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# Modeling Lexical Acquisition Through Networks

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## Abstract

We examine the nature of phonological and semantic similarity in early language learning. We consider how the use of this information might change over the course of development. To this end, we represent the lexicon as either a phonological or semantic network and model the growth of this network. Constructing normative vocabularies from the Communicative Development Inventory norms, we utilize a preferential attachment growth algorithm. We predict and quantify the words which will be learned next, comparing the two network representations. We consider the effect of age, total vocabulary size and language ability as measured through CDI percentile. Our findings suggest that the semantic representation does not outperform the baseline bag-of-words model, whereas the phonological representation conditionally does. More generally, we show that the network representation influences the ability of a model to capture vocabulary growth. We further offer a method of analysis for testing representational assumptions in network models.

**Keywords:** Language acquisition; word learning; lexical acquisition; network modeling; preferential attachment

## Introduction

There is much evidence to support the idea that children learn words systematically. A child's vocabulary relates to that of their parent's suggesting that the environment plays an important role (Weizman & Snow, 2001). The interest of the child further influences language learning (DeLoache et al., 2007), and the words a child knows are useful in predicting the words that child will learn next (Beckage & Colunga, 2013). Concrete nouns are learned earliest, as are shorter words (Gentner, 1982). However, there is still systematicity in learning that is not fully understood. In this paper we look at the changing role of two specific sources of information that influence the learning of words – phonological or semantic information.

Here we examine the systematicity present in word learning. Specifically by focusing on whether phonological or semantic similarity dominate early language learning. We also consider how the role of semantic and phonological information might change over the course of development. In our approach, we model growth in the normative productive vocabulary of 16 to 30 months olds, based on the MacArthur Bates Communicative Development Inventory norms (CDI, Dale &

Fenson, 1996). We use a graph-theoretic network representation where the words are the nodes in the graph and the edges are based on semantic or phonological similarity. Finally, we quantify the extent to which the network representation improves our ability to predict which words a child will learn next. We summarize the modeling results as a function of age, productive vocabulary size, and language skill.

## Growth Networks

By assuming a network representation where the edges are based on phonological or semantic similarity, we can model the acquisition of individual words through a network growth model. We turn to the work of Steyvers and Tenenbaum (S&T) for their model of network growth in the context of language acquisition (2005) and adapt it to our paradigm. We also consider the methodology of Hills and colleagues (Hills et al., 2010, 2009b) for their work of comparing network models and constructing a normative vocabulary.

S&T considered the structure of three semantic networks, showing that these semantic networks had similar large scale structure, with high local clustering and short average path lengths between words. They also found evidence of a power-law in the degree distribution within these networks. This led to the construction of a model of semantic growth where words are more likely to be learned if they connect to known, highly connected words in the graph. They call this model preferential attachment because of its similarity to the growth model of Barabási and Albert (BA model, 1999). Further, the modeling results suggest a correlation between age of acquisition and global network structures of early language networks.

Hills and colleagues extended this work by comparing the content of the vocabulary, as generated by the models, to a normative vocabulary constructed from the CDI norms. Whereas the previous work considered three different models of acquisition, we consider only the preferential attachment model since this model is also used in the work of S&T. We also maintain the assumption that the underlying network is fixed and the nodes are labeled. We extend their definition of normative language acquisition to compare a set of normative vocabularies across different ages and language abil-

ities. Hills and colleagues assumed a semantic network as the underlying network representation and compared different growth models. Here we instead assume a network model and ask whether a semantic or phonological network representation is more predictive in modeling lexical acquisition.

### Linguistic Information

There is evidence to suggest both phonological and semantic aspects play a role in early language learning. First, the phonemic pattern and the length of the word play an important role in early word learning. Not only do length and the number of phonemes matter, but the number of words that are phonologically similar to a given word (the phonological neighborhood) also affects learning. Words that are part of denser phonological neighborhoods are more likely to be learned even when frequency and length are controlled for (e.g., Storkel, 2009).

