

IMPORTANT WORDS IN THE LEXICON: THE INFLUENCE OF CLOSENESS
CENTRALITY ON LEXICAL PROCESSING

BY

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Abstract

Network science is an interdisciplinary field drawing on computational and mathematical tools from mathematics, computer science, and physics. Network Science utilizes networks to examine real world complex systems. Within the network models nodes represent individual entities and links represent relationships between entities. A key finding of network science is that the underlying structure of a system will influence how that system functions. A network model of the phonological lexicon was created by Vitevitch (2008) using nodes to represent words and links to represent phonological similarity. The present work explores the influence of closeness centrality (a network measure of the average distance between a node and all other nodes in a network) on lexical processing. A word with a high closeness centrality value, such as CAN, will be centrally located and close to many other words in the lexicon. A word with a low closeness centrality value, such as CURE, will be located in a remote, sparse area of the lexicon and will be far from many other words in the lexicon. Three experiments were performed. Experiment 1 used a lexical search task in which participants were to turn one word into another by changing one sound at a time in the word. Participants were more successful at completing the task when it began at a word with low closeness centrality than at a word with high closeness centrality. Experiment 2 used an auditory lexical decision task and results show participants responded more quickly to words with high closeness centrality than to words with low closeness centrality. In Experiment 2, confounding variables were controlled during the initial selection of stimuli. However, in Experiment 3 an auditory lexical decision task was used again, but confounding variables were controlled via statistical analysis. In addition, a number of individual differences in participants were measured (e.g., vocabulary size, working memory span, processing speed, and inhibition processing). Experiment 3 results suggest an interaction between closeness centrality and frequency of occurrence on reaction times, but no impact of individual differences was observed on the closeness centrality effect. Results are explained in terms of a partial activation framework and implications of the work are discussed.

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The word BADGE on the left has many neighbors that are neighbors of each other and therefore has a high C . The word LOG on the right has few neighbors that are neighbors of each other and therefore has a low C . Notice that both words have the same number of phonological neighbors: 13. Used with permission of the authors: Chan & Vitevitch (2009).

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Chapter 1: Network Science and the Mental Lexicon

Network science is one way to study real world complex systems. A complex system is any system that consists of entities and relationships between those entities. Complex systems are unique in that collective behavior arises without the direct control of a single entity (i.e. a master-slave communication system) and the group behavior would not be evident if the entities were studied in isolation. For example, a riot is considered collective social behavior. One person does not orchestrate a riot and “riot behavior” would only be evident if more than one person’s actions were observed. Using network science principles, a network model is constructed out of nodes (representing entities) and links (representing relationships). For example, network models are often constructed to represent social groups using nodes to represent individuals and links to represent social relationships (e.g. friendships, professional associations, academic collaborations, etc.) One of the main tenets of network science is that the underlying structure of any system will undoubtedly influence how that system operates (Watts & Strogatz, 1998).

The structure of a system has been shown to influence functioning in networks created from vastly different real world systems. Network models have been created from ecological food webs (Montoya & Solè, 2003), modeling how the extinction of species affects the entire food web. Montoya and Solè created a network model where a node represents a species in an ecosystem and links represent a predator-prey relationship. Their results showed a tendency for food webs to be robust to the removal of a species. That is, if a species becomes extinct (effectively removing the node from the network) the overall structure of the food web will not be irreparably damaged and the ecosystem will continue to survive. If a prey species goes extinct the predators preying on the extinct species will find a source of food elsewhere in the food web. If a predator species goes extinct, other predator species will step in and cull the growth of the affected prey species, avoiding overpopulation and resource depletion.

Network models have examined how power outages spread through a power grid and how to best prevent outages in the future (Albert, Albert & Nakarado, 2004). In these networks a node represents a

substation and a link represents transmission of power between two substations, i.e. a power line. The goal of these studies is to identify ways to create power grids that are robust to damage. That is, substations or power lines can be removed from the power grid without causing the system to fail (i.e. a power outage). Results show that the power grid in North America is robust to random substation failures, but targeted attacks of key substations are successful in impairing function of the power grid. The networks models created are useful in determining where to add substations and power lines to reduce the spread of a power outage due to random failure or targeted attack.

Transportation network models have been created to guide the construction of more efficient airline transportation systems (Guimerà et al., 2005). An airline transportation network consists of nodes representing airports and links representing direct flights between airports. These models allow airline companies to design flight paths that lead to efficient travel across the world and transportation officials to build airports where they are most beneficial to overall transportation needs. Airline transportation networks have to be robust to damage due to inclement weather, which effectively removes an airport from the system temporarily. Network models of this system help identify where to most efficiently redirect flights when necessary.

Academic collaboration networks have also been modeled, leading to insights into the way scientists communicate (Newman, 2001). In these networks a node represents an individual scientist and a link represents at least one co-authorship between authors. Networks created from different research fields have quantified differences in the social organization of disciplines. Authors in experimental fields, such as high-energy physics, tend to have a large number of collaborators, whereas authors in theoretical fields, such as computer science tend to have a small number of collaborators. These networks also allow for identification of influential scientists, such as authors with a large number of links or authors acting as bridges between disconnected subfields.

Network scientists have modeled the neuronal structure in the roundworm *c. elegans* (Watts & Strogatz, 1998). In this network a node represents a neuron and a link connects two neurons that directly communicate via synapses. Results from the model show that the neuronal structure is characterized by small world characteristics, which are common in many networks such as transportation networks, academic collaboration networks, and power grid networks among others. Small world characteristics allow a neuron to communicate with any other neuron while passing through few connecting neurons, increasing efficiency of neuronal communication. This observation is only evident after a network model is created.

Models of cognitive systems have also been constructed using network science principles (Steyvers & Tenenbaum, 2005; Hills et al., 2009). One complex cognitive system, the mental lexicon (or an individual's vocabulary in a given language), has been estimated to contain 20,000 to 240,000 words (Nusbaum, Pisoni & Davis, 1984; Hartmann, 1941). The tools of network science are ideally suited for studying such a large complex cognitive system as the mental lexicon. A study performed by Vitevitch (2008) created a network model of the mental lexicon by using nodes to represent individual words and links to represent phonological similarity (See Arbesman, Strogatz & Vitevitch, 2010 for an analysis of languages other than English). Phonological similarity was determined using a one phoneme metric. That is, words that differ by a single phoneme share a link. Words that differ by a single phoneme are also referred to as phonological neighbors in psycholinguistic literature (Luce & Pisoni, 1998). For example CAT has BAT, CUT, and CAP (among others) as phonological neighbors. A word and all of the associated similar sounding words is called a phonological neighborhood. In the analysis Vitevitch (2008) found that the structure of the mental lexicon shares many network features of other real world systems, encouraging the exploration of the mental lexicon using network science tools. See Figure 1 for a portion of the network analyzed in Vitevitch (2008).

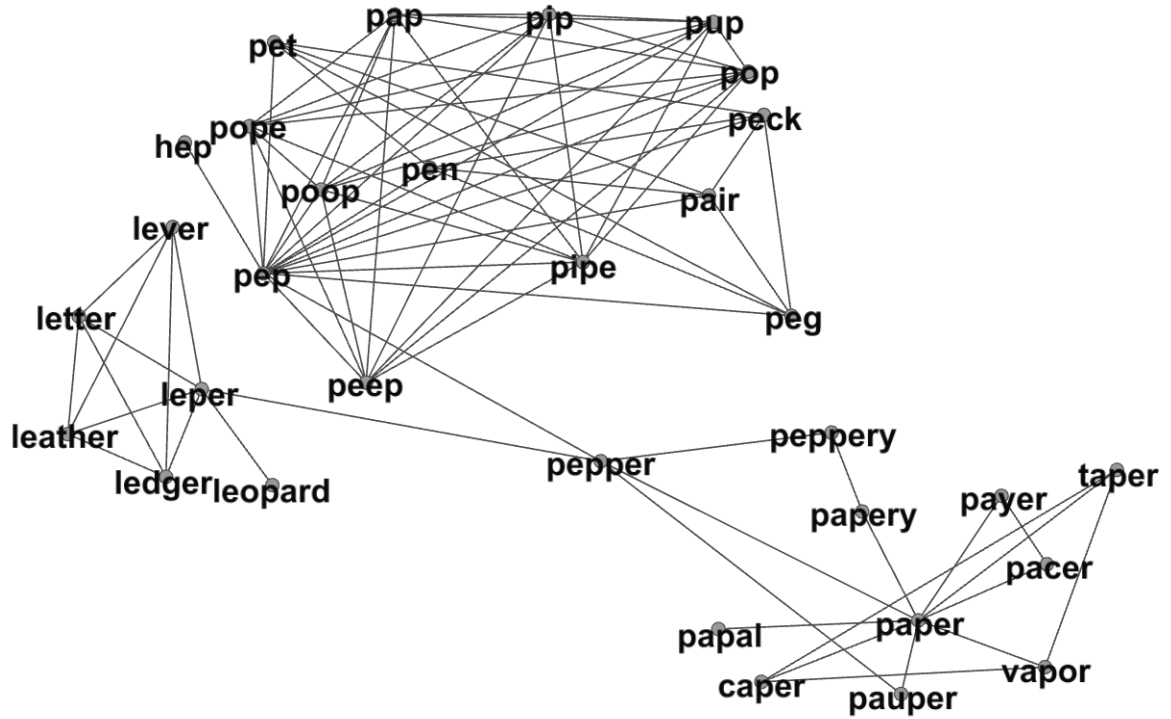


Figure 1. A portion of the phonological network examined in Vitevitch (2008). The network shows the word PEPPER, the neighbors of the word PEPPER, and the neighbors of those neighbors. Notice that a link exists between words when they are phonological neighbors of each other. Adapted from Vitevitch (2008).

Past models of spoken word recognition account for lexical processing, but do not take into account structural characteristics of the mental lexicon (McClelland & Elman, 1986; Norris, 1994). That is, previous models instead focus on how the individual characteristics of words influence the process of lexical retrieval, but do not consider how the overall structure of the lexicon might also influence that process. A vast amount of research has explored factors such as the frequency of occurrence of a word (Jescheniak & Levelt, 1994), the probability of a certain phoneme occurring in a certain position in a word (Vitevitch & Luce, 1999), or the familiarity of a word (Nusbaum, Pisoni & Davis, 1984). Past models of spoken word recognition have immensely increased our knowledge of lexical processing, but a growing body of evidence suggests that the structural organization of words in the lexicon influences how words are processed (Chan & Vitevitch, 2009; Chan & Vitevitch, 2010; Vitevitch & Goldstein, 2014;

Vitevitch, Chan & Roodenrys, 2012; Vitevitch, Chan & Goldstein, 2014), pointing to a clear limitation of these somewhat dated models of spoken word recognition. Models that focus on individual word characteristics are not able to account for the influence that structural characteristics appear to have on lexical processing. Research into lexical processing must recognize the importance of the relationships *among* words, rather than studying words as isolated entities.

Extending the main tenet of network science, that structure influences functioning, to the mental lexicon provides a greater understanding of lexical processing. Indeed, previous studies (described in more detail below) have shown the influence of lexical structure on lexical processing. It is important to note that past models of spoken word recognition do not account for the findings described below. Past models would predict no difference in processing once all individual-level characteristics have been controlled. These past models view the lexicon as a store of individual representations in isolation. Whereas, using network science, the lexicon is more accurately viewed as a connected whole with an organized structure that influences functioning in observable ways. An important step in gaining a greater understanding of lexical processing is to determine what structural characteristics influence processing and how those structural characteristics influence processing.

Before proceeding further an important distinction must be made. The focus of the current work is on the phonological lexicon, or the sounds of words, and how phonological information influences language processing. There are other characteristics of words that influence language processing, such as semantic information (the meaning of a word) or orthographic information (the spelling of a word). It is important to acknowledge the importance of other factors in language processing, however the current work will focus solely on the phonological lexicon. Other lexical networks have been created based on other characteristics of words and have been shown to influence language processing (Steyvers & Tennenbaum, 2005). It may be viewed as a limitation to focus solely on one characteristic of words.

However, linguistic theories have often proposed a distinction between semantic and phonological language processing. Each process has equally important, yet vastly different roles in language use. Phonological information acts as an auditory “key”, unlocking the “chest” of semantic memory information associated with a specific spoken word. Phonological processes rely heavily on perceptual processes, whereas the semantic processes rely heavily on memory processes. The distinction between semantic and phonological processes is made more evident by the arbitrary and meaningless relationship of the phonological “key” to the semantic “chest”. For example, a large animal does not necessitate a large name, nor does a small animal necessitate a small name (see Hockett’s definition of arbitrariness in language; 1960). The distinction between these two processes suggests it is beneficial to study one or the other in isolation before attempting to bridge the gap between these two distinct processes.

Future network science research may be able to bridge the gap between phonological and semantic processing. Presently, network scientists are attempting to develop tools which allow for network layers to be combined. Complex systems often have multiple relationships between nodes and being able to represent the different layers of relationships in a network model would allow for more accurate modeling. For example, work by Sterbenz et al. (2010) explores the interaction of different layers of the internet network and how this interaction affects resiliency of the network. The future possibilities of combining the phonological lexicon layer with the semantic lexicon layer make the network science approach to language processing even more appealing.

Before discussing several network characteristics of the phonological lexicon that influence processing, the reader must be made aware that networks can be examined on many levels or scales. At the local scale, network characteristics measure the network area immediately surrounding a word. Local network characteristics often describe the relationships between a target word and all similar sounding words (a phonological neighborhood). In contrast, at the global scale network characteristics describe the average for the entire network. Global network characteristics have a much broader scope than local

network characteristics in that they measure the relationship between a target word and the entire lexicon. The previous research described below shows the importance of examining a network at multiple levels or scales.

Chapter 2: Local Network Characteristics

At the local level, the clustering coefficient, or C , measures how many nodes connected to a target node are also connected to each other. In the phonological lexicon, C is a measure of how many phonological neighbors of a word are also phonological neighbors of each other. For example, the word BADGE has the neighbors BAG, BAD, and BAT which are neighbors of each other. C is a ratio, a value of 1 indicates that all the neighbors of a word are neighbors of each other. A C value of 0 indicates that no neighbors of a word are neighbors of each other (a more precise definition of C can be found in equation 1; Watts & Strogatz, 1998). As illustrated in Figure 2, BADGE has a high C value, whereas the word LOG, which has the neighbors LOSS, DOG, and LEAGUE that are not neighbors of each other, has a low C value.

$$C_i = \frac{2 |\{e_{jk}\}|}{k_i(k_i - 1)}$$

(Eq. 1)

e_{jk} refers to the presence of a connection between two neighbors (j and k) of node i , $|\dots|$ is used to indicate cardinality (i.e., the number of elements in the set), and k_i refers to the degree (i.e., neighborhood density) of node i .

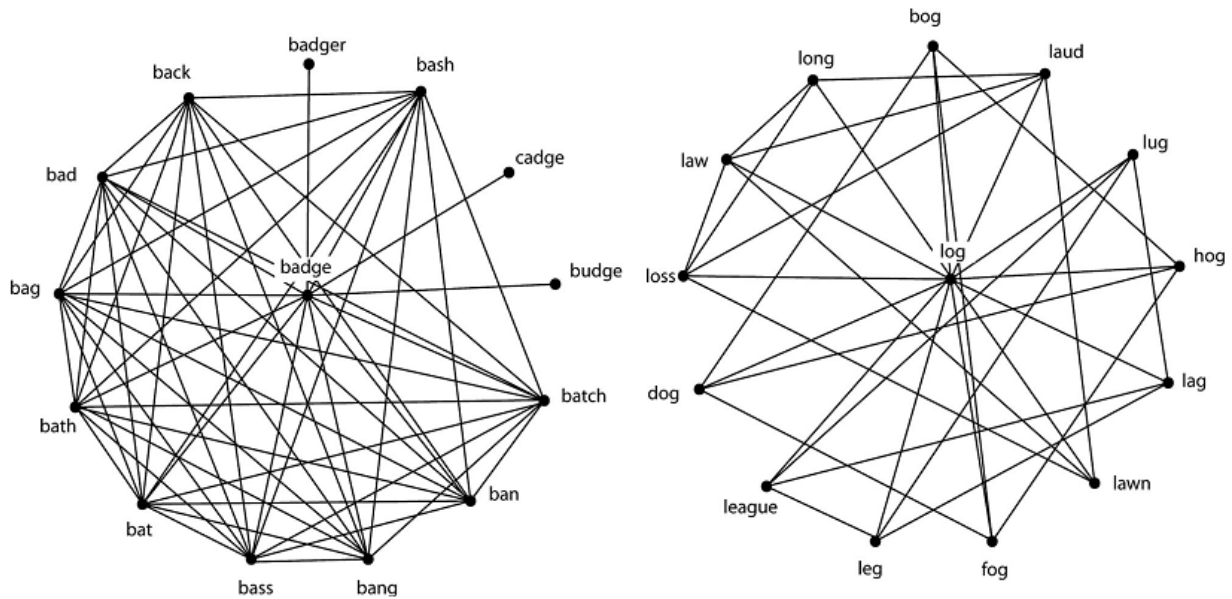


Figure 2. The word **BADGE** on the left has many neighbors that are neighbors of each other and therefore has a high C . The word **LOG** on the right has few neighbors that are neighbors of each other and therefore has a low C . Notice that both words have the same number of phonological neighbors: 13. Used with permission of the authors: Chan & Vitevitch (2009).

