Science*. <http://doi.org/10.1111/cogs.12353>
- Markman, E. M. (1990). Constraints children place on word meanings. *Cognitive Science*, 14, 57–77.
- Markman, E. M. (1992). Constraints on word learning: Speculations about their nature, origins and domain specificity. In M. R. Gunnar & M. P. Maratsos (Eds.), *Modularity and constraints in language and cognition: The minnesota symposium on child psychology* (pp. 59–101). Hillsdale, NJ: Erlbaum.
- McMurray, B., Horst, J. S., & Samuelson, L. K. (2012). Word learning emerges from the interaction of online referent selection and slow associative learning. *Psychological Review*, 119(4), 831–877.
- Medina, T. N., Snedeker, J., Trueswell, J. C., & Gleitman, L. R. (2011). How words can and cannot be learned by observation. *PNAS*, 108(22), 9014–9019.
- Mullen, K., Ardia, D., Gil, D., Windover, D., & Cline, J. (2011). DEoptim: An R package for global optimization by differential evolution. *J. of Statistical Software*, 40(6), 1–26.
- Quine, W. V. O. (1960). *Word and object*. Cambridge, MA: MIT Press.
- Rescorla, R., & Wagner, A. (1972). A theory of pavlovian conditioning: Variations in the effectiveness of reinforcement and nonreinforcement. In *Conditioning ii: Current research and theory*.
- Siskind, J. M. (1996). A computational study of cross-situational techniques for learning word-to-meaning mappings. *Cognition*, 61, 39–91.
- Smith, K., Smith, A. D. M., & Blythe, R. A. (2011). Cross-situational learning: An experimental study of word-learning mechanisms. *Cognitive Science*, 35(3), 480–498.
- Smith, L., & Yu, C. (2008). Infants rapidly learn word-referent mappings via cross-situational statistics. *Cognition*, 106, 1558–1568.
- Stevens, J. S., Gleitman, L. R., Trueswell, J. C., & Yang, C. (2017). The pursuit of word meanings. *Cognitive Science*, 41, 638–676.
- Suanda, S. H., & Namy, L. L. (2012). Detailed behavioral analysis as a window into cross-situational word learning. *Cognitive Science*, 36(3), 545–559.
- Tilles, P. F., & Fontanari, J. F. (2012). Minimal model of associative learning for cross-situational lexicon acquisition. *Journal of Mathematical Psychology*, 56(6), 396–403.
- Trueswell, J. C., Medina, T. N., Hafri, A., & Gleitman, L. R. (2013). Propose but verify: Fast mapping meets cross-situational word learning. *Cognitive Psychology*, 66(1), 126–156.
- Vlach, H. A., & Johnson, S. P. (2013). Memory constraints on infants' cross-situational statistical learning. *Cognition*, 127, 375–382.

Vlach, H. A., & Sandhofer, C. M. (2012). Fast mapping across time: Memory processes support children's retention of learned words. *Frontiers in Developmental Psychology*, 3(46), 1–8.

Yu, C. (2008). A statistical associative account of vocabulary growth in early word learning. *Language Learning and Development*, 4(1), 32–62.

Yu, C., & Smith, L. (2007). Rapid word learning under uncertainty via cross-situational statistics. *Psych. Science*, 18, 414–420.

Yurovsky, D., & Frank, M. C. (2015). An integrative account of constraints on cross-situational word learning. *Cognition*, 145, 53–62.

Yurovsky, D., & Frank, M. C. (2017). Beyond naïve cue combination: Salience and social cues in early word learning. *Developmental Science*, 20(2), e12349.