NIH Public Access
Author Manuscript
J Mem Lang. Author manuscript; available in PMC 2013 July 01.

Published in final edited form as:
J Mem Lang. 2012 July 1; 67(1): 30–44. doi:10.1016/j.jml.2012.02.008.

Complex network structure influences processing in long-term and short-term memory

Michael S. Vitevitch,
Department of Psychology University of Kansas

Kit Ying Chan, and
Department of Psychology University of Kansas

Steven Roodenrys
School of Psychology University of Wollongong

Abstract

Complex networks describe how entities in systems interact; the structure of such networks is argued to influence processing. One measure of network structure, clustering coefficient, *C,* measures the extent to which neighbors of a node are also neighbors of each other. Previous psycholinguistic experiments found that the *C* of phonological word-forms influenced retrieval from the mental lexicon (that portion of long-term memory dedicated to language) during the on-line recognition and production of spoken words. In the present study we examined how network structure influences other retrieval processes in long- and short-term memory. In a false-memory task—examining long-term memory—participants falsely recognized more words with low- than high-*C*. In a recognition memory task—examining veridical memories in long-term memory—participants correctly recognized more words with low- than high-*C*. However, participants in a serial recall task—examining redintegration in short-term memory—recalled lists comprised of high-*C* words more accurately than lists comprised of low-*C* words. These results demonstrate that network structure influences cognitive processes associated with several forms of memory including lexical, long-term, and short-term.

Keywords

network science; STM; LTM; clustering coefficient; mental lexicon

Mathematics, physics, computer science, and other fields use complex networks to model large-scale systems (for a review see Albert & Barabási, 2002). Entities in these systems, such as people, animals, or web-pages, are represented as nodes in the network, and relationships, such as friendships, predator-prey interactions, or hyperlinks connecting web-pages, are represented as connections (*a.k.a.* edges or links) between nodes in the network. The emerging pattern of connections among the nodes may resemble a lattice (*i.e.,* a regular network), appear to be random (*i.e.,* a random network), or, more interesting, contain certain features of both regular and random networks. Network structures that contain certain

Correspondence should be addressed to: Michael S. Vitevitch, Ph.D. Spoken Language Laboratory Department of Psychology 1415 Jayhawk Blvd. University of Kansas Lawrence, KS 66045 mvitevit@ku.edu*ph*: 785-864-9312.

features of both regular and random networks are often found in real-world systems, and are referred to as *complex networks*.

Although complex networks have primarily been used to model social, biological, and technological systems, they can also be used to examine complex *cognitive* systems. The assumptions associated with complex networks should not be confused with the assumptions associated with other types of "networks" that have been used in the cognitive sciences, such as artificial neural networks (Rosenblatt, 1958) semantic networks (Quillian, 1967), or linguistic nections (Lamb, 1970). An example of the complex network approach applied to cognitive science is found in Vitevitch (2008), in which nodes represented approximately 20,000 English words, and connections represented phonological similarity between words (using the metric in Luce & Pisoni, 1998; for semantic relationships see: Hills et al. 2009). A sample of words from the network examined by Vitevitch (2008) is shown in Figure 1.

Analysis of the network of phonological word-forms in English revealed several interesting structural features: (1) a large highly interconnected component, as well as many islands (words that were related to each other—such as *faction, fiction*, and *fission*—but not to other words in the large component) and many "lexical hermits," or words with no neighbors (known as isolated or disconnected nodes in the network science literature); the largest component exhibited (2) the characteristics of a small-world network,[i] (3) assortative mixing by degree (a word with many neighbors tends to have neighbors that also have many neighbors; Newman, 2002), and (4) a degree distribution that deviated from a power-law.

Arbesman, Strogatz and Vitevitch (2010) found the same constellation of structural features in phonological networks of Spanish, Mandarin, Hawaiian, and Basque, and elaborated on the significance of these characteristics. For example, the giant component of the phonological networks contained, in some cases, less than 50% of the nodes; networks observed in other domains often have giant components that contain 80-90% of the nodes. Simulations by Arbesman et al. demonstrated that this characteristic contributes to the robustness of phonological networks when highly connected nodes are targeted for removal or when nodes are removed at random.