The network characteristic C has been shown to influence a number of language processes including spoken word recognition. Chan and Vitevitch (2009) found that spoken word recognition is influenced by C in both a perceptual identification task and a lexical decision task. A processing advantage (i.e. higher accuracy rates or faster reaction times) was observed for low C words in both tasks (see Vitevitch, Ercal & Adagarla, 2011 for a computer simulation of the results). The structural characteristic of C being shown to influence processing strongly supports the idea that the structure of the lexicon should be taken into account when lexical processing is examined. Network science measures exploring the network at the local scale have provided insights into other lexical processes as well.

Chan and Vitevitch (2010) performed a similar study exploring how the process of production is influenced by C . The results show a similar pattern of processing. Results from a speech error corpus analysis and a picture naming task show that high C words are produced with greater errors and with slower reaction times compared to low C words. The results from both studies (Chan & Vitevitch 2009;

2010) suggest that production and recognition processes are influenced by the network characteristic C . Furthermore, the two studies discussed above provide compelling evidence that structural characteristics, as measured using network science tools, influence lexical processing in observable ways. Again, these findings are a departure from past views of lexical processing that study words in the lexicon as isolated representations.

Other language processes beyond recognition and production are influenced by the local network characteristic C as well. Goldstein and Vitevitch (2014) studied how C affects the process of learning new words. In contrast to recognition and production, where an advantage was found for low C words, an advantage was observed for learning new words that have a high C value. Thus, when lexical processing occurs on already established words (i.e. recognition and production) having a high C value impedes processing, whereas when a newly encountered word is being established in the lexicon having a high C value benefits the process. This seeming contradiction can be explained by differing effects of spreading activation in the lexicon.

The concept of spreading activation is common in several models of lexical processing (Collins & Loftus, 1975; Roelofs, 1992; Roediger & Balota, 2001). When a word is retrieved from the lexicon for recognition or production the word becomes activated and transmits activation to similar sounding words. The similar sounding words become activated, to a lesser degree, and in turn transmit their own activation to their own similar sounding words. In this way activation starts from a target word and spreads across the lexicon, diminishing in strength as it disperses.

Consider a word with a high C value. When it is activated in the lexicon for retrieval it transmits activation to its phonological neighbors which in turn transmit activation to their phonological neighbors. The high C value implies that many of the neighbors of a target word are neighbors of each other and therefore a large portion of the activation spreading from the phonological neighbors of a word will continue to spread along the many connections within the phonological neighborhood, effectively

trapping the activation. The trapped activation creates a large amount of interference from neighborhood competitors in the retrieval process and retrieval of the target word is slowed. However, when a word with low C is retrieved from the lexicon the activation stemming from the target word is not trapped in the phonological neighborhood. The phonological neighbors of a low C word do not tend to be neighbors of each other and activation is instead dispersed to other areas of the lexicon, effectively reducing interference in the retrieval process. Therefore the target word in a low C neighborhood stands out relative to its neighborhood competitors and retrieval is aided (see Vitevitch, Ercal & Adagarla, 2001 for a computer simulation of the results).

Now, in the process of learning a new word the advantage changes. A newly encountered word has a very weak representation in the lexicon. If that weak representation has a high C value every time it is retrieved the activation stemming from the weak target word representation will become trapped in its phonological neighborhood. This trapped activation will continually activate the weak representation and repeated activation will actually help it become established in the lexicon. However, when a newly learned word has a low C value the activation that originates from it will not be trapped in the neighborhood, but rather dispersed to other areas of the lexicon. Therefore, no trapped activation will be continually activating the weak representation and the same benefit observed in a high C neighborhood will not occur. In this way, a high C value impedes processing of established representations in the lexicon while helping to solidify weak representations of newly encountered words.

The network characteristic of C has been shown to influence several important language processes. C is considered a local network characteristic since it measures the network structure immediately surrounding a single word and has been shown to influence different language processes in different ways. Networks can also be measured at a global scale, which describes the relationship between a single word and all other words in the lexicon.

Chapter 3: Global Network Characteristics

One way to look globally at a network is to consider which nodes in a network are the most important nodes. What is considered an important node will change depending on the system or process being modeled. For example, in a social network nodes that have a high number of connections are often considered important. Social network nodes with many connections are considered to be influential since they can pass information, diseases, or resources to many other nodes (Dezső & Barabási, 2002). In the world wide web, the search engine Google uses a search algorithm that ranks importance based on the number of connections that nodes connected to a target node have (i.e. how many connections the connected nodes have; Griffiths, Steyvers & Firl, 2007). It is useful to determine the “important” nodes in a network in order to help protect them in cases of targeted attack (e.g. a power grid network), to disrupt a network with targeted attacks (e.g. a terrorist network), to stop the spread of disease through a network (e.g. a sexual relationship network), or to spread information efficiently through a network (e.g. a communication network).

Another way to identify important nodes in a network is to determine whether a node is a keyplayer or not (Borgatti, 2006). A keyplayer is a node, that when removed, will fracture a connected network into smaller disconnected networks. A keyplayer is not simply a node with a large number of connections. Keyplayer nodes occupy a critically important position in the network by acting as a bridge between different components of a network (see Figure 3). The importance of keyplayers can be seen in a social network. A keyplayer in a social network can act as an intermediary between two companies, two law firms, two groups of friends, or two research labs. Without the connections provided by the important keyplayer node the separate parts of the network would have no way of interacting.

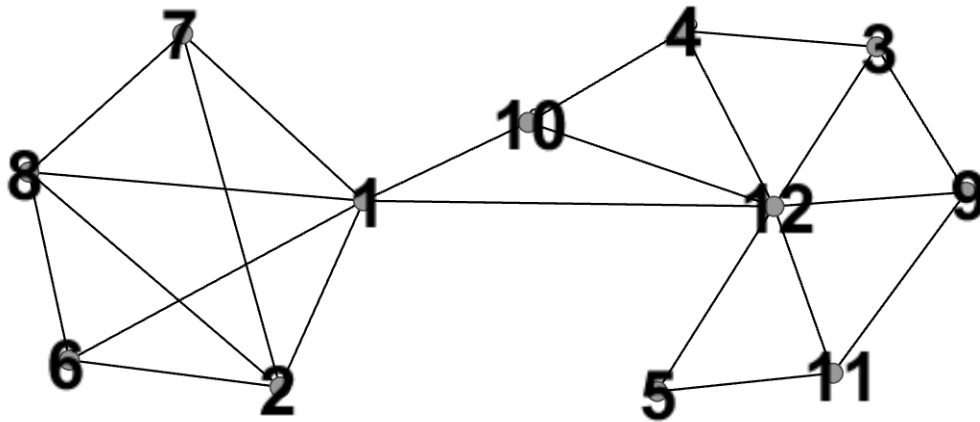


Figure 3. Node 12 has the most connections of any node in the network. However, removing node 1 would fracture the network into two disconnected pieces. Therefore node 1 is considered a keyplayer in this network. Adapted from Borgatti (2006).

Vitevitch and Goldstein (2014) applied a keyplayer analysis to the lexicon and identified a set of “keywords” that when removed will fracture the lexicon. The keywords were identified faster and more accurately in a perceptual identification task with degraded stimuli, a naming task, and a lexical decision task than another set of words that were controlled on all relevant individual word characteristics. The findings of Vitevitch and Goldstein (2014) highlight how important words in the lexical network are retrieved differently than other words. Again, the keywords did not differ on individual level characteristics. However, the relationships between words in the lexicon lead to the processing differences observed in Vitevitch and Goldstein (2014), suggesting that by studying the lexicon as a connected whole (specifically by identifying important words in the lexicon) we will gain a greater understanding of lexical processing than past models will allow.

The findings of Vitevitch and Goldstein (2014) suggest that there may be other “important” words in the lexicon and that these words may be processed in different ways compared to other words. The network science measure of closeness centrality is another way to measure “importance” in a network. Closeness centrality is a measure of the average number of links between a word and all other words in the lexicon, as illustrated in Figure 4. Closeness centrality ranges from 0 to 1 and is the inverse of the average number of links that must be traversed from a node in the network to all other nodes in the network (see equation 2 for a more precise mathematical definition). For example, the word CAN is a small average number of links away from every other word in the lexicon and has a high closeness centrality (i.e. CAN is “close” to the rest of the lexicon). The word CURE is a large average number of links away from every other word in the lexicon and has a low closeness centrality (i.e. CURE is “far” from the rest of the lexicon).

$$C_v = \frac{n - 1}{\sum_{u \in V} d(v, u)}$$

(Eq. 2)

n refers to the number of vertices in the network. $d(v, u)$ refers to the shortest path between nodes v and u . Σ refers to the sum of the path lengths from node v to all other nodes in the network.

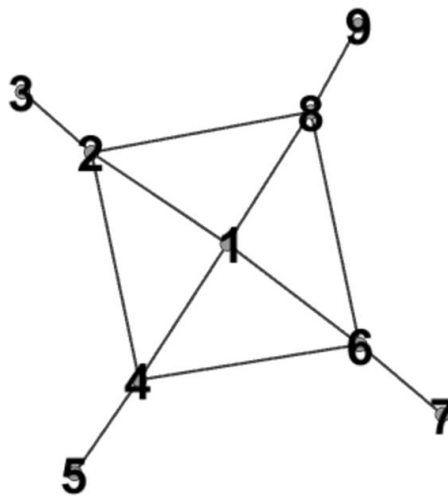


Figure 4. Node 1 has the lowest average path length to all other nodes (1.5) and therefore the highest closeness centrality value (.66). Nodes 3, 5, 7, and 9 have the highest average path length to all other nodes (2.5) and therefore the lowest closeness centrality values (.40).

Closeness centrality values will vary depending on the network being measured (Freeman, 1979). The highest possible closeness centrality value would be 1, meaning the node is 1 link away from all other nodes in the network. What is considered a high or low closeness centrality value will depend on the distance (i.e. number of links between nodes) within a network. The network in Figure 4 is relatively small with relatively short distances between nodes. A node with a closeness centrality value of .4 is considered far from the rest of the network and a node with a closeness centrality value of .66 is considered close. However, when the size of the network is relatively large (e.g. the mental lexicon) what is considered a high or low closeness centrality value will change due to the much larger distances in a large network. The mental lexicon has a range of closeness centrality values from .0001 (which would be considered low in this network) to .08 (which would be considered high in this network). Interpreting closeness centrality values is dependent on the size of the network itself.

In order to remove the influence of network size on closeness centrality values some researchers use a normalized closeness centrality value (Freeman, 1979). The normalized value is independent of network size. The experiments described in this dissertation do not use the normalized closeness centrality values since all closeness centrality values come from the same network (the mental lexicon) and no comparisons are necessary between networks of different sizes.

A recent study showed how important nodes, as measured by closeness centrality, can influence language processing (Iyengar et al., 2012). Researchers used a word-morph game to explore how important words influence word finding in the lexicon. The word-morph game consists of beginning with a start word (e.g. BAD) and attempting to reach an end word. Participants can change one letter at a time and the result must be a real word (e.g. BAD → BAT is acceptable whereas BAD → BAC is not acceptable). Participants soon discover that the task is much easier to complete if certain “landmark” words are utilized. Landmark words are words that have a high closeness centrality. Much like physical landmarks in spatial navigation, once a high closeness centrality word is reached in the lexicon it is easy to navigate to any other word in the lexicon. Therefore, after several attempts, participants would not try

to take as direct a route as possible, but would instead try to reach a high closeness centrality word (i.e. a landmark) and then attempt to reach the end word. A strategy involving landmark words was much more successful than attempting to take a direct route from start word to end word. Iyengar et al. (2012) showed that important words, specifically high closeness centrality words, play a critical role in how the lexicon functions.

The pioneering work by Iyengar et al. (2012) provides evidence that high closeness centrality words are important for lexical processing and warrant further research. There are properties of the lexical network that make closeness centrality an ideal measure to apply to the lexicon. Borgatti (2005) showed through simulations that closeness centrality is a suitable measure for networks where the flow of information spreads from one node to all other connected nodes simultaneously, the connected nodes then spread that information to their connected nodes, and so on. Borgatti (2005) found that other measures of importance, such as betweenness centrality (the number of times a shortest path between two nodes goes through a certain node) and degree centrality (number of nodes connected to a node), were not able to accurately evaluate a network with the flow of information described above. The flow of information ideal for closeness centrality is analogous to the supposed flow of activation in the lexicon. Many models of the lexicon propose that when a word is activated it in turn activates many similar sounding words or phonological neighbors, effectively spreading information from one node to all other connected nodes (Luce & Pisoni, 1998; McClelland & Elman, 1986; Norris, 1994). As the findings of Borgatti (2005) suggest, closeness centrality is an appropriate measure of importance to use in the lexicon, and studying the influence it has on processing should provide insights into the inner workings of the lexicon.

Due to the proximity of high closeness centrality words to all other words in the lexicon, one might reasonably hypothesize that high closeness centrality words will have processing disadvantages. That is, performance in experimental tasks will be worse for high closeness centrality words (i.e. lower accuracy rates or slower reaction times). Many currently accepted models predict increased competition from phonological neighbors, impeding processing. However, these currently accepted models assess

competition from *close* competitors within a neighborhood. Closeness centrality assesses the distance between a word and more “distant” words beyond the neighborhood of a word. A plausible alternative hypothesis is that high closeness centrality words will possess processing advantages due to the increased amount of indirect partial activation from “distant” words in the lexicon.

Many currently accepted models of spoken word recognition propose that many competing similar sounding words are partially activated when a word is retrieved from the lexicon (Luce & Pisoni, 1998; McClelland & Elman, 1986; Norris, 1994). High closeness centrality words, due to their proximity to the rest of the lexicon, will be partially activated often. It is unclear how lexical processing is affected by partial activation, but preliminary evidence shows that it is beneficial. Vitevitch and Goldstein (2014) proposed that due to keywords occupying a crucial “middle-man” role in the lexical structure they receive a large amount of partial activation and this possibly led to the processing advantages observed for keywords.

A similar finding by Sommers and Lewis (1999) using the phonological false memory phenomenon (see Roediger & McDermott, 1995 for semantic false memories) shows how partial activation may influence processing in a memory-related task. Sommers & Lewis (1999) showed that unrepresented lure words are often falsely remembered by participants if many similar sounding words, or phonological neighbors, of the unrepresented lure word are presented during study. For example, the word SLEEP might be falsely remembered if the words LEAP, SEEP, and SHEEP were presented during study. Sommers & Lewis (1999) account for these findings due to the partial activation of the word SLEEP from the nearby retrieved words LEAP, SEEP, and SHEEP. Although phonological false memories are an example of erroneous retrieval it is reasonable to apply the same concept to high closeness centrality words. Due to the proximity of high closeness centrality words to many other words they will receive a great deal of partial activation and this accumulated partial activation might lead to improved processing.

The idea of accumulated activation is thought to benefit language processing in an influential model known as Node Structure Theory (Mackay, 1982). Within Node Structure Theory there are several layers of nodes involved in language production and recognition. Nodes can represent specific muscle movements, specific phonological units (e.g. phonemes, syllables), or specific semantic units (e.g. concepts). The nodes of different layers are connected and the strength of these connections can be increased through activation when a word is used. For example, when the word TREE is produced the links between the muscle movement nodes and the /t/, /ɪ/, and /ē/ sounds are strengthened as well as the links between the TREE node and the semantic concept node of a tree. Strengthening the links between nodes allows for easier transmission of activation and ultimately easier retrieval from the lexicon. Words that are encountered frequently have processing advantages because of accumulated activation increasing the strength of connections between the nodes involved in the processing of that specific word. In contrast, words that are encountered rarely will have less accumulated activation and will lose connection strength between associated nodes, making them harder to retrieve.

