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Global Properties of the Phonological Networks in Child and Child-Directed Speech

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1. Introduction

The relationship between children's phonological and lexical development has long been of interest in child language research. Of central focus has been the notion that the phonological relationships between words determine the level of detail needed to differentiate them in children's developing lexicons, so that children's learning of words with particular phonological properties serves as an indicator of children's current phonological knowledge, and drives phonological development (Beckman & Edwards, 2000; Ferguson & Farwell, 1975; Jusczyk, 2000; Metsala, 1997; Vihman, 1996). The construct of *neighborhood density* (ND) has been especially prominent in this literature. ND is a property of individual words that is traditionally defined as the number of words that differ from the target word by one phoneme addition, deletion, or substitution (Landauer & Streeter, 1973). One approach to ND in the early lexicon has based conclusions about children's early phonological abilities on the under- or overrepresentation of dense phonological neighborhoods in the child's lexicon as compared to the adult lexicon. However, as we review below, making this comparison has proved to be challenging.

In this paper we approach phonological neighborhood structure from a graph-theoretic perspective, in which the lexicon is viewed as a complex network (Vitevitch, 2008). We analyze lexicons drawn from corpora of child speech (CS), child-directed speech (CDS), and adult-directed speech (ADS). Previous work has compared child and adult lexicons along the dimension of ND, a property of individual words. A network-based approach is novel in that it allows us to go beyond properties of individual words to examine the global structure of an entire lexicon, obtaining measures of overall phonological connectivity and

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structure that arise from local relationships between words. Thus, we do not directly ask whether words from dense neighborhoods are more or less likely to appear in children's developing lexicons than words from sparse neighborhoods, but rather whether children favor a lexicon that differs systematically in its global properties from an adult lexicon, and whether caregivers present children with favorable phonological conditions, from this perspective. This offers a fresh way to test whether children favor lexicons that are in some way more advantageous for acquisition and processing, relative to the adult lexicon, and it suggests techniques for more nuanced inquiry into children's sensitivity to phonological similarity between words.

2. Phonological structure in the lexicon

In pioneering work, Charles-Luce and Luce (1990, 1995) compared the distributions of neighborhoods in two child lexicons (for 5 and 7 year-olds, respectively) to an adult lexicon. They compared the neighborhood densities of each word in the child lexicons to the number of neighbors they would have in an adult lexicon (based on a dictionary). The densities measured relative to the adult lexicon were higher than those relative to the child lexicon. This comparison was made separately for words of 3, 4, and 5 phonemes, presumably to control for the fact that the adult lexicon contained a higher proportion of long words than the child lexicon. They concluded that the words in children's lexicons are more discriminable relative to the rest of the child lexicon than they are relative to an adult lexicon.

At the same time, their results showed that a substantial portion of words in the child lexicons still had multiple neighbors (Dollaghan, 1994), and Coady and Aslin (2003) suggested that it might be more relevant to compare lexicons based on the proportion of each lexicon to which a given word was similar. Coady and Aslin first applied the procedure used by Charles-Luce and Luce to the word types in samples of child speech (2 children, aged 2;3–3;6), yielding similar results relative to an adult lexicon (dictionary). They then repeated this analysis, but divided the neighborhood densities by the total number of word types in the relevant lexicon. The pattern of results reversed, showing that children's neighborhoods are *denser* than those of adults, when the size of each lexicon is taken into account.

It is thus unclear whether or not children's lexicons favor denser neighborhoods than the adult lexicon. This is partly due to issues of methodology in previous work—it is unclear how best to normalize for the size of each lexicon, or for differences in the lengths of words between lexicons. But it may also result from limitations of the definition of ND. Since neighbors are defined as words differing by only one phoneme, any more distant words are counted as equally dissimilar, e.g. *state* is as different from *ate* as is *potato*. By dichotomizing phonological similarity in this way, ND may obscure meaningful variability in word similarity at greater distances. In addition, ND is a local property of individual words, and global structural properties that emerge over neighborhood relationships across many words may also be relevant to lexical development. For instance, it may be useful to know how distant words are from each other on average, whether two words that share a common neighbor are likely to be neighbors themselves, or whether words tend to be connected to other words with similar neighborhood densities to their own. When the lexicon is viewed as a network, these properties are quantified by "average shortest path", "transitivity", and "assortative mixing by degree", defined below. The approach we adopt here uses several such metrics of global and local structure, taken from the network theory literature.

