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What Can Network Science Tell Us About Phonology and Language Processing?

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Abstract

Contemporary psycholinguistic models place significant emphasis on the cognitive processes involved in the acquisition, recognition, and production of language but neglect many issues related to the representation of language-related information in the mental lexicon. In contrast, a central tenet of network science is that the structure of a network influences the processes that operate in that system, making process and representation inextricably connected. Here, we consider how the structure found across phonological networks of several languages from different language families may influence language processing as we age and experience diseases that affect cognition during the typical and atypical acquisition of new words, during typical perception and production of speech in adults, and during language change over time. We conclude that the network science approach may not only provide insights into specific language processes but also provide a way to connect the work from these domains, which are becoming increasingly balkanized.

Many contemporary models in cognitive psychology focus on processing, ignoring how the organization of representations in memory may influence processing. In contrast, cognitive network science focuses on the organization of information in memory, and how that structure influences various cognitive processes. Vitevitch reviews work using the cognitive network science approach to understand spoken word recognition and points to some limitations of this approach for cognitive psychology more broadly.

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To understand spoken language, the listener must first identify the specific words that are heard, then access the meaning of those words from that part of memory known as the mental lexicon. Contemporary cognitive psychology models have attempted to explain this important process known as spoken word recognition, but in doing so these models have neglected how memory for the sounds that make up a word (i.e., phonological representations) may influence this process. In the sections that follow, we will first consider evidence for the processing-centric bias in contemporary cognitive psychology. We will then contrast that approach with an emerging view called cognitive network science, which focuses on the organization of information in memory, and how that structure influences various cognitive processes. Given the importance of spoken word recognition to the rest of language processing, we will limit our discussion to phonological networks, and how the structure of phonological networks might influence various language processes.

1. Processing and representation in contemporary cognitive psychology

Cognitive psychology has traditionally examined how information is represented in memory, and the processes used to acquire, encode, retrieve, and manipulate that information represented in memory. In the area of psycholinguistics, there is a significant amount of research focusing on the cognitive processes involved in the acquisition, recognition, and production of language. What is not as well represented in contemporary cognitive psychology is research on the representation of language-related information in the mental lexicon. Specifically, what information is represented, how are those representations organized, and how might the structure of those representations influence cognitive processing? The bias toward processes compared to representations is prevalent in contemporary cognitive psychology.

For evidence of this bias toward processing over representation in contemporary cognitive psychology, consider the numerous journal articles that debated whether spoken word recognition was an interactive process, as exemplified in the TRACE model (McClelland & Elman, 1986) or strictly feed-forward, as exemplified in the Shortlist (Norris, 1994) and Merge models (Norris, McQueen, & Cutler, 2000). A similar debate between interactive (Dell, 1986) versus feed-forward (Levelt, Roelofs, & Meyer, 1999) models occurred about the processes involved in speech production, providing additional evidence for a processing-centric bias in contemporary cognitive psychology.

An extreme example of this processing-centric bias in contemporary cognitive psychology can be found in the computational principles of parallel distributed processing (PDP) in the late 1980s and early 1990s (Rumelhart, McClelland, & PDP Research Group, 1986; see also Rogers & McClelland, 2014). Among the central tenets of the PDP framework is the idea that knowledge “does not exist as a set of dormant data structures in a separate store but is encoded directly in the network architecture, in the values of the connection weights that allow the

system to generate useful internal representations and outputs” (Rogers & McClelland, 2014, p. 1039). (Note that network in this context is referring to a type of artificial neural network, not to the structural networks described below.)

Further to this processing-centric bias, “active representations in the mind are thought to correspond to the patterns of activation generated over a set of units” (Rogers & McClelland, 2014, p. 1038). In other words, in the PDP framework, representations are not explicitly stored in and retrieved from memory but instead are ephemeral and emerge via the processing that occurs over many distributed processing units. In contrast to this view of processing and representation in contemporary cognitive psychology, an emerging approach known as cognitive network science takes a different view of processing and representation (Siew, Wulff, Beckage, & Kenett, 2019).