The research described above shows the importance of studying the lexicon as a connected whole with an organized structure that influences processing in observable ways, rather than a collection of isolated word representations influenced only by their individual characteristics. Furthermore, “important” words in the lexicon influence lexical processing, and closeness centrality is an ideal network science measure to identify them. In order to gain a greater understanding of how processing occurs in the lexicon it is imperative to identify these important words and explore how or if they are processed differently than other words in the lexicon. The experiments described below will help shed light on these issues.

Chapter 4: Experiment 1

Introduction

Experiment 1 was inspired by the task used in Iyengar et al. (2012). In that study, the orthographic word-morph task was employed. Evidence from the task provided the initial evidence to suggest that closeness centrality influences certain aspects of language processing. In the orthographic word-morph task participants are asked to morph one word into another word by changing one letter at a time. For example, in order to morph the word DOG into CAT a participant could use the words: CAT-COT-DOT-DOG. Each intermediate word must be a legal English word. The results from Iyengar et al. show participants initially try to take the most direct route between two words and this strategy is not very successful. Eventually participants learn to utilize “landmark” words, which have a high closeness centrality value, and this makes the task much easier. The time to complete the task dropped dramatically once “landmark” words were utilized, from ~15 minutes in the first 10 games to ~30 seconds after 28 games.

Using “landmark” words to navigate the mental lexicon is similar to how physical landmarks are used to navigate through a city. Oftentimes one does not know the direct path between where they are and where they would like to go. However, if a person can reach a landmark in the city, say a centrally located tall building or a major intersection, they can then reach anywhere in the city with ease. People still use landmarks for navigation, without taking the most direct path, even after years of experience navigating an area (Sorrows & Hirtle, 1999). Similarly, participants trying to complete the word-morph task were unsuccessful at taking the most direct route between two words and instead had to rely on landmarks for navigation.

In the word-morph task participants will find and utilize the high closeness centrality words as landmarks without instructions to do so. Once found and utilized, the high closeness centrality words greatly increase participants’ efficiency in completing the word morph task. However, the task used by

Iyengar et al. has a significant limitation: low closeness centrality words were not used by participants. To fully understand how closeness centrality influences lexical search it is important to show how both high and low closeness centrality words influence lexical search. Low closeness centrality words may have different effects on lexical search and with greater experimental control their influence on lexical search can be explored as well. Thus experiment 1 will use a task similar to the word-morph task used in Iyengar et al., but it will require participants to navigate the lexicon using both high and low closeness centrality words.

Recall that words with high closeness centrality occupy a central location in the lexicon where they are a short lexical distance away from many words. This central location seems to aid *global* lexical search when one has to traverse large sections of the lexicon from a start word to a target word, as in Iyengar et al. (2012). Global lexical search is analogous to traveling through a large city. There are many possible routes to take and many ways to get lost. It may not be the most efficient route, but by making your way to a navigation landmark you are more likely to reach your destination. Imagine starting a route from a landmark, such as a major intersection, navigating to anywhere in the city would be relatively easy. Landmarks aid global search through an entire network, whether it is a lexicon or a city.

However, when one has to traverse short distances in the lexicon the dense lexical area surrounding a high closeness centrality word may harm *local* lexical search. That is, the large number of words a short lexical distance away may provide an overwhelming number of words and paths to discriminate amongst and thus navigating to the target word is made difficult. Consider navigating a short distance through a city when starting from a landmark, there are many possible paths to take and many possible destinations close by. The large number of paths and destinations makes it difficult to reach a nearby destination. A major intersection in a city is an ideal place for roads to lead to, as well as a desirable place for restaurants, bars, retail stores, etc. There are an overwhelming number of choices and the navigator is impeded in his or her success.

In comparison, traversing a short lexical distance in the sparse lexical area surrounding a low closeness centrality word may be easier. Recall that low closeness centrality words occupy a position in the lexicon with few words and paths nearby, even beyond the immediate neighborhood of a word. When a search is conducted in the sparse vicinity of a low closeness centrality word the few words and paths to discriminate amongst may make finding the target word an easy task. Consider starting to navigate a short city route from an “out of the way” intersection. Not many roads lead to the intersection and not many businesses are located nearby. If you were to search in the surrounding city area you could reach your desired destination relatively easy. There are fewer options (roads and destinations) to choose from and the correct option has less competition. Due to the differing lexical areas surrounding high and low closeness centrality words it is predicted that when participants are forced to start a short lexical search from a high closeness centrality word they will be hindered in that search. Therefore they will reach the target word slower and less successfully compared to starting a short lexical search from a low closeness centrality word.

To illustrate the differences in starting a search from a high or low closeness centrality word see Figure 5 below. Finding a targeted path through the lexical area surrounding OVEN would not be difficult as there are few paths to choose from. A searcher would have little difficulty finding the correct path quickly and accurately. However, finding a targeted path through the lexical area surrounding ALIT would be much more difficult as there are many paths to choose from. A searcher would have great difficulty finding the correct path quickly and accurately.

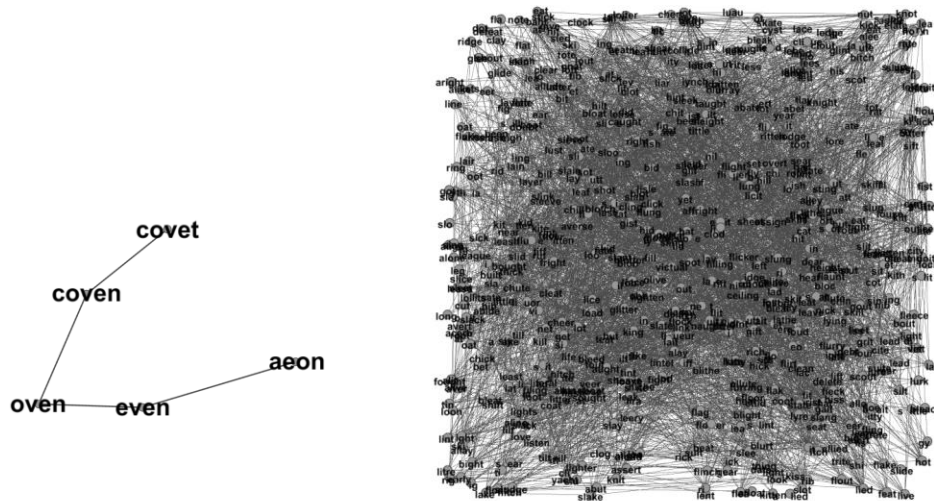


Figure 5. The network on the left is the 2 hop neighborhood (all words that are 2 links away) of the word OVEN. OVEN has a low closeness centrality value (.00017). There are a total of 5 words and 4 links within the 2 hop neighborhood of OVEN. The network on the right is the 2 hop neighborhood of the word ALIT. ALIT has a high closeness centrality value (.066). There are a total of 657 words and 3842 links within the 2 hop neighborhood of ALIT.

The motivation for Iyengar’s word morph task needs to be highlighted to avoid confusion. Iyengar and colleagues were interested in the process of navigation across relatively large distances through space. The researchers were not interested in lexical navigation or language processing at all. The word morph task was used as an approximation of spatial navigation. The results obtained from Iyengar and colleagues’ work needs to be interpreted with their motivation in mind.

Iyengar et al.’s findings credit the idea that humans don’t always find the most optimal path (i.e. the shortest), but instead find a path that is sufficient (i.e. using landmarks). However, a global lexical search (like that used in Iyengar et al; 2012) is not an accurate approximation of search processes in the lexicon. One does not typically start a lexical search for a word by starting from a “lexically distant” and dissimilar word. When searching the lexicon for a word people typically have a good idea of what the word sounds like. For example, when experiencing a tip-of-the-tongue state (where an individual has difficulty retrieving a word they are certain they know) individuals will often recall words that sound similar to the word they are trying to recall (Brown, 1991). Therefore most lexical searches are more

accurately thought of as short, local lexical searches starting from “lexically close” words, like those used in Experiment 1. Iyengar’s global search task explores human navigation across spatial networks, whereas the local search task presently employed in Experiment 1 is intended to explore processes that are relevant to Psycholinguistics.

Additionally, Experiment 1 will explore the robustness of the closeness centrality effect on lexical search by expanding the word morph task into the auditory domain. Recall that in the Iyengar et al. task participants were asked to change one *letter* of a word at a time. It is possible that the effect of closeness centrality is limited to the orthographic domain. Experiment 1 will require participants to navigate the lexicon based on the phonology of words, i.e. participants will be asked to change the individual *sounds* in a word. Finding an effect of closeness centrality in both the orthographic (Iyengar et al., 2012) and the phonological lexicon will bolster evidence of a robust closeness centrality effect in language processing.

Methods

Participants

All 23 Participants in Experiment 1 were healthy, college-aged adults sampled from the University of Kansas community. All participants were right-handed native English speakers with normal hearing as assessed through self-report. Participants received partial course credit for their participation. A power analysis conducted with a .05 alpha level, .80 power, and a medium effect size suggests a minimum sample size of 20 participants is necessary (G*Power program; Faul et al., 2007). Several other participants were then included in the experiment in order to guarantee adequate power.

Stimuli

The stimuli consisted of 12 high closeness centrality starting words and 12 low closeness centrality starting words. 12 pairs of high and low closeness centrality words were formed and a target word was identified for each pair (see Table 1). In each pair the target word was 2 links away from both

starting words, meaning a single word linked every starting word with its intended target. For example the high closeness centrality word WEEP was paired with the low closeness centrality word CHASE. Both words are two links away from CAPE. WEEP is linked to CAPE through the word KEEP, whereas CHASE is linked to CAPE through the word CASE. See table 1 for a list of the high and low closeness centrality starting words, the “link” words that connect the starting words to their targets, and the intended target words for each starting word pair.

The link words, which participants were instructed to find and produce, were matched on relevant processing variables including frequency (frequency of occurrence; Kucera & Francis, 1967) $F(1, 22) = 1.25, p < 0.27$, segment mean (the mean probability that a certain phoneme will occur in a certain position of a word; Vitevitch & Luce, 1998) $F(1, 22) = 0.238, p < 0.63$, biphone probability (the probability that two phonemes will occur together in a word; Vitevitch & Luce, 1998) $F(1, 22) = 2.02, p < 0.17$, neighborhood density (number of phonological neighbors; Luce & Pisoni, 1998) $F(1, 22) = 3.93, p < 0.07$, and the mean of the frequency of the words in the neighborhood (log transformed frequency of occurrence of a phonological neighborhood) $F(1, 22) = 0.001, p < 0.98$.

Table 1. Low and high closeness centrality starting words, link words (which participants needed to discover), and target words used in the word morph task of Experiment 1.

low closeness centrality word	low link word	target word	high link word	high closeness centrality word
noose	newt	knit	nick	thick
jab	jack	sack	seek	siege
vice	rice	rhyme	roam	roach
dove	dope	deep	cheap	cheat
job	sob	sub	dub	dud
dive	dial	pile	pull	put
wag	wig	wit	watt	yacht
knob	knock	sock	soak	folk
much	muck	luck	lick	live
chase	case	cape	keep	weep
gab	tab	tack	hack	hike
tease	teach	reach	rich	ridge

The high closeness centrality starting words ($M = .072$, $SD = .0006$) had a significantly higher closeness centrality value than the low closeness centrality words ($M = .068$, $SD = .0008$) $F(1, 11) = 13.91$, $p < .0001$. The network analysis software Pajek (Batagelj & Mrvar, 1998) provided the closeness centrality measure (see equation 2 above). The measurements provided by Pajek were done on a subset of the lexical network: the giant connected component. The giant connected component is the largest part of the lexical network that is connected, meaning it is possible to traverse links from one word to any other word in the giant component. Focusing on the giant component excludes words in the lexicon that do not have any phonological neighbors (also known as hermits) and words that make up smaller connected components of the network (also known as islands). The hermits and islands are excluded because they cannot be reached via links. Therefore the distance to an island or hermit is undefined and including them in a closeness centrality analysis would provide uninterpretable results. In the lexicon analyzed in Vitevitch (2008) the giant component consists of 6,508 words.

The range of closeness centrality in the giant component is from .0001 to .08, with the majority of values between .05 and .07 (see Figure 6). Most of the words used in the three experiments are drawn from this range, which means that these words are representative of the majority of closeness centrality values in the lexicon. Several words with closeness centrality values in the .0001 to .01 range are included as stimuli in Experiment 3 in order to investigate the influence of the full range of closeness centrality values.

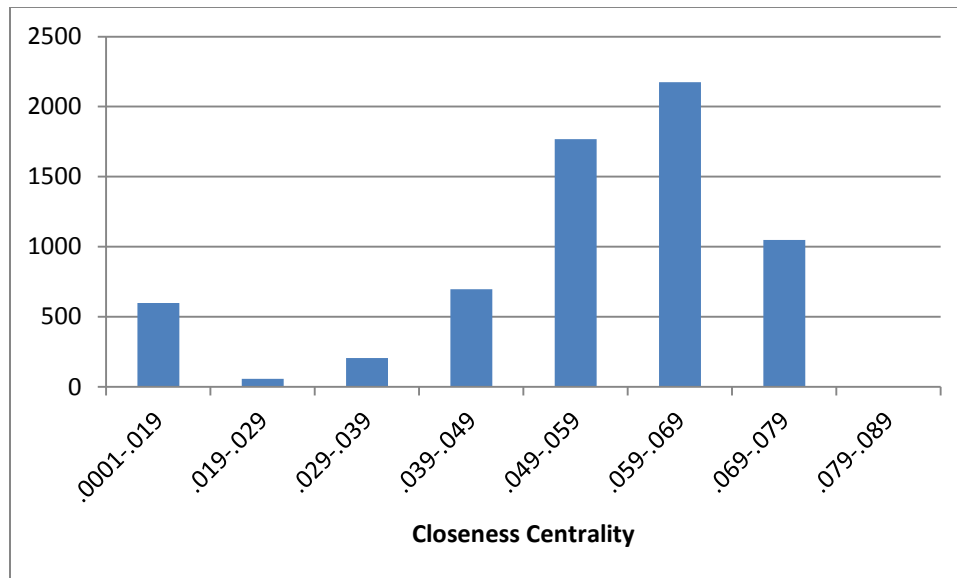


Figure 6. Frequency distribution of closeness centrality values in the giant component of the lexicon.

Procedure

After obtaining informed consent participants were seated in front of a computer. Each of the 24 trials consisted of two words appearing on a screen: the starting word on the left and the target word on the right. Participants were instructed to change one sound in the starting word to form a new word that is one sound different from the target word and also one sound different from the starting word. After several practice trials participants began the experiment proper. Participants were not under time pressure and could take as long as necessary to complete a trial. Participants pressed a button on a Psyscope response box to proceed to the next trial. Participants were instructed to speak the word out loud (responses were recorded for later analysis) and if they did not know an appropriate response to respond with “I don’t know”.

Analysis and Results

Reaction times and accuracy rates are the dependent variables of interest in Experiment 1. Responses were coded as correct (if response was the link word), “don’t know” (if response was “I don’t know”), and incorrect (if response was not the link word). “Don’t know” responses consisted of 87% of

incorrect responses, whereas incorrect responses consisted of 13% of incorrect responses. A multilevel model was constructed for each dependent variable with items as the level 1 units and participants as the level 2 units. Closeness centrality is the level 1 predictor of interest. Again, a multilevel modeling design is an appropriate analysis due to the continuous nature of the independent variable, and to account for variability in both participants and stimulus items. The multilevel modeling analyses were conducted using the statistical software R (R Core Team, 2013) with the package “lme4” (Bates, Maechler & Bolker, 2012).

First, the model using accuracy rates as the dependent, binomial variable was created. Closeness centrality was added to the model as a level 1 predictor with a random slope and random intercept. Results showed a significant and negative coefficient of $\beta = -42.81$, $p < .001$. A negative coefficient indicates an increase in accuracy rate as closeness centrality decreases. That is, participants were more accurate starting from a low closeness centrality word ($M = .79$, $SD = .09$) compared to starting from a high closeness centrality word ($M = .63$, $SD = .16$). Additionally, an analysis was run on the two types of incorrect answers, “I don’t know” responses (coded as 0) and incorrect responses (coded as 1). There was no significant effect on closeness centrality whether participants responded with “I don’t know” or an incorrect word, $\beta = 91.7$, $p < .54$.