3. Network theory

There has been significant interest in recent years among sociologists, mathematicians, physicists, and computer scientists in data that look like a network, broadly defined: a set of objects, with some pattern of "ties" between individual pairs of them (Albert & Barabási, 2002; Newman, 2003b; Scott, 2000). Work in this field considers the structure and function of networks observed in a wide range of settings, such as social networks, the internet, and food webs. Recent work has used network theory to consider the lexicons of different languages as *phonological networks* (Altieri, Gruenenfelder, & Pisoni, 2010; Arbesman, Strogatz, & Vitevitch, 2010a, 2010b; Chan & Vitevitch, 2009, 2010; Gruenenfelder & Pisoni, 2009; Vitevitch, 2008). From this perspective, researchers can compute metrics used in network research to give insight into the properties of a given network.

A *network* (or *graph*) is a set of nodes and a set of edges, each of which connects a pair of nodes. In a phonological network, each word is represented by a node, and two nodes are connected by an edge if their corresponding words are neighbors, in the sense of ND. A node's *degree* is the number of nodes it is connected to by edges; for phonological networks, degree is equivalent to ND. A network consists of at least one *connected component*, a "piece" of the network in which a path (traversing a sequence of edges) exists between any two nodes, but no path exists between any node in the connected component and any node outside of it. The connected component containing the most nodes is the *giant component* (GC).

A variety of metrics are used to describe different aspects of the structure and function of complex networks; some (degree distribution, average degree) correspond to measures traditionally used in the ND literature. We now describe several metrics which have been used in previous work on phonological networks, and which will be used here.

The *average shortest path* (ASP) is measured across all pairs of nodes for which a path exists (that is, all pairs where both nodes are in the same connected component). Note that this is not the same as *edit distance*, the minimum number of additions, deletions, and substitutions of one phoneme required to change one word in a pair into the other (Yarkoni, Balota, & Yap, 2008). ASP adds the requirement that all intermediate steps in this process exist as words in the network.

The *clustering coefficient* of a node is the fraction of pairs of its neighbors which are also neighbors of each other. Here we consider the average of this value across all nodes (henceforth simply "clustering coefficient"; CC). A closely related quantity is *transitivity*; the probability across the whole network that two nodes which are neighbors of the same node are themselves neighbors.[1] In the case of a social network where edges indicate friendship, for example, CC and transitivity reflect the likelihood that any two friends of a given individual will themselves be friends.

Assortative mixing by degree (AMD) is the correlation, across all edges, of the degrees of neighboring nodes. Positive AMD indicates that edges tend to connect nodes of similar degrees: many high-degree nodes are connected to other high degree nodes, and many low-degree nodes are connected to other low-degree nodes. For the friendship network example, individuals will tend to have friends who have around the same number of friends as they do.

Phonological networks were first studied by Vitevitch (2008), who considered the English lexicon; subsequently, Arbesman et al. (2010b) examined the phonological networks of English, Spanish, Mandarin, Hawaiian, and Basque. Both studies showed that phonological networks exhibit several distinctive properties.

First, phonological networks were found to have "small-world" properties (Watts & Strogatz, 1998): low ASP length, compared to a random network with the same number of nodes and average degree, but a high clustering coefficient, relative to such a random network. Low ASP is a prerequisite for a network to be efficiently searchable, while high CC and high transitivity imply the network is "locally dense". Small-world properties have been argued to be desirable properties from the standpoint of processing, particularly if a "spreading activation" model is assumed (Vitevitch, 2008; Arbesman et al., 2010b), and could be beneficial for acquisition as well.

Phonological networks also have high AMD, both relative to a random network and to other types of real-world networks. Relative to networks with negative (or zero) AMD, networks with high AMD tend to allow more rapid transmission of information between nodes, and tend to be relatively robust in the sense that many nodes can be removed without greatly affecting the network's overall structure (Newman, 2003b). Robustness to node removal in phonological networks was shown in simulations by Arbesman et al. (2010b).