Arbesman et al. (2010) also noted that assortative mixing by degree is found in networks in other domains. However, typical values for assortativity in social networks range from .1-.3, whereas the phonological networks examined by Arbesman et al. were as high as .7. Finally, most of the languages examined by Arbesman et al. exhibited degree distributions fit by truncated power-laws (but the degree distribution for Mandarin was better fit by an exponential function). Networks with degree distributions that follow a power-law are called scale-free networks, and have attracted attention because of certain structural and dynamic properties (Albert & Barabási, 2002). See work by Amaral, Scala, Barthélémy and Stanley (2000) for the implications on the dynamic properties of networks with degree distributions that deviate from a power-law in certain ways.

A common assertion in the complex network literature is that the structure of such networks influences processing (Watts & Strogatz, 1998). Chan and Vitevitch (2009; 2010) used several conventional psycholinguistic tasks to examine how one structural characteristic of the phonological network of English influenced the process of lexical retrieval during the on-line production and recognition of spoken words. Of the measurements used to describe

[i]As defined by Watts and Strogatz (1998), a network is said to be a small-world network if (i) the average distance between two randomly chosen nodes in that network is approximately the same distance between two randomly chosen nodes in a network of comparable size with connections randomly placed between nodes ($L \sim L_{random}$), and (ii), the clustering coefficient of that network is much larger than the clustering coefficient of a network of comparable size with connections randomly placed between nodes ($C >> C_{random}$).

the structure of a complex network, two are presently most relevant: *degree* and *clustering coefficient.* Degree is the number of connections incident with a node. In the network of Vitevitch (2008), degree corresponds to the number of words that sound similar to a given word.[ii] Much research in Psycholinguistics shows that degree influences several language-related processes, including the production (e.g., Vitevitch & Stamer, 2006; 2009) and recognition (e.g., Vitevitch, 2002a) of spoken words, word-learning (e.g., Storkel, Armbruster & Hogan, 2006), and serial recall (e.g., Roodenrys et al., 2002). In Figure 2, degree corresponds to the number of connections between the words *badge* and *log* to their respective neighbors (both words have 13 neighbors).

Clustering coefficient, C, (Watts & Strogatz, 1998) measures the extent to which neighbors of a given node are also neighbors of each other, and was examined by Chan and Vitevitch (2009, 2010). *C* is represented in Figure 2 by the connections between a neighbor of *badge* to another neighbor of *badge* (e.g., the connection between *bass* and *bat*), or that connect a neighbor of *log* to another neighbor of *log* (e.g, the connection between *league* and *leg*). *C* ranges from 0 (none of the immediate neighbors of a node are connected to each other) to 1 (all of the immediate neighbors of a node are fully interconnected). In the present study, *C* was computed for each word (*i.e.*, the local clustering coefficient for an undirected graph) as in equation (1):

$$C_i=\frac{2|\left\{e_{jk}\right\}|}{k_i\,(k_i-1)} \qquad \text{(Eq. 1)}$$

e_{jk} refers to the presence of a connection (or edge) between two neighbors (*j* and *k*) of node *i*, |...| is used to indicate cardinality, or the number of elements in the set (not absolute value), and k_i refers to the degree (i.e., neighborhood density) of node *i*. By convention, a node with degree of 0 or 1 (which results in division by 0—an undefined value) is assigned a clustering coefficient value of 0. Note that degree > 1 for all of the words used in the present studies. Thus, the (local) clustering coefficient is the proportion of connections that exist among the neighbors of a given node divided by the number of connections that could exist among the neighbors of a given node.

As reported in Chan and Vitevitch (2010), the correlation between degree, *k*, and *C* for the 6,281 words with 2 or more neighbors (the minimum number of neighbors required to compute *C*) from the network examined in Vitevitch (2008) is $r = .005$, $p = .68$ (a scattergram of those data appears in Appendix A). That is, a word with many neighbors, *k*, could have high or low *C*. Similarly, a word with few neighbors, *k*, could have high or low *C*. In the present experiments (as in Chan & Vitevitch, 2009; 2010) we used words that varied in *C*, but were comparable in *k* (with $k > 1$).