On the other hand, semantic aspects also play a role in early word-learning. For example, sensory-motor semantic features have been shown to be available to even pre-linguistic children (e.g., Bloom, 2002). In fact, Howell et al. showed a significant improvement in word prediction accuracy by including sensory-motor features in a neural network model, suggesting that semantic features inform word learning (2005). Hills and colleagues also explore the issue of semantic features by asking directly what type of semantic edges—perceptual or conceptual—are most useful in predicting acquisition (Hills et al., 2009b). Their results suggest that perceptual features are more robust, but conceptual features are more discriminating and more likely to be used. With our network models, we try to understand the independent contributions of semantic and phonological information to early word learning.

### Methods

In this paper we utilize a network growth model to understand and quantify the relevance of phonological and semantic features on language acquisition in children. To isolate phonological or semantic features from each other and other important components of language acquisition, we make a few initial assumptions. We first assume that the productive vocabulary can be represented as a network with words as nodes and relations between nodes determined by similarity in phonological or semantic space. We define the exact mapping between edges in the network and phonological/semantic similarity in more detail below. Second, we assume that the growth of this vocabulary network can be modeled through a process of preferential growth that is similar to preferential attachment (Barabási & Albert, 1999; Steyvers & Tenenbaum, 2005) and that this model captures some aspects of language acquisition and language learning in children. We finally assume that 'normative vocabularies' as defined below represent individual children's acquisition trends. We hold the underlying process of network growth constant as this allows for direct examination of how the definition of an edge changes the ability of the network growth model to account

for the observed word acquisition data. Thus, we ask: 1) Which linguistic features capture and potentially guide lexical growth? 2) Are there different relevant linguistic features at a) different points in development or b) across different developmental trajectories?

### Normative vocabulary networks

To achieve our modeling goals, we define a 'vocabulary snapshot' to be a starting network (from a specific month) and a goal network—the network one month later. This allows us to test the ability of the model and representation to predict from one month to the next. We utilize the MacArthur-Bates Communicative Development Inventory (Dale & Fenson, 1996, CDI) norms to compute vocabulary snapshots. The CDI is a parent report vocabulary checklist consisting of 680 words, spanning 22 semantic categories and including the most common parts of speech. We utilize the 16-30 month production norms which aggregates productive vocabularies of 1130 children of different ages through parent report. For our modeling study, we focus specifically on nouns, and further consider only the 352 words that are normed in both the CDI and by the Howell sensory-motor features which we use to construct our semantic network.

To construct normative (prototypical) vocabularies, we convert the norms (which include the percentage of children of a given age who produce each word) to vocabulary snapshots. To do this, we consider a word learned if the norm for that word and age is above a certain threshold. We can construct a variety of normative vocabulary snapshots by varying the percentage of the population that was reported to produce a specific word. We consider thresholds between the range of the 10% of the population through 90% (indicating the rate of production) in increments of 5. We create a range of normed vocabularies in the hopes of capturing the developmental differences in vocabulary growth. We consider age, vocabulary size and language ability in our analysis. To assess language ability, we use the CDI percentile which considers the size of the vocabulary for a given age as compared to their peers. This means that a child in the 90th CDI percentile will have a larger vocabulary than a child in the 20th percentile. Thus we use 100-threshold to approximate the CDI percentile in our study. We use this CDI percentile as an approximation of language ability. We also assume that if a word enters the vocabulary, it stays in the vocabulary—a situation that is not always true when we use the norms to calculate the vocabulary. In total there are 206 vocabulary snapshot pairs (starting and predicted), representing 17 different thresholds for normative vocabularies between 16 and 30 months.