Next, a model was created with reaction times (measured in milliseconds) as the dependent variable, using a Gaussian distribution. Only correct responses were included in the reaction time analysis. Closeness centrality was added to the model as a level 1 predictor with a random slope and random intercept. Results showed a significant and positive coefficient $\beta = 712979$, $p < .001$. A positive coefficient indicates a decrease in reaction time as closeness centrality decreases, meaning that participants were faster to find the appropriate link word when starting from a low closeness centrality word ($M = 9329\text{ms}$, $SD = 3725\text{ms}$) than a high closeness centrality word ($M = 12112\text{ms}$, $SD = 5879\text{ms}$).

Discussion

As predicted, closeness centrality influences the lexical search process, such that a lexical search starting from a low closeness centrality word is easier to complete than a lexical search starting from a high closeness centrality word. It appears that the many possible paths and words around centrally located high closeness centrality words impairs the search process making it difficult for participants to find the correct word to link to the target word. Whereas the smaller number of paths and words around a low closeness centrality word provides participants with fewer options for the link word leading to faster and more accurate navigation to the target word.

It is important to highlight the differences between the Iyengar et al. study and the current experiment since the two have seemingly contradictory findings. The word morph task used in Iyengar et al. (2012) required participants to navigate through many words before reaching the target word. Participants in that study had to navigate through an average of 12.3 words to reach the target word. With such a large lexical distance to traverse participants quickly realized that landmarks (in the form of high closeness centrality words) are useful in order to access most areas of the lexicon quickly. Once a landmark word is reached any other area of the lexicon is relatively easy to reach.

However, in the present experiment participants were asked to traverse a very short path through a small section of the lexicon. In this scenario the local structural characteristics of the lexicon will have a large influence on the success of the search. Finding the correct path through many possible paths and words (i.e. the area surrounding a high closeness centrality word) is much more difficult than finding the correct path through few possible paths and words (i.e. the area surrounding a low closeness centrality word). The difference in difficulty is evident in the slower reaction times and lower accuracy rates when participants start their search from a high closeness centrality word. The Iyengar et al. task and the current task are placing different demands on lexical search and therefore show the influence of closeness centrality under different circumstances. Despite the difference in the task demands and the observed

pattern of results, the findings from both studies indicate that closeness centrality influences lexical processing.

It is not surprising that different task demands will yield different influences of a variable. Indeed, the influence of clustering coefficient has been shown to vary depending on the task. An advantage for words with a low clustering coefficient value was observed in production and recognition processes (Chan & Vitevitch, 2009; Chan & Vitevitch, 2010). However, an advantage for words with a high clustering coefficient value was observed in word learning and immediate serial recall (Goldstein & Vitevitch, 2014; Vitevitch, Chan & Roodenrys, 2012).

Another possible explanation for the observed difference is the different types of sounds that needed to be changed to reach the target word. Specifically, some searches required the participant to change the vowel sound in the start word (e.g. NOOSE to KNIT), whereas some searches required the participant to change consonant sounds in the start word (e.g. THICK to KNIT). In 4 of the 12 searches starting from a low closeness centrality word required the participant to change the vowel sound, whereas in 9 of the 12 searches starting from a high closeness centrality word required the participant to change the vowel sound. It is possible that changing a vowel sound is more complex and made the task more difficult for participants when starting the search from a high closeness centrality word.

Indeed, some previous research shows that vowels carry more word recognition information than consonants. When asked to change a nonword into a real word by changing a single sound participants will typically change the vowel sound, suggesting a preference to focus on the vowel sounds in words (Cutler et al., 2000). However, the task in Experiment 1 required participants to change a word into another word; it is unclear if the results in Cutler et al. (2000), in which non words were turned into real words, generalize to the task in Experiment 1, in which a real word was turned into another real word. Furthermore, other research has found that consonants are more important in word recognition. Bonatti et al. (2005) found that when learning an artificial language participants were more successful

identifying words if the consonants remained stable and the vowels varied compared to identifying words if the vowels remained stable and the consonants varied. The findings from Bonatti et al. (2005) suggest consonants give the participant more information than vowels about the identity of the word. Obviously the debate is not settled yet as to whether consonants or vowels carry more information for the language user. However, future experiments will have to control for this variable.

Additionally, results from Experiment 1 show the effect of closeness centrality in the auditory domain. Previous results from Iyengar et al. (2012) were limited to the orthographic domain. Showing that closeness centrality influences more than one type of language processing is an important step in determining the extent of the closeness centrality effect. In sum, Experiment 1 provides good evidence that closeness centrality plays an important role in searching for words in the lexicon.

Chapter 5: Experiment 2

Introduction

The results from Experiment 1 show the effect of closeness centrality on a lexical search through a limited region of the lexicon. The search task used in Experiment 1 is useful in showing how closeness centrality influences language processing. However, the search task used is a somewhat artificial approximation of normal language use. To further establish the effect of closeness centrality on language processing, a more traditional task from psycholinguistics will be used in Experiments 2 and 3, namely the lexical decision task. The auditory lexical decision task requires participants to respond to stimuli by making a “word” or “non-word” judgment. The task is relatively easy and processing differences between stimuli are not usually apparent in accuracy rates of participants’ judgments. However, reaction time analyses are more sensitive in detecting processing differences between groups of stimuli. Assessing the influence of closeness centrality on a recognition task will help establish if closeness centrality influences the basic language process of spoken word recognition.

Recall that Vitevitch and Goldstein (2014) investigated the influence of another global network measure, keywords, on language processing. Keywords are words that occupy an important structural position in the lexicon by keeping the lexicon as a large connected whole rather than disconnected smaller networks. Results showed processing advantages for words occupying keyword positions in the lexicon compared to matched control words. The authors argue that the observed processing advantages for keywords stem from accumulated benefits to partially activated words, which, by virtue of the network location of keywords, will be directed more towards keywords than other words. With the findings of Vitevitch & Goldstein (2014) in mind it is reasonable to predict a processing advantage for high closeness centrality words. Consider that high closeness centrality words are located in areas of the lexicon with many paths and words. Being close to a large number of other words will place high closeness centrality words in a position to receive activation spreading from a large number of other words nearby in the lexicon. Over time the partial activation of such words will accumulate in benefits for processing. Low closeness centrality words, which are located in areas of the lexicon with few words and paths, will receive much less accumulated partial activation and will not have the same advantages. Therefore it is predicted that high closeness centrality words will have a reaction time advantage (i.e. faster reaction times) compared to the low closeness centrality words.

Additionally, it is important to note that as discussed in the introduction structural characteristics are not incorporated into accepted models of spoken language processing. Currently accepted models focus exclusively on the individual processing variables of words in isolation, ignoring the relationships that exist between words in the lexicon. Recent research has shown the influence of local structural characteristics (Chan & Vitevitch, 2009; Chan & Vitevitch, 2010, Goldstein & Vitevitch, 2014) and global structural characteristics (Vitevitch & Goldstein, 2014). Significant results from Experiment 2 will add to a growing body of evidence showing the importance of incorporating lexical relationships between words into future models of spoken language processing.

Methods

Participants

All 48 Participants in Experiment 2 were healthy, college-aged adults sampled from the University of Kansas community. All participants were right-handed native English speakers with normal hearing as assessed through self-report. Participants received partial course credit for their participation. A power analysis conducted with a .05 alpha level, .80 power, and a small effect size suggests a minimum sample size of 44 participants is necessary (G*Power program; Faul et al., 2007). Several other participants were then included in the experiment in order to guarantee adequate power.

Stimuli

Stimuli used in Experiment 2 consist of 40 monosyllabic words split into two groups that vary in closeness centrality. The two groups of words were controlled on several variables that have been shown to influence processing at the individual word level. Variables controlled are: frequency (frequency of occurrence; Kucera & Francis, 1967) $F(1, 38) = 0.001, p < 0.99$ (High: $M = 2.08, SD = .76$, Low: $M = 2.09, SD = .83$), segment mean (the mean probability that a certain phoneme will occur in a certain position of a word; Vitevitch & Luce, 1998) $F(1, 38) = 0.71, p < 0.41$ (High: $M = .04, SD = .009$, Low: $M = .04, SD = .005$), biphone mean (probability of two phonemes occurring together; Vitevitch & Luce, 1998) $F(1, 38) = 0.041, p < 0.84$ (High: $M = .002, SD = .002$, Low: $M = .002, SD = .001$), neighborhood density (number of phonological neighbors; Luce & Pisoni, 1998) $F(1, 38) = 1.14, p < 0.29$ (High: $M = 16.6, SD = 2.96$, Low: $M = 15.7, SD = 1.97$), neighborhood frequency (frequency of occurrence of a phonological neighborhood) $F(1, 38) = 1.61, p < 0.21$ (High: $M = 134.3, SD = 159.3$, Low: $M = 81.2, SD = 98.7$), and word familiarity (familiarity ratings based on a 1-7 scale; Nusbaum et al., 1984) $F(1, 38) = 2.91, p < 0.09$ (High: $M = 6.9, SD = .12$, Low: $M = 6.8, SD = .29$). At the structural level, clustering coefficient was controlled between groups, $F(1, 38) = 0.041, p < 0.84$ (High: $M = .38, SD = .13$, Low: $M = .35, SD = .09$), and none of the words chosen as stimuli were keywords (Vitevitch & Goldstein, 2014), as both these structural characteristics influence processing. Closeness centrality is the crucially

manipulated variable between the groups, $F(1, 38) = 208, p < 0.001$ (High: $M = .072, SD = .001$, Low: $M = .067, SD = .001$). Additionally, variables related to the stimulus sound files were controlled between the groups including stimulus onset time (silence before stimulus begins) $F(1, 38) = 1.99, p < 0.17$ (High: $M = 20\text{ms}, SD = 9\text{ms}$, Low: $M = 20\text{ms}, SD = 9\text{ms}$), stimulus duration $F(1, 38) = 3.48, p < 0.07$ (High: $M = 520\text{ms}, SD = 60\text{ms}$, Low: $M = 560\text{ms}, SD = 80\text{ms}$), stimulus offset time (silence after stimulus ends) $F(1, 38) = 2.19, p < 0.15$ (High: $M = 20\text{ms}, SD = 7\text{ms}$, Low: $M = 20\text{ms}, SD = 7\text{ms}$), and sound file duration $F(1, 38) = 3.70, p < 0.07$ (High: $M = 570\text{ms}, SD = 60\text{ms}$, Low: $M = 600\text{ms}, SD = 80\text{ms}$).

The nonwords used in the lexical decision task were created by changing the last phoneme of a real word to create a nonword not found in the English language. See Table 2 for a list of the stimuli used in Experiment 2.

Table 2. Stimuli used in Experiment 2.

Words	Nonwords	Closeness Centrality Group	Frequency of Occurrence	Familiarity	Segment mean	Biphone Mean	Neighborhood Density	Neighborhood Frequency	Closeness Centrality
chase	tʃev	Low	2.26	7	0.039	0.0018	17	68.412	0.068943
curb	kɜːf	Low	2.11	6.5	0.0478	0.0015	12	9.833	0.068324
dive	daɪb	Low	2.36	7	0.0366	0.0024	17	30.471	0.068976
dove	Dok	Low	1.6	7	0.0416	0.0012	16	28.125	0.068692
gab	gæɪf	Low	1	6.6667	0.0438	0.0029	17	10.471	0.067885
gang	Gæθ	Low	2.34	7	0.039	0.0035	15	15.267	0.068856
hearse	hɜːf	Low	1	7	0.0476	0.0022	15	274.667	0.068086
jab	dʒæɪf	Low	1	6.6667	0.0397	0.0018	14	32.5	0.06688
jar	dʒap	Low	2.2	7	0.0509	0.0086	16	344.937	0.068109
job	dʒaɪf	Low	3.38	7	0.0334	0.0015	19	4.947	0.06749
knob	naf	Low	1.3	7	0.0368	0.0027	21	236.238	0.068602
much	mʌp	Low	3.97	7	0.0348	0.0023	17	87.588	0.068818
noose	nuf	Low	1.48	6.3333	0.0416	0.0018	15	157.067	0.068243
serge	sɜːf	Low	2.15	6.4167	0.0459	0.0022	15	21.067	0.065945
serve	sɜːs	Low	3.03	7	0.0502	0.0023	14	24.714	0.067105
tease	tɪb	Low	1.78	7	0.0321	0.0013	16	124.25	0.067936
verse	vɜːp	Low	2.45	7	0.042	0.0027	15	25.267	0.065174
vice	vYg	Low	2.62	6.8333	0.0452	0.0019	16	30.875	0.068664
wag	wæb	Low	1	6	0.0392	0.0018	14	5.071	0.067657
worse	wɜːp	Low	2.7	7	0.0413	0.0024	14	92.429	0.066786

Table 2 (Continued). Stimuli used in Experiment 2.

Words	Nonwords	Closeness Centrality Group	Frequency of Occurrence	Familiarity	Segment mean	Biphone Mean	Neighborhood Density	Neighborhood Frequency	Closeness Centrality
bike	bɑrg	High	1	7	0.0463	0.0026	19	421.737	0.073579
cheat	tʃɪθ	High	1.48	7	0.0356	0.0015	17	60.824	0.072277
cheek	tʃɪn	High	2.3	7	0.0314	0.0014	21	32.952	0.071921
coach	kɒf	High	2.38	7	0.05	0.0033	14	26.071	0.071831
dud	dʌt	High	1	6.8333	0.043	0.0017	18	120.778	0.071365
folk	fɒp	High	2.53	6.9167	0.0498	0.0044	16	628.5	0.070975
hike	haɪg	High	1.6	7	0.0424	0.003	17	118.941	0.072536
league	li:b	High	2.84	7	0.0279	0.0015	19	24.316	0.071895
leg	le:p	High	2.76	7	0.0416	0.0028	15	79.533	0.071097
live	lɪv3	High	3.25	7	0.0513	0.0046	15	60.8	0.072478
put	pʊθ	High	3.64	7	0.0535	0.0008	14	19.929	0.073599
ridge	rɪdʒ	High	2.26	7	0.0524	0.0092	14	23.929	0.072671
roach	rɔθ	High	1.3	7	0.0358	0.0014	18	51.611	0.073281
robe	rɒf	High	1.78	7	0.0418	0.002	18	41.778	0.073606
shake	ʃedʒ	High	2.23	7	0.0308	0.0013	24	75.792	0.072208
siege	sɪg	High	1.78	6.75	0.0483	0.0016	15	125.067	0.071482
soot	sʊf	High	1	6.5833	0.0595	0.0005	11	132	0.073171
thick	θɪf	High	2.83	7	0.0522	0.0048	13	78.385	0.07137
weep	wɪf	High	2.15	7	0.0297	0.0011	18	191.667	0.07106
yacht	jɑb	High	1.6	6.75	0.0448	0.0016	16	371.25	0.072755

Procedure

After obtaining informed consent, participants were seated in front of a computer. Participants then randomly heard one of the stimulus words or nonwords through headphones. Each stimulus word or nonword was presented only once. After presentation of the stimulus, participants decided if they heard a nonword or a word and pressed a response button to indicate their choice. Reaction times were measured from the onset of the stimulus to the moment a response button was pressed. A short practice session was administered at the start of the experiment in order to familiarize participants with the task.

Analysis and Results

For Experiment 2 the dependent variables of interest are reaction times and accuracy rates. For each dependent variable a multilevel model was created. Items were used as the level 1 units and participants as the level 2 units. The level 1 predictor of interest was closeness centrality of the prompt word. A multilevel modeling design is an appropriate analysis due to the continuous nature of the independent variable, and to account for variability in both participants and stimulus items. The multilevel modeling analyses were conducted using the statistical software R (R Core Team, 2013) with the package “lme4” (Bates, Maechler & Bolker, 2012).

First, a model was created with accuracy rates (coded as “correct” or “incorrect”) as the dependent variable, using a binomial distribution. Responses that were too long (>1800ms) or too short (<300ms) were removed from the analysis, resulting in ~2% of the responses being removed. Closeness centrality was added to the model with a random slope and random intercept. Results showed a non-significant positive coefficient of $\beta = 43.02$, $p = .21$. A positive coefficient indicates an increase in accuracy as closeness centrality increases; however the difference between the groups was not significant at the .05 level. That is, participants were trending towards more accuracy when recognizing a high closeness centrality word ($M = 89.73$, $SD = 6.77$) compared to a low closeness centrality word ($M = 86.49$, $SD = 7.24$).