2. Processing and representation in cognitive network science

Cognitive network science uses the mathematical tools of network science to examine questions commonly studied by cognitive psychologists and cognitive scientists (Vitevitch, 2019a). In this approach, nodes are used to represent entities in a system, like words in the mental lexicon, and edges are used to connect nodes that are related in some way, like words that are phonologically related (Vitevitch, 2008), or words that are semantically related (e.g., Steyvers & Tenenbaum, 2005). See Fig. 1 for a network representation of the word *speech*. Words that are phonologically similar to *speech* (based on the addition, substitution, or deletion of one phoneme in the word to *speech*), such as *peach*, *speed*, and *speak* are known as 1-hop neighbors of *speech*. Words such as *spike*, *preach*, and *spud* that are phonologically similar to *peach*, *speed*, and *speak* (but not to *speech*) are known as 2-hop neighbors of *speech*.

Various measures of the resulting network structure can then be made at the level of individual nodes (known as the micro-level), at the level of the whole network (known as the macro-level), or of subsets of nodes in the network (known as the meso-level). It is important to understand the structure of a network at these three levels because a central tenet of network science states that the structure of a network influences how efficiently a process will operate in that system. For example, Kleinberg (2000; see also Latora & Marchiori, 2001) found that the algorithm that enabled an efficient navigation of a type of network known as a small-world network was less efficient when that algorithm was implemented on a network with the same number of nodes and the same number of edges, but the nodes were connected in a different pattern. In other words, how the representations are structured influences processing. Given the important influence of the structure of a network on processing, the next section will explain the structural characteristics of phonological networks.

3. The structure of phonological networks

Given the important influence that the structure of a network may have on processing, Arbesman, Strogatz, and Vitevitch (2010a) examined whether the structure of the