### Preferential Growth Model

We adapt the S&T model to account for a fixed edge list (Steyvers & Tenenbaum, 2005). The preferential attachment model was tested on normative vocabularies by Hills and colleagues (2009b), though with a different set of edges and to answer different questions. Because of the prevalence and use of variants of preferential attachment in the literature, we

assume, for this study, that lexical networks grow according to a process similar to preferential attachment. Preferential attachment can be seen as a growth model in which, at each step, a new node and some edges are added to an existing network graph. The new node attaches to already existing nodes proportionally to the number of neighbors of the existing node. This results in a ‘rich get richer’ effect as well-connected nodes (high degree words) in the existing graph are likely to acquire edges from new nodes, further increasing their connectivity and thus increasing their likelihood of ‘preferentially attaching’ to new incoming nodes.

This model cannot be directly applied to our vocabulary networks since, in our case, we have a predefined maximal network  $G'(V', E')$ —the nodes ( $V'$ ) are labeled and edges ( $E'$ ) are fixed—such that for any network, two nodes are either connected or not connected. For example, a vocabulary containing words *dog* and *cat* will have a node for each of these two words and those two nodes will always be connected in the semantic network and always be not connected in the phonological network. We are trying to understand how the network grows over time, not only where new nodes could attach. We thus relax the definitions in the BA model to generalize it to our case, as in (Hills et al., 2009b). In each iteration of this model, we select an attachment node from the current vocabulary graph  $G(V, E) \subseteq G'(V', E')$  proportionally to the degree of the word in graph  $G$  (as in the original BA model). We then select an unknown neighbor of the attachment node and assume that this is the newly learned word. Finally, we update the graph such that all edges between existing words and the newly learned word are present in the vocabulary graph. Under this algorithm, the probability that an unknown word  $j$  is learned given the current graph  $G(V, E)$  is defined as:

$$Pr(\text{learn}(j)) \propto \sum_{i \in V, j \neq i} d_i \mathbb{I}_{(j,i) \in E'}$$

where  $d_i$  is the degree of node  $i$  given that node  $i$  is known. This degree contributes to the probability of learning word  $j$  if an edge exists between  $i$  and  $j$  in the full graph  $G'(V', E')$ .

We run this algorithm for each vocabulary snapshot, initializing the current vocabulary graph to the starting CDI vocabulary. Preferential growth runs until the network is size-matched to the target vocabulary. Note that we still update the current graph after each iteration to include the newly learned word, and all its relevant edges, such that sequential effects may appear in the model. That is, if *dog* gets added as an attachment to *cat*, and *puppy* is already a node in the graph (i.e. a known word), the new node for *dog* will link with both *cat* and *puppy*. Further, a new word might attach to *dog* in the next time step. We compare the words selected by a given run of the algorithm to the words that have actually been learned according to the normative vocabulary snapshots. The greater the overlap, the more useful the underlying network is in capturing language learning. To account for the stochasticity and intractability, we simulate a model run—growing the vocabulary—and compare it to the predicted vocabulary 1000 times. We then compute the average model performance.

## Networks

If the network representation is useful, our models will outperform uniform acquisition (where each unknown word has equal probability of being learned). We also consider the importance of the underlying network representation by running the model on a network with the same number of edges but drawn at random. We evaluate the representation by calculating the overlap between predicted words for learning and the words that are actually learned, according to norms, in a single month’s time. These networks, and the comparison to the random models, offer a way of understanding the importance of phonological and semantic similarity on early language acquisition.

**Phonological Network** To construct a phonological network, we convert the set of vocabulary words to the international phonemic alphabet (IPA). This was done using PhoTransEdit, a free Windows tool used to transcribe English texts to phonetic transcriptions. This transcription was used to create a feature by word matrix where the full features were all phonemes in the English language and the word specific features were counts of the number of times a given phoneme appeared in a word. The phonetic similarity of each word was then computed as a cosine similarity of the phoneme-feature vector between two words. The cosine-similarity calculation resulted in a symmetric matrix of words by words where each cell contained a value between 0 (no phonemic overlap) and 1 (complete phonemic overlap). The resulting matrix was thresholded to a binary matrix at a value of 0.6 as there was a noticeable break in similarity between words around this value making it a robust threshold for the greatest range.