A final finding of previous work is that phonological networks tend to have a relatively small percentage of nodes in the giant component (35–66% across the languages considered by Arbesman et al.), compared to many other

[1] CC and Transitivity reflect different ways of measuring the likelihood that any two neighbors of a node are themselves neighbors. They can in principle differ, but pattern together in our data.

networks observed in the literature. This is because they contain many "islands"—connected components consisting of only a few nodes—and thus can be thought of as consisting of a structured core and a large periphery of relatively unstructured pieces. This raises a methodological question of whether the properties we examine here, which are intended to represent global properties of graph structure, should be computed for the whole graph, or for the GC alone. Vitevitch (2008) computes them only for the GC, while Arbesman et al. (2010b) compute some metrics for both the GC and the whole graph, and others only for the GC. In this paper we consider all metrics computed on both the GC and the whole graph.

Previous work, then, shows that phonological networks have properties which may be beneficial from the perspective of search and stability: low ASP, high CC and transitivity, and high AMD. We thus call these four metrics *search and stability properties* (SSPs). Linking these properties with search and stability suggests the intuitive hypothesis that children will favor a lexicon with a larger CC, transitivity, and AMD, and smaller ASP than the adult lexicon. Furthermore, if the global structure of the lexicon of CDS is somehow more favorable for acquisition relative to the ADS lexicon, as has been argued to be the case for other aspects of CDS relative to ADS (e.g. phonetics, prosody, syntax; cf. Brodsky, Waterfall, & Edelman, 2007; Fernald & Kuhl, 1987; Kemler Nelson, Hirsh-Pasek, Jusczyk, & Cassidy, 1989; Liu, Kuhl, & Tsao, 2003), we might also expect CDS to be more stable and searchable than ADS, as measured by these network properties. We examine these hypotheses directly in the remainder of this paper.

4. Methods

In order to test these hypotheses about network structure, we extracted lexicons from corpora of CS, CDS, and ADS, and built the corresponding phonological networks. We then computed global network properties, including the SSPs described above, for each of these networks, and estimated their standard errors using a resampling procedure, allowing us to make comparisons across networks.

4.1. Data and network construction

The CS and CDS lexicons were extracted from a large longitudinal corpus comprising 90-minute spontaneous speech samples from 64 parent-child dyads (approximately 1.5 million word tokens of CS and 1.9 million word tokens of CDS; Huttenlocher, Vasilyeva, Waterfall, Vevea, & Hedges, 2007; Rowe, 2008). Each dyad was recorded 9 times at 4-month intervals beginning at child age 14 months and ending at age 46 months. Twenty-three recording sessions (4%) were missing due to some participants leaving the study or missing a session. Since our goal was to compare CS, CDS, and ADS in general, we did not remove participants with missing sessions. The parent-child dyads were selected to span the socioeconomic and racial diversity of Chicago, except that all were from

Table 1: Corpus properties following removal of words not occurring in CMU dictionary.

Corpus	Utterances	Types	Mean word length
CS	263,824	6,882	4.82
CDS	519,351	12,584	5.29
ADS	32,681	10,964	6.05

monolingual English-speaking families. The network structure of the CS and CDS lexicons from this corpus were compared to an ADS lexicon drawn from the Buckeye corpus of adult interviews (40 speakers, 285,000 word tokens; Pitt et al., 2007).

In the construction of all three lexicons, unlemmatized, orthographically distinct word types were included, and associated with a string of phonemes according to the first listed pronunciation of that word type in the CMU pronouncing dictionary (Carnegie Mellon Speech Group, 1993). Word types not listed in the dictionary were excluded. Note that this process may permit a single pronunciation to appear twice in the lexicon, and consequently in the phonological network, if it is associated with distinct orthographic forms; for example, homophonic but heterographic words like *to*, *two*, and *too*, each contribute separate nodes to the network, with the same neighbor-sets. On the other hand, semantically distinct words that are both homophonic and homographic, such as *rose* (n.) and *rose* (v.), together contribute only a single node.