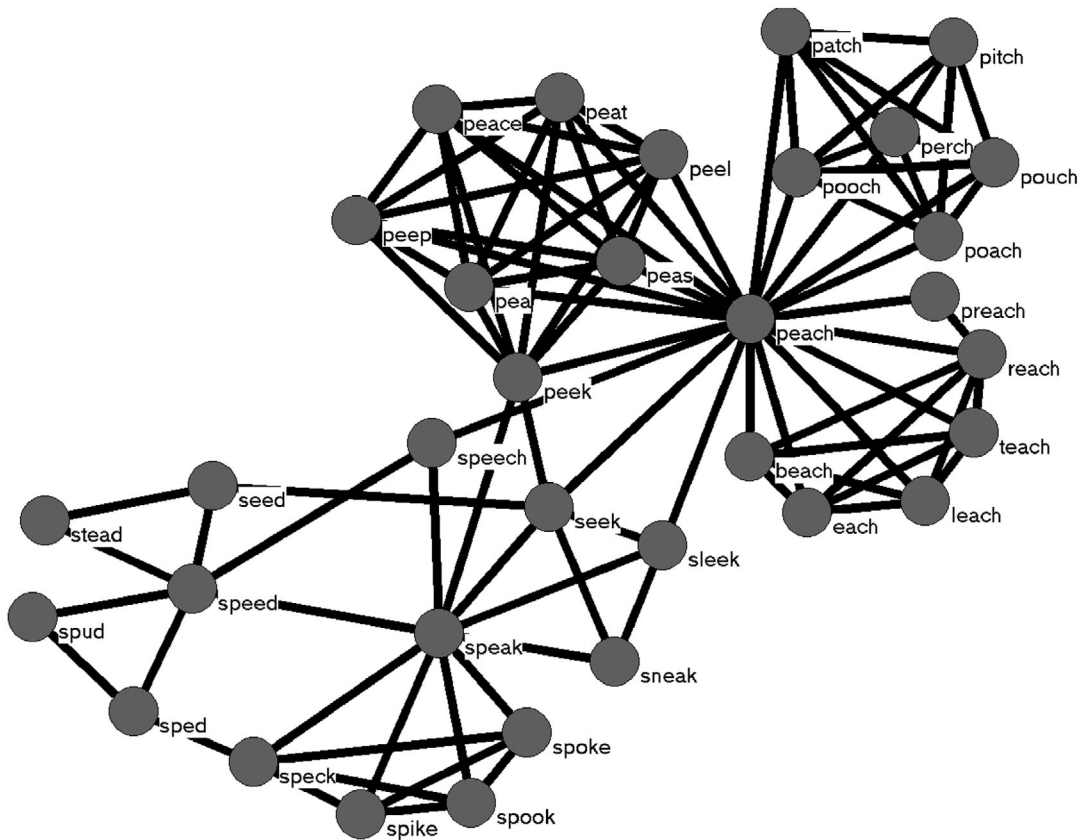


Fig. 1. In a phonological network, nodes are used to represent words, and edges connect words that sound similar to each other. In the present case, phonological similarity is defined by a simple computational metric (add, delete, or substitute a phoneme in a word to form another word). Phonological similarity can be defined in other ways as well.

phonological network observed by Vitevitch (2008) was unique to English or might be found in other languages as well. If the characteristics of phonological networks are found across multiple languages, it might suggest that those structural characteristics are in some way important and may influence language processing.

Arbesman et al. (2010a) compared the structure of the English phonological network to the structure of the phonological networks formed from words in Spanish, Mandarin, Hawaiian, and Basque. These languages were selected to be representative examples of different language families. Although English and Spanish are both from the Indo-European family of languages, English is a Germanic language, whereas Spanish is a Romance language. Mandarin is a Sino-Tibetan language, Hawaiian is an Austronesian language, and Basque (or Euskara) is a linguistic isolate, meaning that it has not (yet) been identified as a member of a given language family.

Despite these five languages differing from each other in their morphology, phonemic inventories, typical word-length, canonical syllable shape, use of tone, etc., Arbesman et al.

(2010a) found that all five languages had similar network structures characterized by (1) a giant component that was smaller than is typically observed in networks of social or technological systems, (2) a small-world structure in the giant component, (3) assortative mixing by degree in the giant component, and (4) the degree distribution of the giant component did not follow a power-law. Below we will discuss each of these structural characteristics and the relevance of them for language processing.

The giant component of a network refers to the largest cluster of interconnected nodes. In social networks that map friendships among people upwards of 90% of the nodes in the network are found in the giant component. However, in the phonological networks examined by Arbesman et al. (2010a), 34%–66% of the lexical nodes were found in the giant component. In addition to observing a smaller giant component, Arbesman et al. (2010a) observed that the phonological networks contained a large number of smaller components (referred to as “lexical islands”) that contained words that were connected to each other, but not to the giant component. (See Arbesman, Strogatz, and Vitevitch [2010b] for an analysis of how the lexical islands differed in English and Spanish.) Further, a large number of isolates (nodes not connected to anything, also referred to as lexical hermits) were also observed in the five phonological networks.

The lack of a large core of highly connected nodes in the phonological networks has some interesting implications. Arbesman et al. (2010a) found that the phonological networks were more resilient to targeted attacks to highly connected nodes and to failures of randomly selected nodes. (Resilient in this context means that the network remained relatively well connected despite increasing amounts of damage.) In contrast, the much larger giant component found in a network model of the Internet was resilient to failures of randomly selected nodes but was vulnerable to targeted attacks to highly connected nodes (Albert, Jeong, & Barabási, 1999). If one views targeted attacks to highly connected nodes and the failures of randomly selected nodes as being analogous to the damage caused by aging, stroke, or disease, then the structure of the phonological networks may confer upon various language processes a level of resilience not typically seen in networks of social or technological systems (see also De Domenico & Arenas, 2017).

The second network structure that was common to the five phonological networks was that the giant component exhibited a small-world structure. Small-world structure is typically identified by (1) the shortest average path length being comparable to the shortest average path length of a network with the same number of nodes connected randomly, and (2) by an average clustering coefficient that is several orders of magnitude larger than the average clustering coefficient of a network with the same number of nodes connected randomly. This method of identifying a small-world network was the one initially proposed by Watts and Strogatz (1998); however, more sophisticated approaches have been developed since that initial paper describing small-world networks (e.g., Humphries & Gurney, 2008). Recall that Kleinberg (2000) found that navigation algorithms were very efficient in small-world networks, suggesting that the small-world structure of the phonological networks may contribute to the rapid and efficient lexical retrieval found in healthy, typically developed language users.