**Semantic Networks** We utilize the sensory-motor feature matrix of Howell and colleagues for our semantic network (2005). In the study by Howell and colleagues, participants were asked to rate early learned nouns on a set of 97 different features. Participants were instructed to make judgments from the perspective of a preschool aged child. These features included aspects such as size, color, texture and other features. These ratings were collected for 352 nouns and were averaged across at least 200 participants. These ratings capture population level averages indicating the extent to which an object possesses a given feature. We compute the semantic similarity of two words by calculating the cosine-similarity of the feature vectors for each words This provided us with a symmetric matrix that we convert to a binary matrix by thresholding. We threshold at a level of 0.85 as there was a break in the cosine-similarity ratings of all vectors at that point. We chose the Howell feature norms for this analysis because it specifically attempts to capture sensory-motor features that might be available and important to young children and, as such, is well suited for our specific research question. Since we only have the sensory-motor features for 352 nouns, we include only these words in our modeling.

Table 1: Model performance: mean accuracy per word predicted, standard deviation of prediction, and performance compared to 1/n random.

	word prob.	s.d.	% better	% worse
semantic	.178	.007	31.55	64.56
phonological	.192	.006	43.68	51.45
1/n rand	.191	.008	58.00	37.62
sem rand	.191	.013	64.56	31.55
phon rand	.191	.021	54.36	40.77

## Model Comparison

The main point of this paper is to test which representations are useful in predicting words to be learned, and how this may change with development. We mentioned briefly baseline models we use for comparison. In this section we cover them in more detail. In our 1/n or bag-of-words model each unknown word has an equal probability of being learned. A bag-of-words, just learn anything model, has been shown to produce early lexical graphs with structure similar to that of the lexical graphs of children (Beckage et al., 2011) and thus provides an interesting baseline model. The other random model, our r-graph model, is based on network structure but instead of a principled edge-list, the same number of edges are randomly drawn. This measures any effect that the network structure might have in isolation from the linguistic information present in the semantic and phonological graphs. Since we run many iterations and count the number of overlapping words, if we generate graphs entirely at random, our r-graph model will approach our 1/n random model for large numbers of simulations. Thus we fix the random graph representation for 100 runs before drawing a new random graph.

## Results

Once we calculated the number of correctly predicted words for each model, we consider trends in the data. We can look at multiple levels of data analysis to shed light on different underlying mechanisms. The first question we ask is whether or not the collective fits across all snapshots are better than our random baseline models. To do this, we have to normalize the network runs across snapshots since each snapshot captures a different number of words to be learned. Thus, we consider the probability that the model correctly predicts a word. This allows us to average each snapshot equally and to compare performance across models. The results, summarized in Table 1 suggest that the probability of correctly predicting a word for learning is nearly equal across models. The semantic network seems to be performing slightly worse than the other models. We include the average standard deviation of the probability of correctly choosing a word to suggest that the model converged and that there is not much variability across runs.

### Semantic Network Results

Averaging across all vocabulary snapshots, and comparing each model to the random models further suggests that the semantic network does not outperform random. For each of the snapshots, we utilize an unpaired t-test between each iter-

ation of the linguistic model and an iteration of the 1/n random model. We find that only 31.55% (or 65 snapshots) are statistically better fit by the semantic network than by the 1/n random model. In fact the 1/n random model performs statistically better in 64.56% (or for 133 snapshots). See Table 1 for results. When we perform the same comparison on the semantic network and the r-graph baseline model, we find the exact same results, with each snapshot either beating both random models or none. Over all of our analyses, we find that there is no meaningful difference between the comparison of the linguistic network to the random graph that is not captured by considering only the 1/n bag-of-words model. Thus we talk only about the 1/n random model with the knowledge that the results also extend to the random graph (r-graph) model.