Next, a model was created with reaction times (measured in milliseconds) as the dependent variable, using a Gaussian distribution. Once again, responses that were too long (>1800ms) or too short (<300ms) were removed from the analysis, resulting in ~2% of the responses being removed. Only correct responses were included in the reaction time analysis. Closeness centrality was added to the model with a random slope and random intercept. Results show a decrease in reaction times for the high closeness centrality group ($M = 909\text{ms}$, $SD = 74\text{ms}$) compared to the low closeness centrality group ($M = 950\text{ms}$, $SD = 130\text{ms}$) with a coefficient of $\beta = -14447$, $p < .001$. A negative coefficient indicates a decrease in reaction time as closeness centrality increases, meaning that participants were faster to respond to the high closeness centrality words than the low closeness centrality words.

A possible explanation for the significant difference in reaction times between the groups is the difference of file durations between the groups. Although the difference between the groups was not significant, the difference in file durations between the groups was 40ms. In order to further account for this variable a model was created with file duration as a predictor. The results show that closeness centrality is still a significant predictor $\beta = -1.04$, $p < .01$ and file duration is also a significant predictor $\beta = 3.95$, $p < .001$. The results from the model support the claim that closeness centrality accounts for the observed reaction time differences even with file duration controlled through stimuli selection and statistical analysis.

Discussion

The results from Experiment 2 provide evidence that closeness centrality influences the fundamental language process of spoken word recognition. Results show that high closeness centrality words are processed faster and tend to be responded to more accurately than low closeness centrality words. Again, the advantage observed for high closeness centrality words may stem from the advantageous lexical position they occupy, allowing for partial activation to show accumulated benefits over time. The low closeness centrality words are located in areas of the lexicon that will receive much

less partial activation and therefore accumulate less of a processing advantage from nearby words being activated.

Additionally, the results from Experiment 2 are not explained by currently accepted models of spoken word recognition, which predict processing differences based on characteristics of individual words, not on the structural characteristics of the mental lexicon. The results from Experiment 2 bolster the body of evidence suggesting that structural characteristics must be taken into account when considering spoken language processing. Not only does the lexical structure immediately surrounding a word impact processing, but the current results further suggest global lexical structure influences the processing of individual words.

Furthermore, the results observed in Experiment 2 warrant further investigation as to how closeness centrality influences language processing. Experiment 1 and 2 provided initial evidence of closeness centrality influencing language processing. To further examine how closeness centrality influences language processing Experiment 3 considered how individual differences among participants might interact with this structural characteristic to influence processing.

Chapter 6: Experiment 3

Introduction

In order to further explore the influence of closeness centrality on spoken word recognition and to replicate the results from Experiment 2 (i.e. a processing advantage for high closeness centrality words); Experiment 3 was developed with a different set of stimuli and a different approach to the multilevel modeling analysis. The stimuli used in Experiment 2 removed the influence of other variables by selecting stimuli that were strictly controlled on a number of other variables known to affect processing. In contrast, the stimuli used in Experiment 3 have a wider range of variability for a number of processing

variables, with the respective influence of these variables being controlled in the statistical analysis. Two advantages stem from this approach: a wider range of processing variable values can be included in a stimulus list (e.g. the range of closeness centrality values in the tightly controlled Experiment 2 is 0.0084, whereas the stimuli used in Experiment 3 have a range of closeness centrality values of 0.0675) and the influence of interactions between processing variables on the dependent variable can be examined. Additionally, the approach used in Experiment 3 will allow for direct comparisons between closeness centrality and other processing variables by observing how much variability is accounted for by each variable added to the model as a predictor. In sum, results from Experiment 3 will help to establish how closeness centrality interacts with other relevant processing variables, how a wider range of closeness centrality values influence processing, and how much variability in processing is accounted for by closeness centrality compared to other processing variables.

Additionally, Experiment 3 is designed to explore the influence of individual differences on the closeness centrality effect. For example, it may be possible to observe a greater closeness centrality effect in a participant with a large vocabulary. In a large lexicon with many words and paths between words there will be paths of varying lengths allowing for words with differing values of closeness centrality to emerge and influence processing. It may be more difficult to observe a closeness centrality effect in a participant with a small vocabulary. In a small lexicon there will be few words and paths between words will be uniformly short, leading to no observable differences in closeness centrality values of words and no influence on processing. The size of one's vocabulary may have a large impact on the effect of closeness centrality and a vocabulary measure included as a participant level predictor in a multilevel model analysis will illuminate this impact.

Differences in executive control may also have an impact on the effect of closeness centrality. Consider the executive control process of inhibition, or the ability to ignore distracting information (Connelly, Hasher & Zacks, 1991). Participants with more efficient inhibition processing will be more adept at ignoring the lexical competitors of words. High closeness centrality words are located in areas of

the lexicon with many words and paths, where many potential lexical competitors are close by. Participants with greater inhibition processes will be more proficient at ignoring competitors and retrieving the high closeness centrality words, leading to processing advantages. However, participants that have inefficient inhibition processes and are more easily distracted will be less proficient at ignoring competitors and retrieving high closeness centrality words from dense areas of the lexicon. The influence of inhibition processes on the closeness centrality effect can be explored by adding an inhibition measure as a participant level predictor in a multilevel model analysis.

Processing speed is another important individual cognition difference that may influence the closeness centrality effect. Processing speed is a measure of how fast an individual can perform cognitive functions (Kail & Salthouse, 1994). Those who are fast processors are able to search the lexicon quickly and retrieve words quickly. If a word is located in a remote part of the lexicon, such as a low closeness centrality word, it will require a large lexical distance to be traversed in order for retrieval to occur. Thus if a participant is a fast processor they will likely have an advantage retrieving low closeness centrality words over slow processors. An advantage for fast processors should disappear when retrieving high closeness centrality words located in central areas of the lexicon due to the fact that short lexical distances will be traversed, essentially eliminating the advantage of fast processors traversing large distances quickly. Including a measure of processing speed in the multilevel model analysis will explore the influence of processing speed on the closeness centrality effect.

Lastly, working memory may play an important role in the closeness centrality effect. The capacity of an individual's working memory limits how much information can be processed at one time. The larger one's working memory capacity, the more information can be processed simultaneously. Individuals with low working memory capacity will have reduced processing capacity, which may actually aid recognition of high closeness centrality words. Consider the region of the lexicon where high closeness centrality words are located; there are many competitors in close proximity. An individual with low working memory capacity will be restricted in how many competitors are processed, leading to the

target word standing out relative to competitors and easing processing. However, individuals with high working memory capacity will be forced to process more of the competitors close to a high closeness centrality word thereby slowing processing of the intended target word. Working memory capacity should not influence the processing of low closeness centrality words, which are located in sparse areas of the lexicon. The dearth of competitors surrounding low closeness centrality words will cause few competitors to be processed, leading to no differences in high and low working memory capacity participants. The individual differences included in Experiment 3 will help uncover the full range of influence that closeness centrality has on language processing.

Methods

Participants

All 37 Participants in Experiment 3 were healthy, college-aged adults sampled from the University of Kansas community. All participants were right-handed native English speakers with normal hearing as assessed through self-report. Participants received partial course credit for their participation. A power analysis conducted with a .05 alpha level, .80 power, a small effect size, and multiple predictors suggests a minimum sample size of 34 participants is necessary (G*Power program; Faul et al., 2007). Several other participants were then included in the experiment in order to guarantee adequate power.

Stimuli

Stimuli used in Experiment 3 include 80 bisyllabic words that vary on closeness centrality as well as the relevant processing variables discussed in Experiment 2. All words were four phonemes and two syllables in length. The nonwords used in Experiment 3 were created by changing the last phoneme of the real words into a pronounceable nonword. For a list of stimuli used in Experiment 3 and the associated variable values see Table 3. Stimuli were chosen in a fashion to capture a representative range of processing variables. Words were chosen randomly at first and then individual words were pseudo-randomly replaced if they were outliers on any given processing variable (i.e. greater than 2 standard

deviations from the mean). The resulting list gives a broad and representative range of processing variables while excluding words that have an extreme value of any processing variable. See Appendix A for comparisons of processing variable frequency distributions in the giant component and stimuli used in Experiment 3.

Procedure

After obtaining informed consent, the series of individual difference measures was obtained from the participants including: processing speed (total number of colored Stroop XXX's named in 45 seconds), inhibition (difference between total number of Stroop XXX's named in 45 seconds and total number of Stroop color words named in 45 seconds divided by Stroop XXX's total), reading span (Friedman & Miyake, 2004), and size of vocabulary (Shipley, 1946). Following the individual difference measures the same procedure used in Experiment 2 was followed in the present experiment for the lexical decision task.

Table 3. Experiment 3 stimuli and associated variable values.

Word	Nonwords	Clustering Coefficient	Closeness Centrality	Frequency	Segment Sum	Biphone Sum	Neighborhood Density	Frequency of Neighborhood Mean
Allied	əlɔɪp	0.14	0.0591	2.46	0.1288	0.0073	12	24.58
Allure	əlɔɪ	0.50	0.0565	1	0.1229	0.0071	4	11.00
Amass	əmæb	0.33	0.0601	1.3	0.1294	0.0047	3	37.33
Anchor	æŋkɹ	0.33	0.0511	2.18	0.1363	0.0041	7	8.71
Angel	endʒo	0.00	0.0406	2.26	0.0958	0.0017	1	0.00
Appear	əpɪg	1.00	0.0623	3.07	0.1301	0.0079	2	9.00
Arid	æɹɪtʃ	0.17	0.0238	1.3	0.1859	0.0089	4	1.00
Assess	əsɛp	0.00	0.0001	1.78	0.1176	0.0063	1	0.00
Avid	ævək	0.00	0.0222	1	0.1019	0.0025	1	2.00
Beggar	bɛgm	0.00	0.0601	1.3	0.1928	0.006	3	142.00
Caddy	kæde	0.30	0.0641	1	0.2533	0.0183	12	9.58
Callow	kæɹl	0.58	0.0582	1	0.2667	0.0234	9	1.89
Canoe	kəne	0.00	0.0494	1.85	0.2422	0.0274	2	3.50
Channel	tʃænəl	0.20	0.0583	2.2	0.2072	0.018	6	30.83
Chasm	kæzəl	0.00	0.0474	1.3	0.1939	0.013	1	0.00
Chauffeur	ʃɔfm	0.00	0.0424	1.6	0.1294	0.0029	1	0.00
Cheddar	tʃɛdɹ	0.00	0.0499	1	0.1705	0.0093	2	1.00
Coerce	kɔɹtʃ	0.33	0.0596	1.3	0.1961	0.0067	3	162.33
Colonel	kəɹnəl	0.20	0.0569	2.6	0.2362	0.005	5	9.20
Corrode	kəɹp	0.00	0.0612	1	0.1605	0.0018	1	40.00
Curtain	kɹtu	0.20	0.0624	2.11	0.1934	0.0064	5	77.60

Table 3 (Continued). Experiment 3 stimuli and associated variable values.

Word	Nonwords	Clustering Coefficient	Closeness Centrality	Frequency	Segment Sum	Biphone Sum	Neighborhood Density	Frequency of Neighborhood Mean
Allege	ələf	1.00	0.0587	1	0.1134	0.0088	3	3.00
Dagger	dægŋ	0.00	0.0465	1	0.1999	0.0059	1	6.00
Dazzle	dæzə	0.17	0.0521	1	0.1742	0.0034	4	0.50
Diaper	djpl	0.17	0.0557	1	0.174	0.0083	4	3.00
Diva	divo	0.00	0.0001	1	0.187	0.0089	1	1.00
Bushel	bʊʃŋ	0.00	0.0538	1	0.092	0.0019	1	14.00
Edit	ɛdɪk	0.00	0.0001	1.3	0.1217	0.0023	1	4.00
Ember	ɛmbər	0.33	0.0394	1	0.1135	0.0064	3	48.00
Envy	ɛnvu	0.00	0.0548	1.85	0.1426	0.0076	2	672.50
Equal	ikwə	0.00	0.0002	2.95	0.0587	0.0044	2	31.50
Evade	ɪvəm	0.00	0.0001	1	0.1242	0.0021	1	5.00
Even	ivæg	0.00	0.0001	4.07	0.0818	0.0044	2	4.00
Father	fɑðŋ	0.13	0.0507	3.26	0.1609	0.0039	6	46.50
Foray	fɔɪ	0.00	0.0542	1	0.1559	0.0066	1	1.00
Galley	gælər	0.36	0.0609	1.6	0.2223	0.0178	13	11.69
Garage	gəʌb	0.00	0.0001	2.32	0.0569	0.0008	1	0.00
Geyser	gəɪzŋ	0.60	0.0566	1	0.1311	0.0026	5	5.40
Gopher	gɒfɪ	0.00	0.0486	1	0.1457	0.0033	2	2.00
Hula	hulo	0.00	0.0444	1	0.215	0.011	1	0.00
Incur	ɪnke	1.00	0.0328	1.7	0.1823	0.0413	2	1.50
Journal	dʒɜ:n	0.33	0.0500	2.62	0.1573	0.0044	3	23.00
Kayak	kɔræb	1.00	0.0572	1	0.1974	0.0044	3	10.00

Table 3 (Continued). Experiment 3 stimuli and associated variable values

Word	Nonwords	Clustering Coefficient	Closeness Centrality	Frequency	Segment Sum	Biphone Sum	Neighborhood Density	Frequency of Neighborhood Mean
Lethal	liθə	0.00	0.0513	1.7	0.096	0.003	1	72.00
Lighter	ljtj	0.22	0.0658	2.08	0.1851	0.0171	14	51.71
Liver	lɪvɪ	0.09	0.0622	2.2	0.2047	0.0122	10	41.30
Madam	mædɪ	1.00	0.0615	1.3	0.1762	0.0125	3	19.00
Marrow	mæɹɹ	0.42	0.0589	1.7	0.2359	0.0197	9	11.56
Merry	mɛɹɹ	0.40	0.0627	1.9	0.2516	0.0204	11	177.64
Shabby	ʃæbɹ	0.38	0.0584	1.7	0.1583	0.0055	7	1.29
Moral	mɔɹɹ	0.47	0.0490	3.15	0.1748	0.0051	6	3.00
Naïve	nɑɪvɛ	0.00	0.0001	1.85	0.1178	0.0046	1	0.00
Nettle	nɛtɹɹ	0.36	0.0637	1	0.1855	0.0099	8	15.63
Meadow	mɛdɑɹ	0.17	0.0529	2.23	0.189	0.0105	4	2.50
Nozzle	nɔzə	0.33	0.0523	1.6	0.1272	0.0051	4	15.25
Ocean	oʃɪb	0.40	0.0007	2.53	0.0638	0.0026	6	17.67
Office	ɔfək	0.00	0.0003	3.41	0.0871	0.0033	3	156.33
Patter	pæto	0.19	0.0672	1.48	0.2806	0.0248	20	32.25
Pebble	pɛbɹ	0.50	0.0572	1	0.206	0.0078	4	7.75
Pepper	pɛpu	0.10	0.0616	2.11	0.2452	0.0109	5	32.00
Pommel	pɒmɹɹ	0.33	0.0540	1	0.1958	0.0081	3	7.33
Putty	pʌto	0.17	0.0648	1	0.2328	0.0079	9	3.67
Rowdy	ɹɑudɹ	0.33	0.0549	1.6	0.141	0.0046	3	48.67
Saga	sɑgo	0.00	0.0459	1.85	0.2606	0.0042	1	3.00
Saucer	sɔsɹ	0.00	0.0560	1	0.2485	0.0038	1	20.00
Shatter	ʃæti	0.62	0.0619	1.3	0.2059	0.0175	10	44.20

Table 3 (Continued). Experiment 3 stimuli and associated variable values

Word	Nonwords	Clustering Coefficient	Closeness Centrality	Frequency	Segment Sum	Biphone Sum	Neighborhood Density	Frequency of Neighborhood Mean
Shuffle	ʃʌfɪ	0.33	0.0553	1.48	0.0913	0.0025	4	1.25
Sofa	sɒfə	0.00	0.0452	1.78	0.2512	0.0055	1	3.00
Soggy	səʒi	0.33	0.0531	1.48	0.224	0.0034	3	18.33
Subtle	sʌtə	0.10	0.0581	2.4	0.2303	0.011	5	4.60
Suet	suɪk	0.00	0.0620	1	0.2204	0.0036	1	48.00
Suffer	sʌfɪ	0.19	0.0559	2.52	0.212	0.0091	7	27.57
Valley	vælu	0.42	0.0593	2.86	0.2187	0.0171	11	4.46
Veto	vi:tə	1.00	0.0002	2	0.1412	0.0048	2	2.50
Virile	vi:li	0.20	0.0599	1.6	0.2198	0.0103	5	0.60
Visa	vi:zə	1.00	0.0002	1.7	0.1542	0.0036	2	3.00
Washer	wɒʃɪ	0.33	0.0523	1.3	0.0953	0.0027	3	159.67
Willow	wɪlə	0.11	0.0633	1.95	0.2111	0.0162	8	285.50
Worthy	wɜ:ðu	0.00	0.0563	2.45	0.0913	0.0021	2	27.50
Written	ˈrɪtə	0.18	0.0653	3.19	0.2224	0.0255	8	4.25

Analysis and Results

For Experiment 3 the dependent variables of interest are reaction times and accuracy rates. For each dependent variable a series of multilevel models was created using stepwise regression with all item-level (level 1) variables as fixed effects (participants as level 2 units). Item level variables were added as fixed effects due to the large range of variable values included in the stimuli. Level 1 predictors included closeness centrality, clustering coefficient, frequency (frequency of occurrence; Kucera & Francis, 1967), neighborhood density (number of phonological neighbors; Luce & Pisoni, 1998), segment mean (the mean probability that a certain phoneme will occur in a certain position of a word; Vitevitch & Luce, 1998), biphone mean (probability of two phonemes occurring together; Vitevitch & Luce, 1998), and neighborhood frequency (log transformed frequency of occurrence of a phonological neighborhood). Nonword responses were removed from the reaction time analysis and only responses between 300ms and 1800ms were included in the analyses (1.5% of the data were dropped as outliers).