Table 1 gives the number of utterances in each corpus, as well as the number of unique orthographic word types and mean word length in phonemes after removing word types not occurring in the CMU pronouncing dictionary. While the ADS corpus contains far fewer utterances than the others, it includes a similar number of types as the CDS corpus, which is somewhat less than twice the number of types in the CS corpus.

We constructed the lexical networks over all word types, regardless of length in phonemes, in contrast to Charles-Luce and Luce (1990, 1995), and Coady and Aslin (2003), discussed above. In those studies, the distribution of neighborhood densities was compared separately for 3, 4, and 5-phoneme words. In the present study, however, we are interested in the impact of phonological connectivity across the entire lexicon, rather than in connectivity among, e.g. 3-phoneme words. Concepts like ASP are defined over the shortest paths between each pair of nodes, including nodes of different lengths (provided they are in the same component). There is no reason to expect that ASP for the whole network would be similar to ASP over subsets of the network that are uniform in word length, and we argue that, to the extent that global connectivity is related to lexical acquisition or processing, the global measure is most relevant.

4.2. Jackknife resampling

For each lexical network, it is possible to compute all global network properties of interest (ASP, CC, etc.). However, as in most corpus-based work, we view the base of data from which the networks are constructed as inherently stochastic. It is therefore important to estimate the amount of variability that each metric is expected to exhibit in each network, as a result of the random process assumed to be generating the corpus on which the network is based. Such estimates allow us to judge whether differences between the network properties of the three corpora are greater than could reasonably be expected to arise by chance in samples of the size that we have.

In our case, we have three finite samples (the corpora), together with a set of sample statistics (network properties), which depend on the samples in some complicated way. We wish to estimate the sampling variance of those statistics on the basis of the single sample available to us. One general method of obtaining such estimates is to use a *jackknife resampling* procedure (e.g. Efron & Tibshirani, 1993). The sample is divided into a set of blocks, each of which is removed from the sample in turn, each time recalculating the statistics of interest on the resulting truncated sample. One can then estimate the sampling variances of the statistics by examining how much their values deviate during this process from what would be obtained on the entire, untruncated sample. In order to apply this procedure to our data, we divide each corpus into 100 equal blocks. We then remove each block in turn, generate the resulting network, compute its properties, and compare the resulting values to those obtained on the network derived from the entire corpus. The error bars in Figure 2 (below) indicate twice the standard errors estimated by this method.

5. Results

We begin our comparison by examining the degree distribution, which is closest to the earlier approaches of Charles-Luce and Luce, and Coady and Aslin. For each of the three lexicons, Figure 1 plots the empirical degree distribution, and the fitted probability distribution over node degrees.[2] Note that this includes all words in each lexicon (that appear in the CMU dictionary), without restricting length in phonemes or syllables. The CS and CDS lexicons show a higher proportion of nodes with high degree, both from visual inspection of the degree distributions, and by comparison of edge-to-node ratios for the three lexicons, both within the GC and in the whole network (Figure 2). Thus, CS and CDS appear to rely on a denser lexicon than ADS, when normalized for the size of the lexicon. Since the edge-to-node ratio is simply one half the mean ND, this makes our results consistent with those of Coady and Aslin (2003), in which neighborhood

[2]Fitted distributions are truncated power laws, following Arbesman et al. (2010b), computed using methods from Clauset et al., (2009). All fits were highly significant ($p < 10^{-10}$), relative to a simple power law.

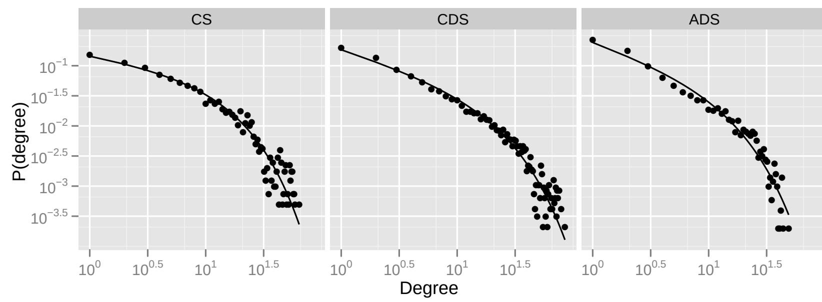

Figure 1: Empirical (dots) and fitted (lines) degree distributions for CS, CDS, and ADS.

sizes were divided by the number of words in each lexicon. However, we note that it is not clear how useful edge-to-node ratio and the degree distribution are for comparing lexicons of different sizes, since the maximum values of the edge-to-node ratio and the maximum degree increase as network size increases.