Though it seems that the random model is outperforming the semantic network, it could be that there is some systematicity in the 31% of cases where the semantic network actually outperforms the random models. For example the semantic network might outperform the random model for vocabulary snapshots of young/older children or for vocabulary snapshots created to capture high/low language ability. To explore this possibility, we cluster the results with respect to age, CDI percentile, and vocabulary size. Figure 1 shows the same data as table 1 aggregated to capture possible trends in development. The y-axis indicates the change from random, with the scale varying across graphs. The x-axis aggregates the data by relevant developmental features and varies across plots. We consider effects of age, percentile, vocabulary size. The results for the semantic network is shown in dark grey. If performance was equal to random, this would be indicated as a 0 on the graph. If the performance was better than random, the line would be above the 0 mark. While we do not show the results here, we also consider the number of words the model is predicting in case there is an effect of the size of the prediction set.

If the semantic network model captured learning of a subset of developmentally interesting and research motivated snapshots, we should see this as a systematic increase of the network performance over random. Instead, we find that regardless of age, percentile, vocabulary size or the size of the prediction set, the semantic network is not performing better than the random models. In fact there is evidence of a trend that, for higher CDI percentiles, the semantic model decreases in performance and is actually worse than random. A similar trend is seen for the vocabulary size as well, where aside from vocabulary sizes around 450, there is a steady decrease in performance of the semantic model as compared to random for larger vocabularies.

However, this is averages of averages, which could mask trends due to poor performance of the semantic network on a subset of snapshots. When we consider the proportion of snapshots that are better fit by the sensory-motor features than any random network, we find that, regardless of the dimension used for clustering, there is no reliable trends in the data.

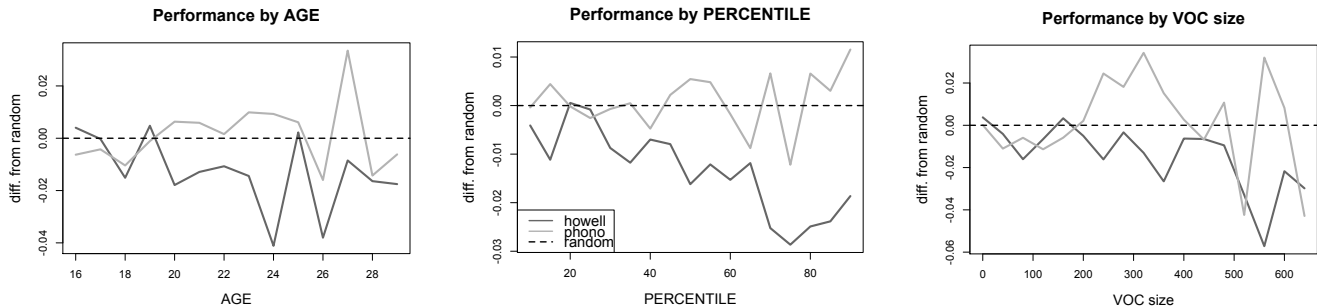


Figure 1: Performance on snapshots compared to random aggregated by either age, percentile or vocabulary size. Dark grey indicates semantics and light grey indicates phonology.

In all cases, there are some snapshots that are best fit by the semantic network but there seems to be no systematicity to which snapshots they are.

### Phonological Network Results

When the phonological network of overlapping phonemes is considered, 43% of the snapshots are significantly better fit by phonology than by random, and 51% are significantly worse fit. This suggests that a phonological representation performs worse than random acquisition on average. However, when we look at the trends across age, vocabulary size and language ability, we find that certain types of snapshots are reliably better fit by the phonological network than by the random models. Figure 1 shows the performance of the phonological model (light grey) again aggregated over different features of interest. We can see in the first frame that when we consider age, snapshots generated from norms for children between 20 and 25 months are reliably better fit by the phonological preferential growth model than by the random models. Similarly, there is a general trend of an increase in performance over random as the percentile of the snapshot increases. We also see a large increase in performance of the phonological model for vocabulary sizes between 200 and 550 words. Further, when we consider the proportion of vocabularies that are better than the random model, similar trends emerge—we don’t see just an increase in probability but also an increase in the number of snapshots that are better fit by phonology than random. It is important to point out that, in general, vocabularies that are larger are also more likely to be from normative vocabularies constructed from norms of older children and are, with our assumptions, also representative of higher language ability. So in some sense it is not surprising that the effect of phonology seems to increase in performance in all three cases. However, the redundancy also confirms that the effect is not due to random noise but is a property of the vocabularies. In the next section we discuss these findings to understand the significance of the results.