Using several conventional psycholinguistic tasks, Chan and Vitevitch (2009, 2010) examined how the structural characteristic, *C,* influenced the process of lexical retrieval during the on-line recognition and production of spoken words. Chan and Vitevitch (2009) found in two word recognition tasks—perceptual identification and lexical decision—that words with high *C* (*badge* in Figure 2) were responded to more slowly and less accurately than words with low *C* (*log* in Figure 2), even though the words were equivalent in degree and a number of other relevant characteristics. Similarly, Chan and Vitevitch (2010) found in an analysis of a corpus of speech production errors and a picture-naming task that words

[ii]In the psycholinguistic literature, this measure is commonly referred to as *phonological neighborhood density* (Luce & Pisoni, 1998). However, in the present report, we will use the term **degree** rather than neighborhood density. This does not mean we are reinventing, or redefining the term “neighborhood density” in any way, we simply wish to use the term degree to maintain consistency with the network science literature that motivated the present study.

with high *C* were responded to more slowly and less accurately than words with low *C*. Thus, network structure, as measured by *C,* influences the speed and accuracy with which spoken words are retrieved from the *mental lexicon*—traditionally defined as that portion of long-term memory dedicated to language.

In the present experiments we examined whether the influence of phonological network structure on cognitive processing was limited to the on-line production and recognition of spoken words examined by Chan and Vitevitch (2009, 2010), or if network structure might also influence other phenomena associated with long-term and short-term memory. To examine how network structure influences retrieval from long-term memory we used, in Experiment 1, the false memory paradigm (Deese, 1959; Roediger & McDermott, 1995). To examine how network structure influences retrieval of veridical memories (rather than generating "false" memories) we used an old-new recognition task in Experiment 2. In Experiment 3, we used a serial recall task to examine how network structure influences the process of *redintegration* (Schweickert, 1993), in which information in *long-term memory* is used to reconstruct degraded representations in *short-term memory*.

We recognize that these tasks are often used to examine very different types of memory and very different theories about cognitive processing, but it is not our intention in the present study to test specific theories of long-term or short-term memory. Rather, we wished to use well-understood memory tasks and phenomena to further examine how the network structure exhibited among words in the phonological lexicon influences cognitive processing.

Experiment 1

The work of Roediger and McDermott (1995) renewed interest in the study of false memories (Deese, 1959), where participants report in a recall or recognition task events that never happened. In this paradigm, participants typically hear a list of words containing close semantic associates of a critical item, and are tested for their recall or recognition of list items that were studied, and of the non-studied critical items. For example, participants might hear the words *thread, pin, sewing, sharp*, etc., which are semantic associates of the word *needle* (which, crucially, is not presented for study). Immediately after study, participants are asked to recall as many of the words from the list as possible. Participants correctly recalled items from the list 65% of the time, and falsely recalled the non-studied critical item (*needle,* in the example above) 40% of the time, despite specific instructions to the participants to recall only items that had been presented.

The results of Roediger and McDermott (1995) have been replicated and extended in a number of interesting ways. One study germane to the present investigation is by Sommers and Lewis (1999), in which false memories were elicited for *phonologically* rather than semantically related words. That is, participants studied words like *fat, cab, cot, sat, cut, kit, mat, cad*, etc. that were phonological neighbors of the (non-studied) critical item *cat*. As when semantically related words are studied, Sommers and Lewis found false memories (in recall and recognition) for the non-studied phonologically similar critical item (i.e., *cat*).

To examine how the structure of the phonological network in the mental lexicon influenced one aspect of long-term memory we used the phonological false memory paradigm developed by Sommers and Lewis (1999). As in Sommers and Lewis (1999) we presented phonological neighbors of a (non- studied) critical item. That is—referring to the items in Figure 2—we presented words like *bad, bag* and *back* (but not *badge*), and *long, leg* and *lawn* (but not *log*), and measured how often participants falsely "recalled" hearing the non-presented critical items (*badge* and *log*). A crucial difference between the current study and the study by Sommers and Lewis (1999) is that the non-studied critical items in the current experiment varied in *C*. That is, some of the non-studied critical items had many neighbors that were also neighbors of each other (consider the neighbors of *badge* in Figure 2), whereas other non-studied critical items *had the same number of neighbors*, but few of those neighbors were neighbors of each other (consider the neighbors of *log* in Figure 2).

The current experiment provides not only the opportunity to demonstrate that the structure of representations in the mental lexicon influence more general memory processes, but it also represents an interesting test of the account inspired by the network science approach described in Chan and Vitevitch (2009) and simulated in Vitevitch, Ercal and Adagarla (2011). Current models of spoken word recognition view the mental lexicon as a collection of arbitrarily ordered phonological representations, and the process of lexical retrieval as a special instance of pattern matching. Lexical retrieval occurs in these models because a given word-form best matches the acoustic–phonetic input (or other sources of evidence). Chan and Vitevitch (2009) instead suggested that the mental lexicon could be viewed as a (small-world) network, and lexical retrieval could be viewed as a search through that network, much like the PageRank algorithm (Page, Brin, Motwani & Winograd, 1998) searches through the structured network of information that is the World-Wide Web. Interestingly, Griffiths et al. (2007) demonstrated that the PageRank algorithm could be used in a semantic network constructed from word association data to predict performance of participants who were shown a letter of the alphabet and asked to name the first word beginning with that letter that came to mind.