The third network structure that was common to the five phonological networks was assortative mixing by degree in the giant components of the phonological networks. Assortative

mixing by degree means that nodes with many connections tended to be connected to nodes that also had many connections. Similarly, nodes with few connections tended to be connected to nodes that also had few connections. In contrast, disassortative mixing by degree, often found in technological networks (e.g., the Internet), occurs when a highly connected node tends to connect to nodes that themselves have few connections (Newman, 2002). Although assortative mixing by degree is not unique to phonological networks—it is observed often in social networks (Newman, 2002)—the values of assortative mixing by degree were much higher than those values typically observed in social networks. The work of Vitevitch, Chan, and Goldstein (2014) suggests that this characteristic in phonological networks may result in the graceful degradation typically observed in instances of failed lexical retrieval. That is, you retrieve a similar sounding word rather than fail to retrieve anything from the lexicon (i.e., a catastrophic failure in lexical retrieval).

The final network structure that was common to the five phonological networks examined by Arbesman et al. (2010a) was that the degree distribution of nodes in the giant component (i.e., the number of nodes with 1 connection, the number of nodes with 2 connections, etc.) did not follow a power law. When a degree distribution follows a power law, the distribution appears as a straight line with an exponent in the range of 2–3 when the x and y axes are plotted on logarithmic scales. This relationship indicates that there are many nodes with only a few connections and a few nodes with many connections (often called *hubs*).

Networks with degree distributions that follow a power law are known as *scale-free* networks (Barabási & Albert, 1999), meaning similar patterns in the network are observed across multiple levels of analysis. The presence of a scale-free degree distribution may indicate that a particular growth algorithm known as preferential attachment produced the structure of that network. However, work by Keller (2005) and others has shown that other algorithms can also produce power-law distributions. Further, work by Broido and Clauset (2019) suggests that scale-free networks/power-law degree distributions may not be as common as previously thought.

The deviation of the degree distribution in the phonological networks from a power law is interesting because work by Amaral, Scala, Barthélémy, and Stanley (2000) suggests that degree distributions may deviate from a power-law when there is a cost associated with the attachment of a new node in the network. In the case of phonological networks, the phoneme inventory, canonical syllable structures, and phonotactic constraints (e.g., Vitevitch & Luce, 2016) of a given language may all impose costs that constrain the attachment of a new node in the network. The presence of more than one language in the lexicon (i.e., being bi- or multi-lingual) may also impose a cost that constrains the attachment of a new node in the network (e.g., Bilson, Yoshida, Tran, Woods, & Hills, 2015; Tiv, Gullifer, Feng, & Titone, 2020). Alternatively, growth algorithms other than preferential attachment may influence the acquisition of words in the phonological network and may result in a degree distribution in the phonological networks that deviates from a power law (e.g., Hills, Maouene, Maouene, Sheya, & Smith, 2009; Siew & Vitevitch, 2020a, 2020b).

As described above, computer simulations and analogy to networks in other domains suggested that the constellation of network structures observed in phonological networks may influence lexical processing in interesting ways. The possibility of certain network structures