First, a model was created with reaction times as the dependent variable without any interactions between predictors. The reaction time model showed significant predictors of frequency, clustering coefficient, and log mean frequency of neighborhood. The predictor frequency showed a negative coefficient ($\beta = -22.20, p < .0001$) meaning as frequency of occurrence increased time to respond decreased. The predictor clustering coefficient showed a positive coefficient ($\beta = 52.72, p < .0001$) meaning as clustering coefficient increased time to respond increased. Recall that clustering coefficient is a measure of how many phonological neighbors of a word are also neighbors. The predictor log mean frequency of neighborhood showed a negative coefficient ($\beta = -0.09, p = .03$) meaning as log mean frequency of neighborhood increased time to respond decreased. The results found in the model are consistent with previous findings (Forster & Chambers, 1973; Chan & Vitevitch, 2009; Grainger, 1990). No significant effect of closeness centrality on reaction times was observed.

Table 4. Significant predictors observed in Experiment 3 models with interaction terms and reaction time as the dependent variable.

Interaction Term Included in Model	Predictor	β coefficient	p value
Closeness Centrality and Clustering Coefficient	Frequency	-82.74	.00004
	Clustering Coefficient	22.24	.0005
	Log Frequency of Neighborhood Mean	-.11	.02
Closeness Centrality and Frequency	Frequency	-1.88	.85
	Clustering Coefficient	52.40	< .0001
	Log Frequency of Neighborhood Mean	-.09	.02
Closeness Centrality and Neighborhood Density	Frequency	-55.77	.0002
	Clustering Coefficient	20.92	< .0001
	Log Frequency of Neighborhood Mean	-.09	.03
Closeness Centrality and Segment Sum	Frequency	-16.7	.003
	Clustering Coefficient	40.9	.003
	Log Frequency of Neighborhood Mean	-.08	.04
Closeness Centrality and Biphone Sum	Frequency	-42.8	.0002
	Clustering Coefficient	20.5	.001
	Log Frequency of Neighborhood Mean	-.08	.06
Closeness Centrality and Log Frequency Neighborhood Mean	Frequency	-52.98	< .0001
	Clustering Coefficient	23.41	< .0001
	Log Frequency of Neighborhood Mean	.11	.33

Following the first model, a series of models was created including an interaction term in each model. A total of six different models were run, one for each interaction of a predictor (clustering coefficient, frequency, number of neighbors, segment sum, biphone sum, and log mean frequency of neighborhood) with closeness centrality. Once again, frequency, clustering coefficient, and log mean frequency of neighborhood were significant predictors in most models (see Table 4). The only significant interaction coefficient was observed between closeness centrality and frequency ($\beta = -510.40, p = .01$). The significant interaction term was negative; meaning when participants were presented with a lower frequency word a high closeness centrality value makes recognition slower. When presented with a higher frequency word a high closeness centrality value makes recognition faster (see figure 7).

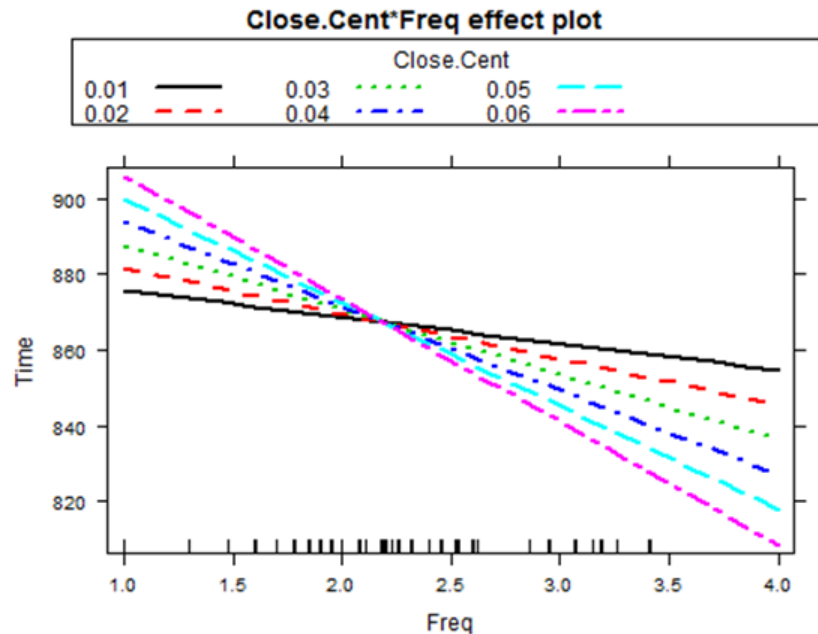


Figure 7. The interaction plot of the significant Frequency and Closeness Centrality interaction on reaction times.

The significant interaction between frequency and closeness centrality is an interesting finding, one that can be explained by differing levels of lexical discrimination required to make a word/non-word judgment. High frequency words are encountered frequently and are easily retrieved. When a high frequency word is encountered the decision of whether the stimulus is a word or not requires less discrimination from close competitors, i.e. the participant “knows” the high frequency stimulus is a word before bothering to determine which particular word was encountered. Therefore the high closeness centrality value aids processing, as in Experiment 2. An example of a high frequency word with high closeness centrality would be WRITTEN. However, when the stimulus encountered is a low frequency word with high closeness centrality (such as ALLURE) processing will be impaired. Determining the lexicality of a low frequency word requires slower processing since the word is rarely encountered and retrieved. When a low frequency word is encountered the participant is less confident that the stimulus is a word and will need to engage in further discrimination of the stimulus to pinpoint the actual word encountered. The process of determining the low frequency word encountered will be impaired by

competitors close to a high closeness centrality word, thereby slowing processing. To put it simply, less discrimination is necessary to determine that a high frequency word is a word and high closeness centrality aids processing, whereas more discrimination is necessary to determine that a low frequency word is a word and high closeness centrality will impair processing due to the increased number of competitors in close proximity.

The nonwords used in the experiment may have influenced how participants discriminate between words and nonwords, adding to the interaction observed between frequency and closeness centrality. Nonwords that are unusual (and differ by several phonemes from a real word) are easy to recognize as nonwords and discrimination processes are not overly burdened. However, when a participant is presented with nonwords that sound similar to real English words (such as the nonwords used in the present experiment that differ by a single phoneme) they must rely on all the information available to make a decision. Thus, when a low frequency word with high closeness centrality is presented the participant is not exposed to the processing benefits of high frequency and must continue to use the fine-grained discrimination processes, which are burdened by the many words lexically close, to determine the stimulus is a word.

The significant interaction observed in Experiment 3 suggests the same interaction might exist in Experiment 2. Using results from Experiment 2, a model was created which included an interaction term of frequency and closeness centrality. The interaction term was not significant when analyzing accuracy data $\beta = 1.002, p = .24$ or reaction time data $\beta = -783, p = .18$. The lack of a significant interaction term in Experiment 2 is likely due to the restricted range of frequency and closeness centrality, recall that stimuli in Experiment 2 were controlled on a number of other variables including word frequency. The interaction between frequency and closeness centrality was observable in Experiment 3 due to the wider range of frequency and closeness centrality values.

Furthermore the range of frequency values in Experiment 2 is predominantly beyond 2.11, which is the approximate frequency value where high closeness centrality becomes an advantage rather than a disadvantage (see figure 7). There are 17 words below a frequency value of 2.11 and 23 words above the 2.11 value. Since most words in Experiment 2 come from the range of frequency values where high closeness centrality is an advantage for processing then it is not surprising that an advantage was found for high closeness centrality words in Experiment 2. Therefore, the high closeness centrality advantage observed in Experiment 2 and the frequency and closeness centrality interaction observed in Experiment 3 are in agreement.

A series of 4 models was then created including the individual difference measures as participant level (level 2) cross level interaction predictors (inhibition, processing speed, reading span, and vocabulary). No significant coefficient of individual differences was found (see table 5). The lack of significant results suggests closeness centrality is not processed differently between participants.

Table 5. Coefficient values for individual difference measures included in Experiment 3 models with reaction time as the dependent variable.

Individual Difference Measure	β coefficient	p value
Processing Speed	-1.66	.65
Inhibition	-6.27	.71
Working Memory	-6.7	.67
Vocabulary	-8.1	.84

The same process of model creation was repeated with accuracy as the dependent variable. The model with all level 1 predictors and no interaction terms showed frequency ($\beta = .008, p < .0001$) and log mean neighborhood frequency ($\beta = .0003, p < .001$) as significant predictors. Once again, frequency and log mean frequency of neighborhood were significant predictors in the series of models with an interaction term included, but clustering coefficient was no longer significant in the models (see table 6). No significant interactions were found and individual difference measures showed no significant predictors (see table 7). The lack of significant interaction between closeness centrality and frequency is not surprising given that the lexical decision task is an easy task and most participants perform close to

ceiling. Reaction times are a more sensitive measure of processing differences in the task and the models using reaction time as a dependent variable are more likely to observe the subtle influence of closeness centrality.

Table 6. Significant predictors observed in Experiment 3 models with interaction terms and accuracy as the dependent variable.

Interaction Term Included in Model	Predictor	β coefficient	<i>p</i> value
Closeness Centrality and Clustering Coefficient	Frequency	.08	< .0001
	Log Mean Neighborhood Frequency	.0003	< .0001
Closeness Centrality and Frequency	Frequency	-.002	.17
	Log Mean Neighborhood Frequency	.0003	< .0001
Closeness Centrality and Neighborhood Density	Frequency	.09	< .0001
	Log Mean Neighborhood Frequency	.0003	< .0001
Closeness Centrality and Segment Sum	Frequency	.08	< .0001
	Log Mean Neighborhood Frequency	.0003	< .0001
Closeness Centrality and Biphone Sum	Frequency	.07	< .0001
	Log Mean Neighborhood Frequency	.0003	< .0001
Closeness Centrality and Log Frequency Neighborhood Mean	Frequency	.08	< .0001
	Log Mean Neighborhood Frequency	-.001	.07

Table 7. Coefficient values for individual difference measures included in Experiment 3 models with accuracy as the dependent variable.

Individual Difference Measure	β coefficient	<i>p</i> value
Processing Speed	.0004	.68
Inhibition	.0006	.69
Working Memory	.0002	.99
Vocabulary	.004	.26

The inhibition measure predictor included in the models was also non-significant (accuracy: $\beta = .0006, p = .69$, reaction times: $\beta = -6.27, p = .71$), suggesting the executive control function has no

impact on the closeness centrality effect. The ability to ignore distracting information does not appear to influence the process of retrieving high closeness centrality words from dense areas of the lexicon. The inhibition measure was obtained from a Stroop color naming task, where the participant is intentionally and rather dramatically distracted by words in different colors of ink; a somewhat artificial laboratory task. However, in normal lexical processing there is no overt distraction occurring. Perhaps an inhibition measure sensitive to the more subtle inhibition processing necessary to ignore lexical competitors (a process relied upon constantly throughout the day outside of the laboratory) would have yielded significant results.

Additionally, the predictor of processing speed was not significant in either of the models (accuracy: $\beta = .0004$, $p = .68$, reaction times: $\beta = -1.66$, $p = .65$). The lack of significant results suggests the closeness centrality effect is not influenced by the speed of the participant's cognition. Evidence suggests participants do not traverse lexical distance when retrieving a single word from the lexicon. That is to say, there is no starting point for a lexical search to begin and participants do not have to traverse from central areas to remote areas of the lexicon in order to retrieve low closeness centrality words. However, if participants were forced to start from a specific point in the lexicon (e.g. Experiment 1) it may be observed that slow processors take longer to reach and retrieve low closeness centrality words in the remote areas of the lexicon compared to fast processors.

The working memory measure was not a significant predictor in the reaction time $\beta = -6.7$, $p = .67$ or accuracy models $\beta = .0002$, $p = .99$. Recall that closeness centrality does not measure the lexical space immediately surrounding a word, but rather the position of the word in the overall lexical structure. Words that are immediately surrounding a word, i.e. phonological neighbors, may enter a participant's working memory, but words that are more than one phoneme removed from the target word (which is primarily what closeness centrality is measuring) may not enter working memory and impede processing. Therefore, differences in working memory may influence neighborhood density effects, but working memory is not influenced by the number of words and paths surrounding a word. The lack of significant

individual difference measures suggests the closeness centrality effect is similar across participants and does not vary based on inhibition processes, processing speed, or working memory span.

It is possible that the lack of significant individual difference predictors is due to a lack of variability in the sample of participants used. The lack of variability may stem from ceiling effects, where most participants are performing very well on the individual difference measures leading to a lack of variability between participant scores. Previous studies have found an influence of individual differences on language processing (Rozek, Kemper & McDowd, 2012). It is possible these authors found effects due to the greater variability in their sample (i.e. no ceiling effects). However, an analysis of variability within the samples shows relatively the same amount of variability within the different studies (see Table 8).

Table 8. Comparison of variability in individual difference measures between experiment 3 and Rozek, Kemper & McDowd, 2012. Means in bold and standard deviations in parentheses.

	Experiment 3	Young Adult Group in Rozek, Kemper & McDowd, 2012
Vocabulary Size	28.2 (4.05)	31.4 (3.4)
Inhibition	57.3 (9.49)	60.4 (11.5)
Processing Speed	80.7 (13.98)	84.5 (14.1)
Reading Span	3.3 (.71)	3.3 (.6)

Lastly, no evidence was found that the size of one’s lexicon influences the closeness centrality effect, as the vocabulary measure was not a significant predictor of accuracy $\beta = .004, p = .26$ or reaction times $\beta = -8.1, p = .84$. The results suggest differing values of closeness centrality will emerge in an individual’s lexicon regardless of size. Indeed, many network characteristics do not rely on network size (i.e. the number of nodes in a network), but rather the arrangement of the nodes in a network is the more important influence on network characteristics. For example, the network characteristic of a small average path length (the average path length between any two nodes in a network) has been observed in social networks as large as the International Movie Database film actors network (approximately 225,000 actors; Watts & Strogatz, 1998) or as small as the neural network of the round worm *C. elegans*

(approximately 282 neurons; Watts & Strogatz, 1998). Therefore, the arrangement of the words in a lexicon could give rise to differences in closeness centrality, rather than individual differences such as total number of known words.

Discussion

The results from Experiment 3 show the utility of the approach used in Experiment 2. Frequency of occurrence has long been shown to be a very important variable in language processing and typically accounts for a large amount of the variability in responses. When frequency is added into a multilevel model the variability associated with most other processing variables is overshadowed and their influence is not apparent. When these variables are explicitly controlled during stimulus selection (as in Experiment 2) other variables with a more subtle influence on language processing (such as closeness centrality) can be observed. Although the influence of these other variables, like closeness centrality, may not be as large as the influence of word frequency, the presence of such effects provides important insight into how the spoken word recognition system works.