Chan and Vitevitch (2009) started with the network structure for the phonological lexicon observed by Vitevitch (2008). Overlaying that structure was the additional assumption that “activation” would “spread” from an initially activated node to the nodes that it was connected to, and then on to the nodes that they in turn were connected to (which included the node from which activation was initially received). Although other models of cognitive processing often include additional parameters such as inhibition, decay of activation, threshold levels, etc., no such assumptions were made in the description offered by Chan and Vitevitch (2009).

In the case of a word with low *C* in the mental lexicon (*log* in Figure 2), Chan and Vitevitch (2009) suggested that the small number of interconnections among the neighbors would result in some of the activation from the neighbors spreading back to the target word, some of the activation from the neighbors spreading to other neighbors of the target word, and some of the activation from the neighbors spreading to the rest of the network (i.e., words related to the neighbors of *log*, but not shown in Figure 2). In the case of a word with high *C* in the mental lexicon (*badge* in Figure 2), some of the activation from the neighbors would spread back to the target word, and some of the activation from the neighbors would spread to the rest of the network, just as in the case of words with low *C*. However, given that the neighbors of a word with high *C* are highly interconnected with each other, *most* of the activation will remain amongst the interconnected neighbors rather than spread back to the target word or to the rest of the network, in contrast to words with low *C*. The larger amount of activation spreading from the neighbors back to target words with low *C,* compared to words with high *C* where most of the activation is circulating amongst the neighbors, will result in higher activation levels for words with low *C* compared to words with high *C*, and therefore rapid and accurate retrieval from the lexicon of words with low *C*.

Viewing the simple spreading activation model described in Chan and Vitevitch (2009) as a special instance of diffusion dynamics in network science (that is, how a disease or a fad spreads across a system), Vitevitch, Ercal, and Adagarla (2011) replicated in a network simulation not only the influence of *C* on spoken word recognition observed in Chan and Vitevitch (2009), but also the influence of phonological neighborhood density (i.e., degree) often seen in studies of spoken word recognition (e.g., Luce & Pisoni, 1998). For examples of studies exploring diffusion dynamics in other cognitive domains see Borge-Holthoefer & Arenas (2010), and Borge-Holthoefer, Moreno, & Arenas (2011).

Note that the account above explains how processing of a target word (like *badge* or *log*) is influenced by the structure found among the neighbors that are stored in the mental lexicon. In the psycholinguistic tasks used in Chan and Vitevitch (2009; 2010), only the target words, not the neighbors were presented to participants. In the current false memory experiment, however, the neighbors, not the target words are presented to participants, providing an interesting test of this (verbal) model. Based on the spreading-activation account described in Chan and Vitevitch (2009, 2010; see also Vitevitch, Ercal & Adagarla, 2011), we hypothesized that the different amount of activation spreading from the neighbors back to the target word for words with low versus high *C* will impact the rates of false memories of the (non-studied) critical item (i.e., the target word). Note that the words with low and high *C* used in Chan and Vitevitch (2009, 2010)—as well as in the present studies (as described in the Methods section)—are comparable on a number of other relevant psycholinguistic measures, so the initial activation of the target words will be the same. Only *C*, and therefore the amount of activation that feeds back to the target words from the neighbors, will differ.

For words with low *C* (like *log* in Figure 2), the neighbors of *log* will spread activation to the rest of the network—including to the non-studied critical item, *log*—resulting in the “erroneous” activation of the critical item, and higher rates of false memories for critical items with low *C*. However, in the case of words with high *C* (like *badge* in Figure 2), most of the activation will remain amongst the highly interconnected neighbors of *badge* resulting in less activation being sent to the rest of the network and, crucially, to the non-studied critical item, producing lower rates of false memories for critical items with high *C*.

Methods

Participants

Twenty-one native English speakers from the Introductory Psychology students enrolled at the University of Kansas received partial credit towards the completion of the course for their participation. None of the participants reported a history of speech or hearing disorders, or participated in the other experiments reported here.