### Discussion and future directions

The results suggest that in most cases the semantic network based on the Howell sensory-motor features is not able to outperform the random semantic network model or the bag-of-

words model. However, we find that the phonological network shows some systematic increase in performance over the random network and bag-of-words model. This is an interesting result as it suggests that phonological features contain useful information in understanding how language may be learned. Further, we can see that this type of phonological information and this process of growth are best able to capture acquisition for snapshots created for older children, children with larger vocabularies and normative vocabulary snapshots that are constructed to mirror children with high language ability.

We interpret the conditional success of the phonological network in the context of the failure of the semantic network and revisit our initial assumptions as laid out in the first paragraph of the methods section in light of these results. We assumed that the phonological representation of overlapping phonemes and the semantic representation of sensory motor features provided a useful initial network representation. This is an assumption that could easily be expanded upon or directly challenged. However, even with the limited choice of representations, we showed two important things. First, this result shows how the representation chosen influences the ability of the model to capture vocabulary growth. Further, this modeling approach suggests a way to compare network representations by holding the process of network growth constant. This type of model comparison may tell us about structures useful to young learners as well as about how language itself might be structured from the perspective of a young children.

Our assumption of a preferential growth process of acquisition was not directly explored in this paper. In future work we do hope to explore this model as compared to other types of network growth models to understand both the nature and variability of learning. But the fact that the phonological network representation and the preferential growth model were able to outperform random for a certain class of snapshots suggests that this model is able to capture aspects of the process of acquisition, if somewhat imperfectly.

Our final assumption that the normative vocabulary snapshots captures individual behavior is the most informative. The vocabulary snapshots do provide a way in which the vocabulary of a child may change over time but this does not

capture the vocabulary of any individual child directly. It is a big assumption that words that are reported as learned by the fewest children are also the words that early talkers learn, for example. This assumes that word learning proceeds in a systematic and predictable fashion—that late talkers are just typical talkers who are older—a result that has been shown to be untrue (Thal et al., 1999; Beckage et al., 2011). The normative vocabularies may not capture any individual child very well, but capture the aggregate instead. This could be particularly problematic in the domain of semantics since the averaging of multiple vocabularies and the further assumption of creating snapshots to indicate different language ability would likely cancel out any sort of semantic consistency that wasn't shared across the majority of children. For example, the vocabulary snapshots would not necessarily show preferences for animals or vehicles unless a large amount of children in the norming study showed such preferences at similar times and with base rates roughly equal to their peers.

The aggregation process may also explain why the phonological model was especially useful for larger vocabularies and normative vocabularies created for older children. The CDI is a measure of productive vocabulary, meaning to check as word as "known" the parent needs to recognize the word the child is producing. It has been established that there is much regularity in the order in which phonemes are mastered in development (e.g., Sander, 1972; Grunwell, 1981). Thus the vocabulary snapshots are likely able to capture general properties of the difficulty of production. In the case of large vocabularies or high language ability, the phonological network does the best. This could be due to the fact that the vocabulary contains a large set of phonemes which allows the model to 1) distribute probability of learning over a greater set of words and 2) to implicitly model the difficulty in production of phonemes that may play a role in learning. This feature of phonology is likely to be more systematic across children than semantic similarity, especially with the aggression procedure used to construct normative vocabularies.

The results, as they stand now, are intriguing in that we have gained direct information as to the performance of the preferential growth model within the context of language acquisition. We test the model and representations the model uses and conclude that given this model and these data, phonology outperforms the random models more often than semantics does. This confirms that phonological information may play a role in the learning of new words or it could suggest instead that, in averaging, the systematic nature of semantics is washed out while the phonological aspects are accentuated.

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