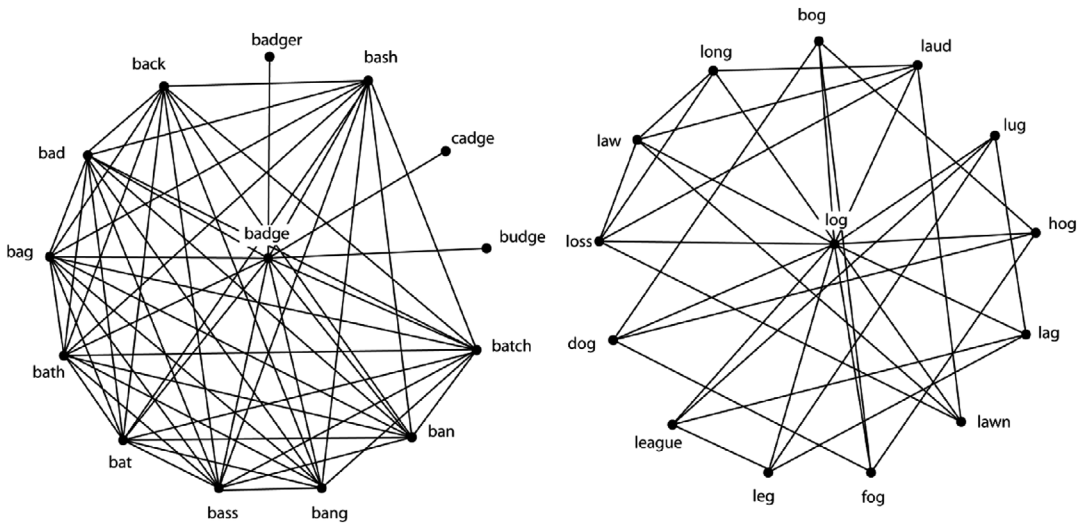


Fig. 2. An illustration of the local clustering coefficient for the words *badge* and *log*. Notice that both *badge* and *log* have the same number of phonological neighbors (i.e., the words encircling *badge* and *log*). However, the neighbors of *badge* are also neighbors of each other to a greater extent than are the neighbors of *log*.

influencing lexical processing prompted additional research using traditional psycholinguistic tasks to directly determine how certain network features influenced lexical processing. By using traditional psycholinguistic tasks that are widely used and well understood, one could be confident that the results of those psycholinguistic experiments—some of which are reviewed in the next section—were actually demonstrating the influence of certain network measures on processing.

4. Psycholinguistic evidence that structure influences processing

The first characteristic of phonological networks to be examined with psycholinguistic experiments was clustering coefficient, which measures in a phonological network the proportion of phonological neighbors of a word that are also phonological neighbors of each other (see Fig. 2). The clustering coefficient, C , has a range from 0 to 1. When $C = 0$, none of the neighbors of a given word are neighbors of each other, and when $C = 1$, every neighbor of a given word is also a neighbor of all of the other neighbors of that word.

Given the well-studied and widespread influences of phonological neighborhood density in psycholinguistics (Vitevitch & Luce, 2016)—which refers to the number of words that are phonologically similar to a given word and corresponds to the term *degree* in network science—it was reasoned that if any network science measure should influence lexical processing, it would be a measure that captured something about the internal structure of the phonological neighborhood, that is, clustering coefficient. Indeed, earlier attempts to assess the internal structure of the phonological neighborhood suggested that such influences could

be observed (Vitevitch, 2002, 2007), making the local clustering coefficient a reasonable network measure to examine first.

Chan and Vitevitch (2009) used a perceptual identification task and an auditory lexical decision task, two conventional psycholinguistic tasks used to study spoken word recognition, to examine how clustering coefficient might influence lexical processing. In the perceptual identification task, they found that words with low clustering coefficient were responded to more accurately than words with high clustering coefficient. In the lexical decision task, they found that words with low clustering coefficient were responded to more quickly than words with high clustering coefficient.

Reasoning from work done in other domains that also used network science, Chan and Vitevitch (2009) proposed a verbal model to account for the differences they observed in performance. They suggested that activation would spread from the target word to the phonologically related words and from those words to other words that were phonologically related, etc. For words with low clustering coefficient, the activation would tend to disperse to the rest of the network, allowing the target word to “stand out” from the background of partially activated phonological neighbors, and therefore be retrieved quickly and accurately. However, for words with high clustering coefficient, the spreading activation would tend to recirculate among the highly interconnected phonological neighbors, resulting in the target word being “buried” in the background of partially activated phonological neighbors.

To further explore how the structure of representations in the lexicon may influence processing, Chan and Vitevitch (2009) also reported the results of a computer simulation of the TRACE model of word recognition (McClelland & Elman, 1986; Strauss, Harris, & Magnuson, 2007). Given that (j)TRACE is a connectionist model of the *process* of spoken word recognition, and that it does not consider how representations in the lexicon are *structured*, or how that structure may influence processing, it is perhaps not surprising that (j)TRACE was not able to simulate how differences in the clustering coefficient might influence processing as was observed in the two psycholinguistics tasks used by Chan and Vitevitch (2009).