Materials

Thirty words were used as critical items (CI) in the present experiment (see Appendix B). Fifteen critical items had high *C* (*mean* = .576, *sd* = .12) and 15 had low *C* (*mean* = .218, *sd* = .02; $F(1, 28) = 128.42$, $p < .0001$). *C* was computed as in Equation (1) using Pajek, a computer program used for network analysis (Batagelj & Mrvar, 1988). Although the two sets of words differed in *C*, they were equivalent (all *p*'s > .10) in *familiarity* (measured on a seven-point scale), *word frequency* (Kučera & Francis, 1967), *degree/neighborhood density* (Luce & Pisoni, 1998), *neighborhood frequency* (the mean word frequency of the neighbors of the target word), *neighborhood spread* (the number of phoneme positions in a word that form a neighbor [Vitevitch, 2007]), *segment* and *biphone frequency* (Vitevitch & Luce, 2004), *concreteness ratings,* and *network density* of the 2-hop neighborhood (See Table 1). Network density measures the number of connections that exist in an entire network in relation to the maximal number of connections that could exist in that network. A network density value near 0 indicates that there are actually few connections in the network compared to the number of connections that could exist in the network. A network density value near 1 indicates that the number of connections in the network is approaching the maximal number of connections that could exist in the network. (The term “network density" is from the field of network science, and should not be confused with the term "phonological neighborhood density" from the field of psycholinguistics.) The region of the network that was measured in the following experiments contained the critical item, the neighbors of the critical item (known as 1-hop neighbors), and the neighbors of the neighbors (known as 2-hop neighbors).

For each of the critical items, participants studied 10 phonological neighbors. Note that each critical item has more than 10 neighbors, but only 10 were used due to time constraints in the experimental session. Phonological similarity was assessed with a commonly employed metric: a word was considered a neighbor of the critical item if a single phoneme could be substituted, deleted, or added into any position of the critical item to form that word (Greenberg & Jenkins, 1967; Landauer & Streeter, 1973; Luce & Pisoni, 1998). For example, the word *cat* has as phonological neighbors *_at, scat, mat, cut, cap*. Note that *cat* has other neighbors, but only a few are listed for illustration. The order of the 10 neighbors of each CI in the word lists was randomized, and the same order was used for all participants.

For the purpose of counterbalancing, the 30 stimulus lists were divided into three sets of 10 lists. Each set contained five lists from the high *C* condition and five lists from the low *C* condition. Each participant was presented with two sets of the 10 lists (i.e., 20 of the 30 lists) for study. The remaining set of 10 lists was not presented to the participants, but was used as foils in the recognition task following the final study list. The specific lists presented for study were counterbalanced across participants such that the 30 lists were presented equally often for study. The order of list presentation was pseudo-randomized such that no more than three lists of the same condition could be presented consecutively, and the same order was used for all participants.

The 120-items in the recognition test consisted of an equal number of studied (also referred as "old") and non-studied (also referred as "new") items. The old items included the 60 studied items, three taken from each of the 20 studied lists from the 2nd, 4th and 8th positions. The new items included the 30 CIs (20 from the studied lists and 10 from the non-studied lists) and the 30 non-studied items, three taken from each of the 10 non-studied lists (positions 2, 4, 8). All of the stimulus words were produced by the first author at a normal rate and loudness in an IAC sound-attenuated booth into a high-quality microphone, and recorded digitally at a sampling rate of 44.1 kHz with a Marantz PMD671 Portable Solid State Recorder. Each stimulus word was edited into an individual sound file using SoundEdit 16 (Macromedia, Inc.).

Procedure

The procedure we used in the present experiment followed that used in Experiment 1 of Sommers and Lewis (1999). Participants were tested individually. Each participant was seated in front of an iMac computer running PsyScope 1.2.2 (Cohen et al., 1993), which controlled the presentation of stimuli and the collection of responses. Participants were instructed that they would hear a list of words, complete as many math problems as they could in 1.5 minutes, and after all of the lists had been presented, complete a 120-item recognition task where they would indicate by pressing the appropriately labeled button on a response box if the word they heard was one of the items from the previously presented lists.