Nonetheless, the degree distribution, and also the relative size of the GC, which is larger in CS and CDS than in ADS (Figure 2), suggest that the global network structure of CS is much more similar to that of CDS than it is to ADS. This pattern of similarity between CS and CDS also holds for search and stability properties (ASP, CC, transitivity, and AMD), to which we now turn.

Figure 2 shows the results for the search and stability properties, measured for the entire network as well as in the GC alone. These show two general patterns. First, as above, the values for CS and CDS tend to be much more similar to each other than to ADS, and second, they suggest that CS and CDS networks are in general more stable and more efficiently searchable than ADS.

The higher values of CC and transitivity in CS and CDS, which are considerably greater than those in the ADS lexicon, reflect the higher likelihood that two neighbors of any given target word will themselves be neighbors in CS and CDS than in ADS. As described above, this indicates that the CS and CDS lexicons are more "locally dense" than ADS. Similarly, the values for AMD show a tighter correlation in the degree of neighboring nodes in CS and CDS than in ADS, with CDS measuring slightly higher than CS as well. In other words, the tendency for words to have neighbors with similar degree to their own is strongest in CS and CDS, and weakest in ADS. This suggests that CDS and CS have more stable phonological networks in the sense that removing nodes will have the least impact on global structure (as measured by metrics such as ASP and GC%) for those lexicons, given the connection between robustness and high AMD discussed above. Finally, the values for ASP contrast slightly with this pattern, in that words tend to be least distant from each other in the CS network, and it is the networks from CDS and ADS that are most similar to each other. Of all pairs of nodes

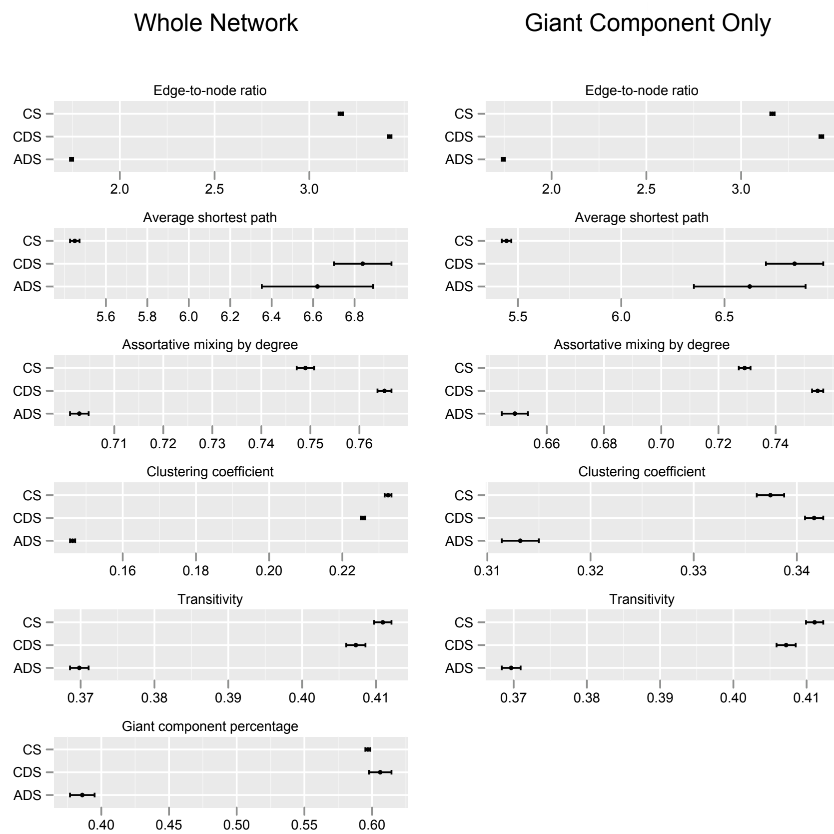

Figure 2: Network properties measured in the whole networks (left) and giant components only (right), with error bars indicating twice the standard errors estimated by jackknife resampling.

between which a path exists, those paths are shorter, on average, in CS than in the other two lexicons. Note that in the case of ASP it is the smaller values that indicate more efficient searchability, in contrast to the other metrics.