Additional studies demonstrated that the local clustering coefficient of words in the lexicon influenced other psychological processes, including speech production (Chan & Vitevitch, 2010), word learning (Goldstein & Vitevitch, 2014), and long-term and short-term memory (Vitevitch, Chan, & Roodenrys, 2012). Further, the verbal account first put forth in Chan and Vitevitch (2009) was subsequently modeled computationally by Vitevitch, Ercal, and Adagarla (2011) (see also Siew, 2019). They simulated on 2-hop networks (like those in Fig. 1) the spreading of activation among words with high and low clustering coefficient to provide a more formal account of the influence of clustering coefficient on processing.

It is important to note that measures of the network structure at the level of individual nodes (i.e., the micro-level)—like local clustering coefficient—are not the only network structures that influence various lexical processes. Other measures at the meso- and macro-level have also been observed to influence lexical processing. Mixing by degree, described above, is considered a macro-level measure describing a characteristic of the whole network. Recall that Vitevitch et al. (2014), also described above, examined how this structural characteristic might influence how individuals recover from instances of failed lexical retrieval

(see also Vitevitch, Goldstein, & Johnson, 2016 for a study of path-length and misperceptions of speech).

A study by Siew and Vitevitch (2016) looked at the macro-level structure of where words were located in the phonological network—either in the giant component or in a lexical island—and how that location might influence lexical retrieval in a naming task and a lexical decision task. They also examined how the location of a word in the phonological network might influence short-term memory processes by using a serial recall task. In all of the tasks considered, Siew and Vitevitch found that words from the lexical islands were recognized more quickly and accurately than words from the giant component despite being comparable in their frequency of occurrence, neighborhood density, word length, etc., demonstrating that macro-level structures of the phonological network can also influence cognitive processing.

Turning to the meso-level—which measures subsets of nodes in the network rather than a characteristic at the individual level or of the overall network (e.g., Siew, 2013)—we see that key players in a network (Borgatti, 2006) also influence the process of spoken word recognition. Key players constitute a set of nodes in a network that, when removed, result in the network fracturing into several smaller components. When compared to another set of foil words that were comparable to the key players in frequency of occurrence, neighborhood density, word length, etc., Vitevitch and Goldstein (2014) found in a perceptual identification task that the key players were responded to more quickly and accurately than the foil words. Similar results were obtained in a naming task, a lexical decision task, and in an analysis of data from the English Lexicon Project (Balota et al., 2007). Together the studies described above demonstrate that the micro-, meso-, and macro-level structures of the phonological network influence various language-related and cognitive processes.

5. Network structure and speech and language disorders

In addition to leading to insights about the typical perception and production of speech in adults (as described above), the network approach has also been used to shed light on the atypical perception and production of speech in adults and children. Consider the work of Castro, Pelczarski, and Vitevitch (2017), who found that closeness centrality influenced reaction times in a lexical decision task of adults who stutter. Closeness centrality measures the distance from one node to all other nodes in the network (following the shortest path between any two nodes being considered). Although stuttering is often viewed as a disorder that primarily affects the fluent production of speech, subtle differences—that are not yet well understood—have been observed in the phonological processing abilities of people who stutter as compared to typically fluent peers (e.g., Byrd, McGill, & Usler, 2015; Newman & Bernstein Ratner, 2007; Pelczarski & Yaruss, 2014, 2016; Sasisekaran & De Nil, 2006). The tools of network science might be able to reveal more of these subtle differences in people who stutter, which are not always revealed using traditional psycholinguistic tasks.

Another study that used network science to gain insights that could not have been observed with standard measures (of phonetic accuracy) comes from Benham, Goffman, and Schweickert (2018), who examined novel sound and syllable production in typical and atypical

language learners (i.e., children with developmental language disorder [DLD], also known as specific language impairment). Benham et al. asked children to repeat specially constructed nonwords with two syllables, and they used networks in which nodes represented syllables, and links connected the first to the second syllable in the production of each child. Although a more conventional kinematic analysis could not distinguish between the two groups of children, the nonword networks revealed higher variability and more disorganized production patterns in the children with DLD, despite both typical children and those with DLD exhibiting similar patterns of learning over time. The work of Benham et al. further demonstrates how the network approach can be used to gain insights into typical and atypical language development that might not be observed using more conventional or traditional measures and techniques (see also Carlson, Sonderegger, & Bane, 2014; Siew & Vitevitch, 2020a, 2020b).