The experiments detailed above show that closeness centrality plays an interesting role in language processing. Experiment 1 provided initial evidence that closeness centrality affects language processing (i.e. closeness centrality influences a local lexical search task). Experiment 2 used a more conventional psycholinguistic task, the lexical decision task, to show the influence of closeness centrality on a more natural language process: spoken word recognition. Experiment 3 used an alternative approach to show that the influence of closeness centrality is subtle and confounding variables need to be tightly controlled during stimulus selection in order for the influence of closeness centrality to be observed. Experiment 3 also showed an interesting interaction of closeness centrality with frequency, namely that increasing frequency of occurrence changes the influence of closeness centrality from detrimental to beneficial for processing, which may have been at least partially a result of the nonwords used.

Chapter 7: Discussion

The experiments described above explore how a network measure, closeness centrality, influences processing of words in the lexicon. This investigation was made through 3 experiments. Experiment 1 was inspired by the work of Iyengar et al. (2012) and used a unique lexical search task. Experiment 2 used a traditional psycholinguistic task, the auditory lexical decision task, to examine the influence of closeness centrality on spoken word recognition. Experiment 3 also used an auditory lexical decision task with a different approach to the analysis by exploring interactions of closeness centrality with other processing variables and individual differences. In general, the results from these three experiments show an influence of closeness centrality on language processing.

The data from Experiment 1 indicate that lexical search is easier when starting from a low closeness centrality word. A short lexical search, such as the task used in Experiment 1, is aided by the few words and paths around a low closeness centrality word. The few paths and nodes allow for the searcher to find the correct path to the target word with ease. However, a short lexical search around a high closeness centrality word is slowed by the large number of paths and words close by, which obscure the correct path to the target word. Experiment 1 provided good evidence that closeness centrality influences language processing in the phonological lexicon and that when conducting a local lexical search network characteristics influence the success of that search.

The data from Experiment 2 point towards a processing advantage for words with high closeness centrality. These results can be explained with the mechanism of partial activation proposed by several widely accepted models of lexical retrieval (Luce & Pisoni, 1998; McClelland & Elman, 1986; Norris, 1994). Partial activation refers to several similar-sounding words receiving partial activation when a single word is retrieved from the lexicon. Due to their close proximity to many other words in the lexicon, over time high closeness centrality words will receive a greater amount of partial activation than other words. Even though the high closeness centrality words are not retrieved with greater frequency

(frequency of occurrence was controlled), the repeated partial activation of such words may lead to small changes that accumulate over time, and which may have beneficial properties that aid recognition processes.

While it is a tentative explanation of the results, partial activation is a common mechanism used to explain psycholinguistic phenomena. The Neighborhood Activation Model proposed by Luce and Pisoni (1998) incorporates partial activation to explain some of their findings. The authors found that words with many similar sounding words (or a dense phonological neighborhood) were recognized slower and less accurately than words with few similar sounding words (or a sparse phonological neighborhood). When a target word with a dense phonological neighborhood is recognized there are many partially activated words that might be retrieved, hindering processing. However, when a target word with a sparse phonological neighborhood is recognized there are few partially activated words that might be retrieved, quickening processing. The research described above shows that partial activation may indeed be influencing processing in the lexicon and this influence may lead to the observed and predicted influence of closeness centrality.

Accumulated activation explains the processing advantages of high frequency words observed in older adults in MacKay's Node Structure Theory (1982). The activation of links between lexical levels (e.g. phonemes, syllables, words, and semantic information) benefits the processing of words. The repeated recognition and production of a word will maintain strong links between lexical levels of that word, leading to the observed advantages of high frequency words. Words that are retrieved rarely will not have the associated links between lexical levels activated and will begin to decay with time, eventually making the word difficult to retrieve.

Partial activation is also used to explain results in the phonological false memory task employed by Sommers & Lewis (1999). The researchers found that by presenting many phonological neighbors of a target word during study participants falsely recognized the target word at test. The results can be

accounted for by partial activation of the target word during presentation of the phonological neighbors. The target word was partially activated several times during the study phase which lead many participants to believe the target word was actually presented.

The above examples show how partial activation can influence processing when the activation arises within a phonological neighborhood. However, the current work addresses the idea of partial activation stemming from more distant sources in the lexicon. Evidence for partial activation influencing lexical processing beyond a neighborhood comes from the work of Vitevitch and Goldstein (2014). The authors propose that due to keywords occupying a critical position in the lexical network, that in some ways acts as a bottle neck, the keywords will receive more partial activation than other words. Similar to the present results, Vitevitch & Goldstein (2014) found that keywords possessed processing benefits possibly arising from the accumulated partial activation.

Experiment 3 results are less clear about the influence of closeness centrality. Experiment 2 used a more traditional approach to the lexical decision task. Stimuli were selected in a manner that controlled for other processing variables, removing the influence of other variables at stimuli selection. Experiment 3 used a multilevel modeling analysis to remove the influence of other processing variables and to examine the influence of individual difference measures. Closeness centrality was not a significant predictor in any of the models in Experiment 3, suggesting that closeness centrality may have a subtle influence on language processing. In order for this subtle influence to be observed other processing variables may need to be controlled in the stimuli list, otherwise variables with a more dominant influence on processing (such as frequency) will overshadow the influence of closeness centrality.

In Experiment 3 an interesting interaction was observed between frequency and closeness centrality. The interaction indicates that processing of low frequency words is impeded by high closeness centrality, but processing of high frequency words is aided by high closeness centrality. It is possible that participants were employing two different discrimination strategies. A high frequency word is

encountered often and when a participant is asked to make a word/non-word judgment about a high frequency word they may know the stimulus is a word before they know what specific word it is, reducing the need to make a slow, fine-grained distinction of the word. The high closeness centrality of a high frequency word will aid processing, as was observed in Experiment 2. However, when a low frequency word is encountered the participant does not have the same confidence that the stimulus is a word. Further discrimination of the stimulus is necessary before a decision of “word” can be made and the increased number of words close to a high closeness centrality word will delay the discrimination process by increasing the number of potential competitors. The results from Experiment 3 highlight the interaction of processing variables in the lexicon, and may have been due to the nonwords that sounded very similar to real words.

Implications for Language Processing Models

The current results are not accounted for by currently accepted models of spoken word recognition which would predict no difference in processing once all individual-level characteristics are controlled for (McClelland & Elman, 1986; Norris, 1994). The present work shows the importance of studying the lexicon as a connected whole consisting of interacting words, rather than individual words stored in isolation. The tools of network science are ideally suited to study the lexicon as a connected whole.

Network scientists have repeatedly demonstrated that structure and function are closely intertwined. The phonological lexicon is no different, how phonological representations are organized influence how quickly and accurately those phonological representations are retrieved. The results also show an important and interesting effect. Closeness centrality is a measure of how many links away (on average) a word is to *every other word* in the lexicon. This finding bolsters the claims made in Vitevitch and Goldstein (2014) showing that another network measure assessing the entire lexicon, keywordness, influences language processing. These findings highlight the fact that the entire, overall structure of a

language needs to be considered in theories of spoken language processing. In other words, the mental lexicon is not a series of independent word representations, but rather a connected system that must be studied as a whole.

Furthermore, the present work shows the utility of using network science to study complex cognitive systems such as the lexicon. Network science provides many useful tools that are applicable to a wide range of cognitive systems; however caution must be taken when applying network science tools as there is no “one size fits all” measure. The network measure of closeness centrality is ideal to use when studying the lexicon as it is able to capture some key characteristics of processing in the lexicon. Borgatti (2005) showed that depending on how information flows through a network, certain network measures are not applicable as they will provide inaccurate or uninterpretable results. When attempting to use the tools of network science great care must be taken to use the appropriate measures for the appropriate system being modeled. Even the definition of a node or link in a network must be carefully considered when creating network models (Borgatti & Halgin, 2011). In summary, there exists much potential for network science to aid cognitive research, but the tools must be used wisely.

Important Words in the Lexicon

Similar to the keywords research by Vitevitch and Goldstein (2014), the proposed research has several important applications. Important words, as measured by global network measures, may be ideal words to learn initially in a second (or first) language. The research described above shows the importance of viewing the lexicon as a unified system rather than isolated words. In order to build a robust network framework for the lexical system to grow upon it would seem beneficial to direct the building of that network in an organized, systematic way. It may prove beneficial to create lists of important words for language learners, controlling and directing the language learning process in the most efficient way possible. For example, if high closeness centrality words are learned first this may provide stable areas of the lexicon for other words to attach to, facilitating growth.

Impaired populations may benefit from this research as well. Showing how important nodes are processed differently may lead to therapy wherein important words in the lexical structure are practiced. Ferrer i Cancho & Solè (2001) note that patients with agrammatic aphasia (characterized by telegraphic speech and a lack of function words) have difficulty with important words in a lexical network based on syntactic relationships. The authors observations seem to suggest training on these important words may benefit overall lexical processing in agrammatic aphasia patients.

Work with semantic dementia patients, a language impairment related to aphasia, also poses a promising avenue of application. Current approaches to language training in patients with semantic dementia attempt to preserve patient's currently known words from decay. The words chosen for preservation are often frequently occurring words with high imageability (Reilly, Martin & Grossman, 2005). Both characteristics aid retention of the specific words that are practiced. However, if important words in the lexical network are practiced it may show a benefit for words other than the specific words practiced. For example, if a list of high closeness centrality words was repeatedly practiced the words surrounding the high closeness centrality words in the lexicon may also receive a benefit through partial activation even though those items are not actually retrieved. In this way a training list of words could be constructed to provide the maximum language benefit possible. Semantic dementia and aphasia are indeed different disorders, but may have a similar underlying cause of difficulty in retrieving words from the lexicon. Therefore, similar training therapies, which target different words or types of words (e.g., semantically related versus phonologically related) for the different disorders may lead to benefits in both disorders.

The approach described above seems feasible when considering another approach to aphasia therapy known as Verbal Network Strengthening Treatment. Verbal Network Strengthening Treatment (Edmonds, Nadeau & Kiran, 2009) consists of exposing a patient with aphasia to words that are related to a specific verb, such as similar verbs or the agent of the target verb. The target verb being strengthened is not presented and patients often show improvement in use of the target verb. This treatment approach

highlights the idea that retrieval of a word can be strengthened through training on related words. The most efficient way to train patients with aphasia on as many words as possible may not be to create large lists, but rather to identify words that have the largest potential benefit for *other* words. High closeness centrality words, by definition, are close to many other words in the lexicon and when activated during retrieval will partially activate the greatest possible number of other words. A training list consisting of important words may be extraordinarily beneficial for patients with aphasia.

Conclusions

The work described above highlights several important points in psycholinguistic research: 1) models of spoken word recognition that focus on individual characteristics of words are excluding the important relationships between words, 2) the lexicon may be more accurately viewed as a complex system and the tools of network science are useful for measuring the structure of this system, and 3) important words exist in the lexicon and closeness centrality is one way to measure importance in the lexicon. The variable of closeness centrality influences processing in some interesting and important ways and further study is necessary to fully understand its impact on processing. Finally, applications of this work include language learning and language patients.

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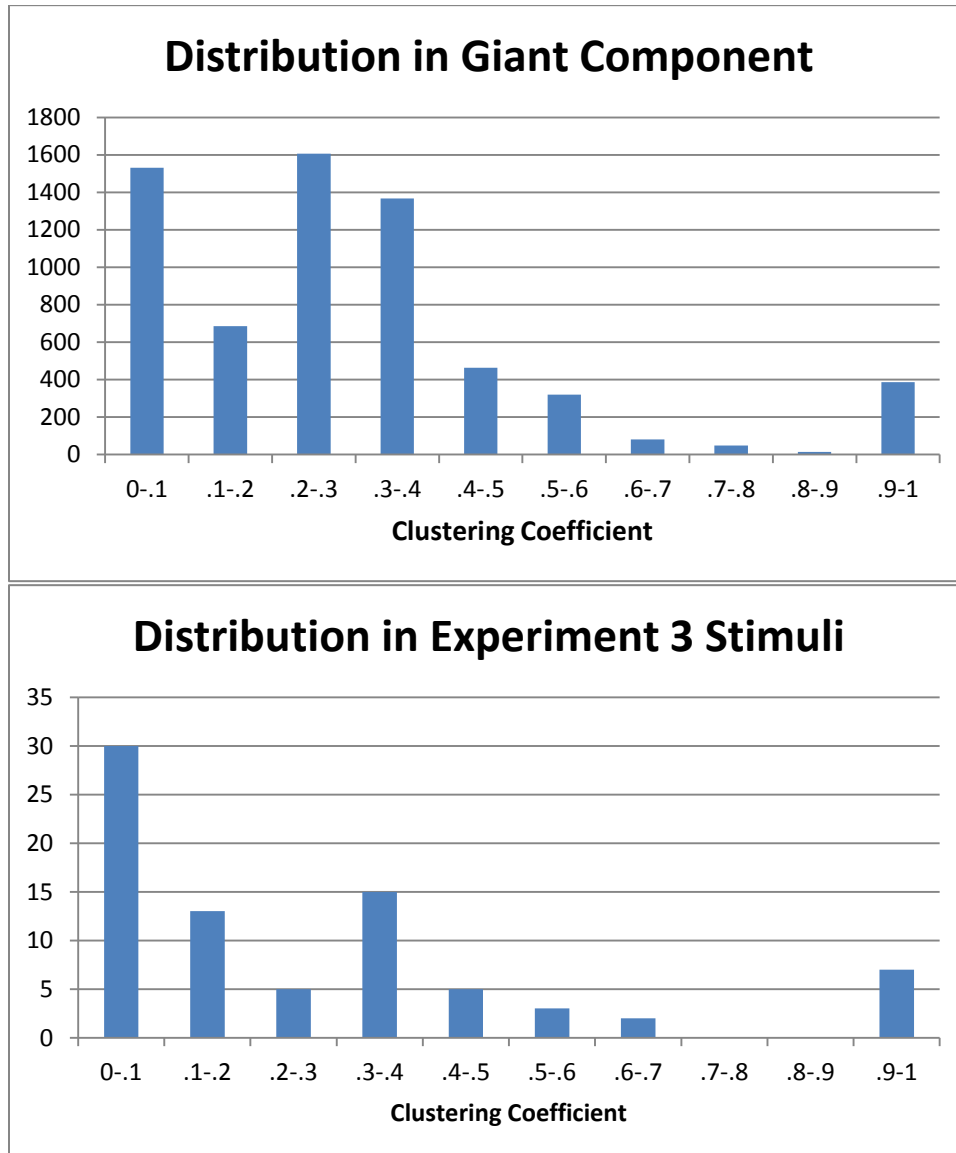
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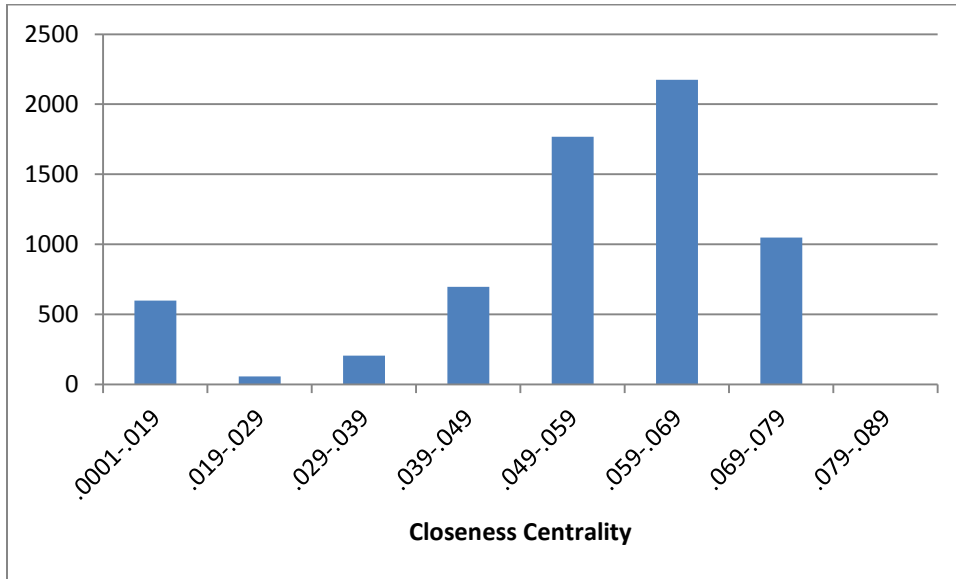
Appendix A

Comparison of processing variable frequency distributions in giant component of the lexicon and stimuli used in Experiment 3.