6. Discussion

In general, the phonological networks analyzed here exhibit properties that are consistent with stable and searchable networks. Importantly, the higher values of CC, transitivity, and AMD in CS and CDS, and lower ASP in CS, suggest that children's phonological networks are more stable and more efficiently searchable than the network of ADS, and that they are very similar to the network of the CDS that they are exposed to. Analyzing children's productive and input lexicons as phonological networks thus supports the hypothesis that the integration of words into a global network structure, and the functioning of that structure during language use, are important determiners of early lexical development. This includes the notion that children favor a lexicon whose global phonological structure allows for efficient functioning during speech production and comprehension. Note that this hypothesis differs substantially from the notion that dense or sparse neighborhoods are favored in children's lexicons (or CDS) through the effect of ND on how easily individual words can be acquired.

While intuitive from the standpoint of network theory, interpreting the present findings in terms of searchability and stability is dependent on a theory of children's lexical acquisition and processing mechanisms that allow them to exploit the network properties we have discussed. In terms of processing, the rapid spread of information in networks with high CC, transitivity, and AMD, and short ASP presuppose the use of some search algorithm(s) for which the observed network conditions are favorable. This seems most compatible with spreading activation models of lexical processing, which are already being explored from a network perspective in adults (e.g. Altieri et al., 2010; Chan & Vitevitch, 2009, 2010).

The helpfulness of these properties in acquisition also depends on the assumed theory of word learning. However, the present paper only considers the cumulative state of the network at a single point in time, and as pointed out by Gruenenfelder and Pisoni (2009), this does not allow us to infer the mechanism(s) underlying the growth of the network. This thinking thus remains speculative, but the present results suggest a longitudinal hypothesis; namely, that children will gravitate towards a stable and searchable lexicon fairly quickly. We are currently using the longitudinal nature of the CS and CDS corpora analyzed here to explore the development of network structure, by examining children's productive and input lexicons at different ages. This may be helpful in two ways. First, it allows us to examine the specific properties of words added at each time point, relative to both the child lexicon at the previous time point and to the input lexicon. This would help clarify how network structure impacts the acquisition of words with particular properties. Second, the trajectories of the individual network properties would shed light on which properties are favorable early in development.

Comparison of the developmental trajectories of network metrics in CS and CDS over the first 5 years of life may also illuminate how children's early phonological abilities constrain acquisition. Since the children's aggregated lexicons across all time points were very similar to their input (CDS), the present results do not allow us to distinguish hypotheses about children's phonological preferences from the possibility that children simply acquire a network that veridically reflects their input, which may or may not present favorable phonological conditions. On the other hand, CDS might be shaped by children's abilities, either because caregivers have some sense of what sound patterns are difficult for children, or because they simply favor words that the child understands. In the latter case, CDS might be better seen as an indicator of children's receptive lexicons, rather than their input (see Coady & Aslin, 2003). However, if the network properties of CS and CDS show different trajectories over time, we might begin to tease apart these hypotheses.

7. Conclusion

The present study reveals a striking similarity in the network properties of the CS and CDS lexicons, and the pattern of results may imply greater stability and searchability in CS and CDS than in ADS. This is important for two reasons. First, it suggests that the phonological conditions presented by the CDS lexicon are favorable for lexical acquisition, perhaps because caregivers actively tailor their lexical choices to present such conditions, or because they favor words that the child appears to understand. Second, it suggests that children favor a lexicon with certain global phonological properties, defined over local similarity relationships between words. We conclude that the global perspective offered by a network-based approach allows us to ask more general questions about what kind of lexicon presents favorable phonological conditions for children's speech comprehension and production as well as for word learning.

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