Turning to acquired language disorders in adults, work by Vitevitch and Castro (2015) showed that individuals with Wernicke's or Broca's aphasia experienced problems in speech production as measured by the Philadelphia Naming Test that correlated with differences in the closeness centrality and the location in the phonological network (giant component vs. lexical island or a lexical hermit) of the words to be named. Studies like this further demonstrate the utility of the network approach to increase our understanding of acquired language disorders like aphasia.

Although the present paper has focused primarily on phonological networks, interesting work looking at other language disorders has been done with semantic networks, where connections are placed between words that are similar in their meanings instead of similar in how they sound. Some of this work is summarized here to provide further evidence that networks can provide insight into the atypical processes and representations that may characterize certain developmental and acquired speech and language disorders.

Beckage, Smith, and Hills (2011) demonstrated that networks that grow over time could provide insight not only into word learning in typically developing children but also provide insight into "late talking" children, who have vocabulary that are smaller than age-matched children. Importantly, Beckage et al. (2011) found that late talkers had semantic networks that were less small-world-like than the semantic networks of typically developing children. Further, Beckage et al. (2011) observed a bias among the late talkers to learn "oddball" words that were semantically unique, rather than new words that were well connected to other words in the lexicon as typically developing children tend to do (e.g., Hills et al., 2009). It is not clear if other analysis approaches could have provided the insights that Beckage et al. (2011) observed with the network approach.

The tools of network science have also been used to examine the semantic networks of children with cochlear implants (Kenett et al., 2013) and may hold promise for increasing our understanding of the changes that take place in the lexicon as we age and possibly experience certain diseases often associated with aging (e.g., Wulff, De Deyne, Jones, & Mata, 2019). Although many of the diseases often associated with aging, like Alzheimer's disease, typically affect the semantic rather than phonological aspects of language, the work being done on semantic networks (e.g., Zemla & Austerweil, 2019) serves at the very least as a proof of concept of how network science can be used to provide insight into other aspects of the aging lexicon, like phonology.

6. The social network influences the lexical network

Up to this point, we have considered how network science can be used to capture the structure of the linguistic knowledge that individuals represent internally, and how that internally represented linguistic knowledge is acquired and develops over time. However, language does not occur solely in the black box of the mind but is inherently social as evidenced by the need for a language learner to be immersed in a community of language users (either speakers or signers) that transmit the ambient language to the learner. By having nodes represent people and edges connecting people who are friends with each other, the tools of network science can be used to examine the influences of one's social network on language processing.

Lev-Ari and colleagues provide examples of how the size of one's social network can influence the ability of an individual to correctly interpret semantic information (Lev-Ari, 2016), and also to process the phonetic/phonological information used to perceive speech (Lev-Ari, 2018). These studies demonstrate how network science can help us better understand social influences on certain language processes rather than ignore those social influences as is more often done in the typical approach of cognitive psychology to examine language processing.

Further, changes in language occur not only at the developmental time-scale of an individual but also occur at longer and shorter time-scales. An example of language change that occurs on a longer time-scale is seen by the changes in language that occur across generations of language users. An example of language change that occurs on a shorter time-scale is seen when an individual accommodates to various linguistic features—such as a foreign accent—of a newly encountered interlocutor. The tools of network science can also be used to examine the influences on processing that occur at these shorter and longer time-scales.

A study by Iacozza, Meyer, and Lev-Ari (2020) demonstrates that social influences on cognitive processing can be induced very quickly (i.e., on very short time-scales). Participants in their experiment were asked to learn the names of novel objects. Crucially, the names of the objects were taught to the participants by (ostensibly) students from their own university (inducing an in-group bias) or by students from another university (inducing an out-group bias). Participants with stronger in-group biases (as assessed by a perceptual matching task; Moradi, Sui, Hewstone, & Humphreys, 2015) were less accurate at identifying matching speaker-label pairs when the speaker was from the out-group, indicating more specific encoding of information for members of the in-group than for members of the out-group.