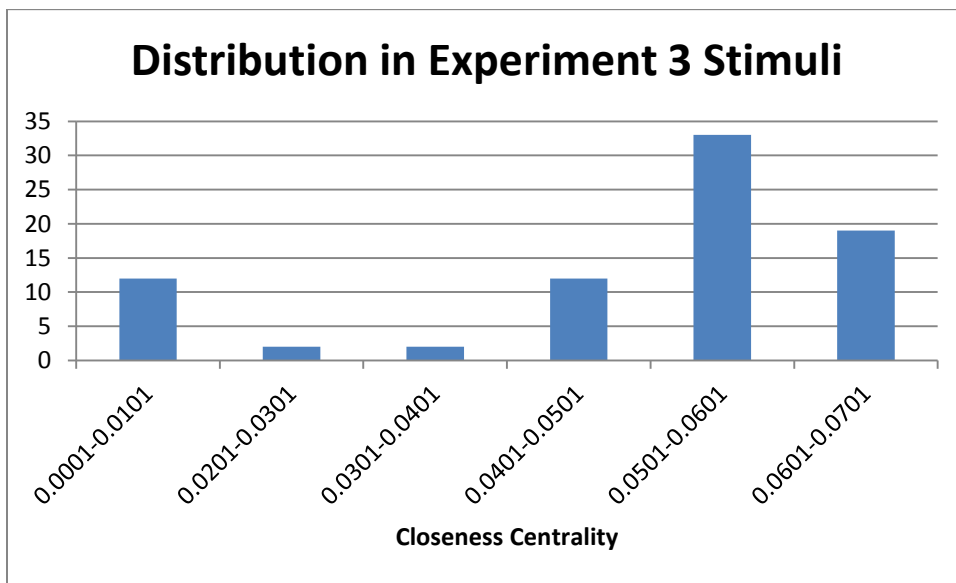
Clustering Coefficient



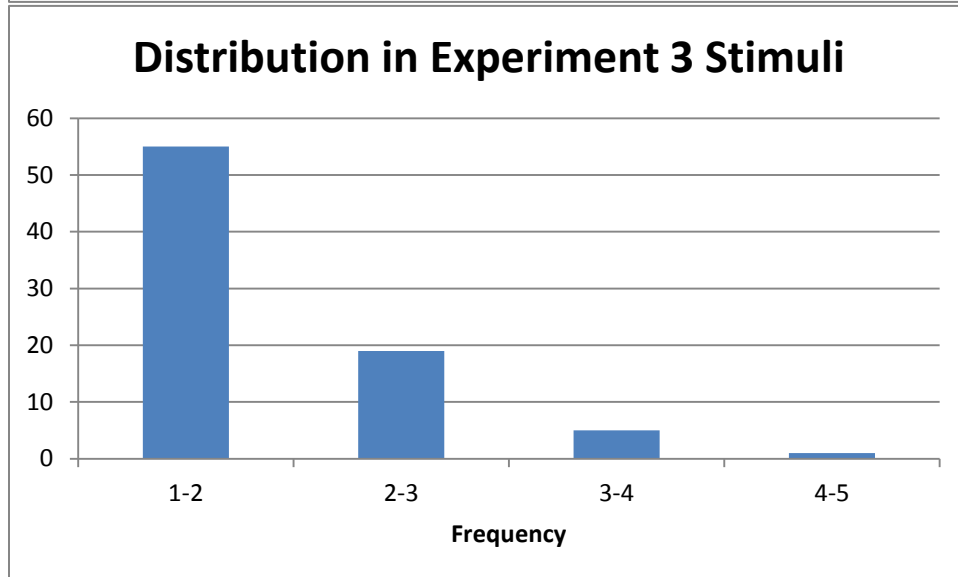
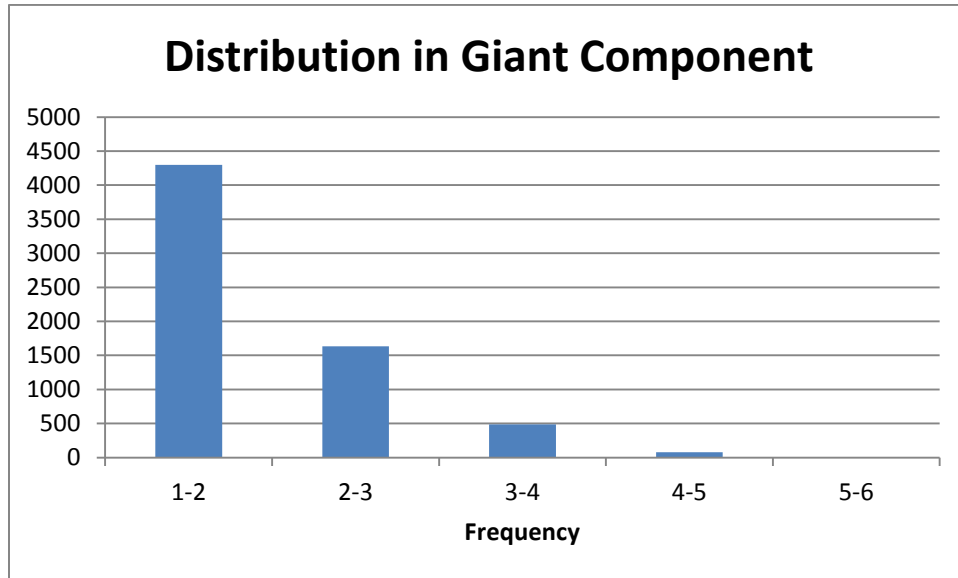
Closeness Centrality



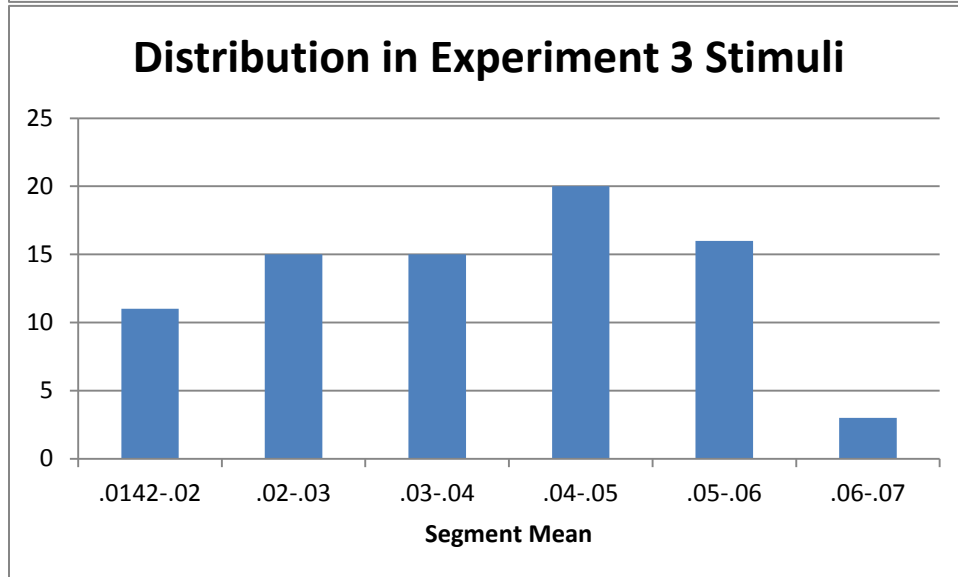
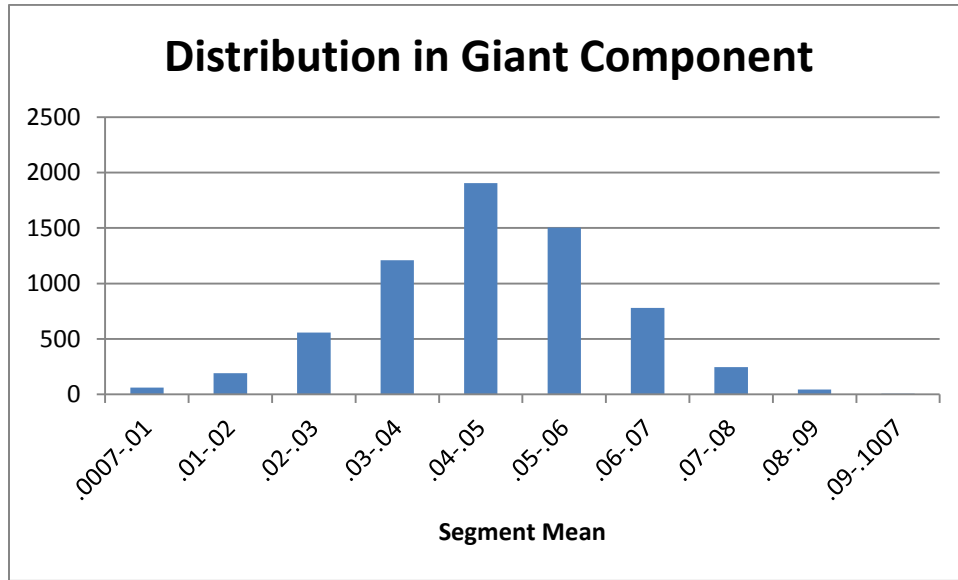
Distribution in Experiment 3 Stimuli



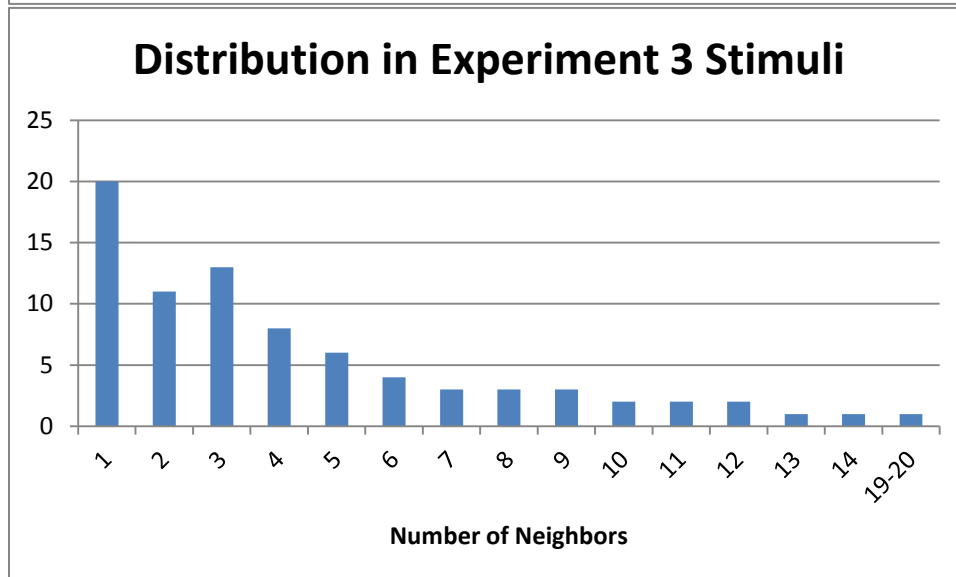
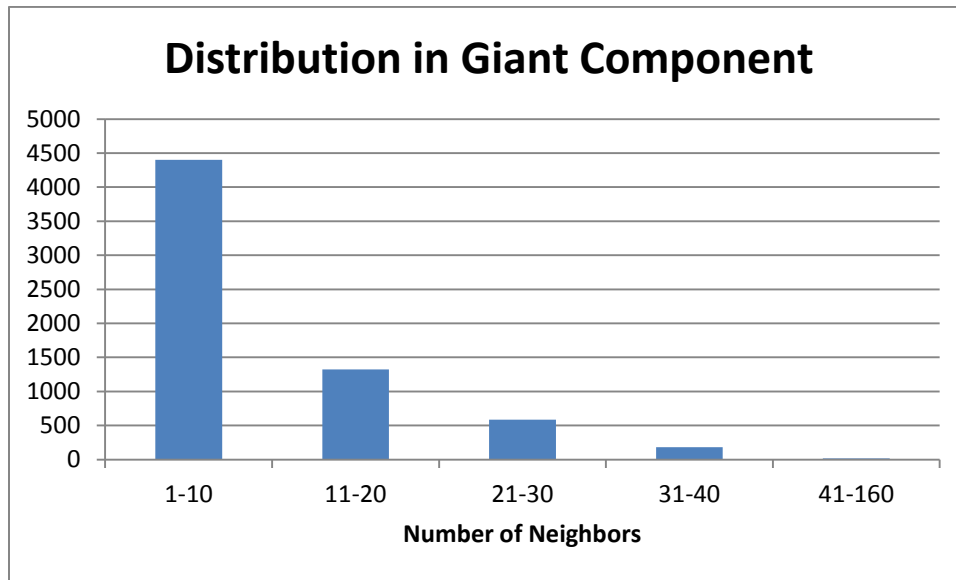
Frequency



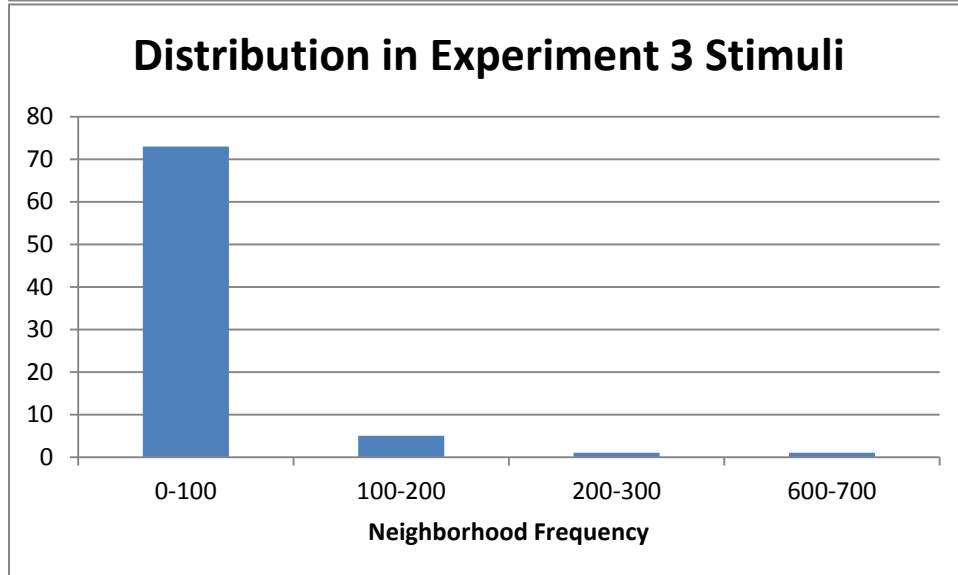
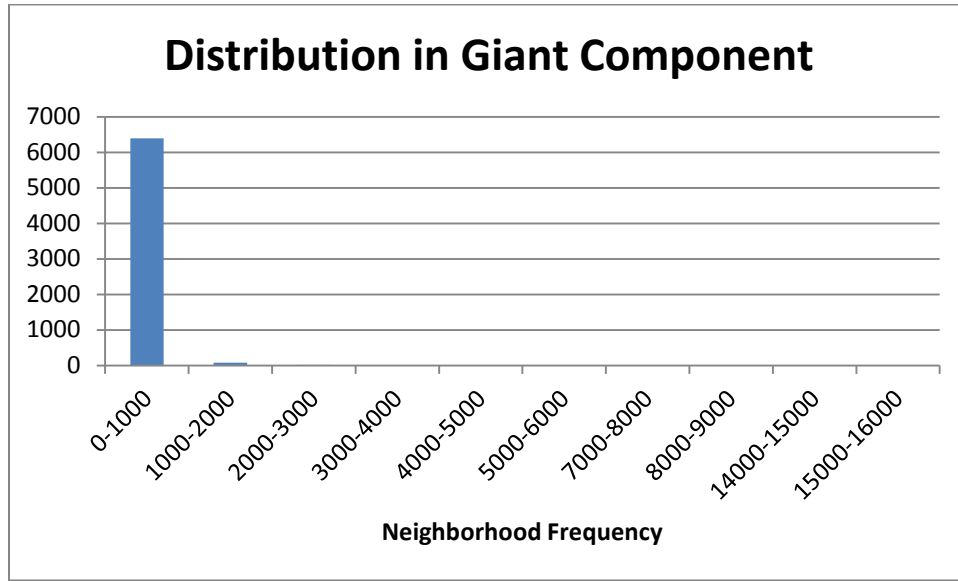
Segment Mean



Number of Neighbors



Neighborhood Frequency



Biphone Mean