Although Iacozza et al. (2020) did not use network analysis in this study, their work does show that whether a person is in or out of one's social network (i.e., in-group versus out-group, see also Frable & Bem, 1985) can influence certain cognitive processes, and those influences can be induced on a relatively short time-scale. For an example of the use of network analysis on a longer, evolutionary time-scale see, for example, Centola and Baronchelli (2015).

Network science may not only provide insights into internal language processes often studied by cognitive psychologists and other language scientists, as described above, but it may also provide a way to connect the work from various domains of language science. The work of Lev-Ari (2016, 2018) provides one example of how the tools of network science might connect social psychology/sociolinguistics to cognitive psychology/psycholinguistics. The next

section examines other ways that network science can be used to connect various domains of language science.

7. Multilevel networks in psycholinguistics

Another way the tools of network science may connect various domains of language is through the use of multilevel networks, also known as a network of networks. In a multilevel network, for example, words in one level are connected to each other via their phonological relationship but connected to each other in another level via their semantic relationship. An additional connection would link *cat* at the phonological level to *cat* at the semantic level, for example. Other relationships among words—such as morphology or orthography (Siew & Vitevitch, 2019)—could also be included in another network level to further examine the way different types of linguistic information interact during language processing.

Much progress has already been made using multilevel networks to understand word learning (Stella, Beckage, Brede, & De Domenico, 2018) and acquired language disorders (Castro, Stella, & Siew, 2020). Continued exploration of multilevel linguistic networks may provide new insights into various types of language processes and into language disorders, especially if additional levels are incorporated in the network of networks. With the right additional levels, one might even be able to finally connect the physiological network in the brain to the cognitive network in the mind (Vitevitch, 2019b).

8. Challenges for cognitive network science

The cognitive network science approach has been criticized because “these networks do not ‘do’ anything; they have no function” (Brown et al., 2018, p. 16). On the contrary, what such networks “do” is capture certain regularities and relationships among entities in the world around us. Work by Karuza, Kahn, Thompson-Schill, and Bassett (2017) suggests that humans are able to extract those relationships among entities from the world around us and exploit that information in subsequent tasks. This suggests that these networks indeed “do” something and “function” to internally organize representations of the world around us.

With the regularities and relationships among entities in the world around us captured in the structure of the network, a simple processing algorithm—like a random walk on the network—may be sufficient to reproduce the behavior exhibited by humans in various tasks (e.g., Abbott, Austerweil, & Griffiths, 2015; Schweickert, Xi, Viau-Quesnel, & Zheng, 2020). Alternatively, diffusion of activation across the network may also reproduce the behavior exhibited by humans in certain tasks (e.g., Siew, 2019; Vitevitch et al., 2011).

However, simple processes such as random walks and activation diffusing across a structured network may not be sufficient to capture the richness of all of human cognition. Human cognition also has many examples of directed search through memory (e.g., Hills & Pachur, 2012). Therefore, cognitive network science may also need to consider algorithms that employ a mixture of random and directed walks such as the taxi-drive algorithm proposed

by O’Keeffe, Anjomshoaa, Strogatz, Santi, and Ratti (2019)). The taxi-drive algorithm was inspired by real taxis serving passengers in a city. Typically, a taxi drives around randomly until a passenger flags them down for a ride to a specific location. The taxi then proceeds along the shortest route to the randomly prescribed location, deposits the passenger, and then proceeds to roam around randomly until flagged down for the next randomly selected yet directed destination. This mixture of random and directed walks may better capture certain aspects of human cognition (i.e., executive function) and navigation across a structured network of the mental lexicon.

The tools of network science may enable us to understand how many of the pieces of language and cognition (and social influences) fit together, and how that underlying structure influences the behavior of cognitive and linguistic systems (Barabási, 2009, 2012). Additional computer simulations and psycholinguistic experiments will be required to assess how cognitive network science can examine in new ways the typical and atypical perception and production of speech (in mono- and multi-lingual individuals), the influences of age and disease on language processing, the typical and atypical acquisition of new words, and to language change over time. Work using multilevel networks also holds much promise for reconnecting work from various domains of language science, which have become increasingly balkanized and disconnected over the years.

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