Presentation of a list began with the word READY appearing on the screen for 500ms. After the 10 items in the list were presented (each item separated by 1.5s interstimulus interval), the prompt MATH appeared on the screen to indicate that the participant should complete as many math problems (e.g., addition of two-digit numbers) on a pre-printed test sheet as possible in 1.5 minutes. After 1.5 minutes had elapsed, a 500 ms warning tone was presented

NIH-PA Author Manuscript

NIH-PA Author Manuscript

and the word READY appeared on the screen to indicate the next list of words was about to be presented.

After all 20 lists had been presented, participants completed the recognition task. Participants heard individual words presented over headphones, and indicated whether each word was old (i.e., a word from the studied lists) or new (i.e., it was not from the studied lists). Participants were instructed to call an item old only if they were sure it had appeared on one of the lists. It is common for both recall and recognition tasks to be used in the false memory paradigm. However, we chose to use only a recognition task for several reasons: (1) the pattern of results in recall and recognition are similar, (2) as in Sommers and Lewis (1999), we were concerned that false recall in the recall task might inflate false recognition rates in the recognition task, and (3) (serial) recall memory was tested in Experiment 3.

Results and Discussion

In addition to following the methodology used in Sommers and Lewis (1999), we also conducted analyses that were similar to those reported in Sommers and Lewis (1999). Therefore, to test how network structure—as measured by clustering coefficient—influences long-term memory, we compared the rate of false memories that occurred for non-studied CIs with high and low clustering coefficient. Although other types of analyses of false memories are possible (e.g., comparisons of *d'*), they do not affect our interpretation of the most relevant comparison in the present experiment: the rate of false memories for words with low *C* compared to the rate of false memories for words with high *C*. More false memories occurred for words with low *C* (*mean* = .64, *sd* = .18) than for words with high *C* (*mean* = .51, *sd* = .18; $F(1, 20)$ 8.437, $p = .009$, $\eta^2 = .297$). The greater false memory rate for words with low *C* is consistent with our hypothesis that the activation of the neighbors spreads primarily to the network, including to the non-studied CI, producing a high false memory rate for CIs with low *C*. In the case of words with high *C*, presentation of the neighbors leads to activation that spreads mostly amongst the highly interconnected neighbors, with relatively less activation going to the rest of the network and to the non-studied CI, yielding lower false memory rates for CIs with high *C*.

Furthermore, to check whether the influence of *C* on false memory rates for CIs would also be found with a different set of words, a linear multiple regression analysis was performed on the 24 critical items used in the experiments by Sommers and Lewis (1999). The variables clustering coefficient, concreteness, word frequency, phonotactic probability (i.e., segment and biphone frequency), degree, and neighborhood frequency were used to predict the *false alarm rates* observed in Experiment 1 (as reported in Figure 2) of Sommers and Lewis (1999).

Although the overall analysis was not statistically significant (R^2=.34, $F(7, 16) = 1.18$, $p = .36$), we report in Table 2 the beta coefficients (ß; also known as standardized coefficients) for each variable. The magnitude of ß allows one to compare the relative contribution of each independent variable in the prediction of the dependent variable. The sign (+ or -) associated with the ß coefficient indicates the direction of the relationship between the independent and dependent variables. We also report for each ß coefficient the results of a *t*-test, which indicates that the independent variable made a statistically significant contribution to the prediction of the dependent variable (even though the value of ß might be numerically small).

None of the independent variables made a statistically significant contribution to the prediction of the false alarm rates in Sommers and Lewis (1999), by the conventional standard of $p < .05$. However, *C* does have the largest ß coefficient, and it is negative (indicating few false alarms for higher *C* values, and many false alarms for lower *C* values).

Replicating the effect—at least in direction—observed in the present experiment with a different set of words provides a reassuring piece of converging evidence, and minimizes the concern that the observed effect was due to a "specially selected" set of items. [iii]

Before discussing the implications of these findings we address a few other ancillary issues in the present experiment. First, one might wonder if the false memory phenomenon was actually observed in the present experiment. The mean proportion of studied items called old in the recognition task was .58 (sd = .12), and the mean proportion of CIs that were falsely recalled was .57 (sd = .17). This difference was not statistically different (F(1, 20) = .323, p = .576, η^2 =.16), suggesting that participants were as confident that they studied the CIs as they were that they had studied items from the lists that had actually been presented. Furthermore, the false recognition rate for non-studied items other than CIs was less (.43, sd = .17) than the false recognition rate for the CIs (.57, sd = .17, F(1, 20) = 19.76, p < .0001, η^2 = .497), indicating that participants did not indiscriminately respond "old" to most items in the recognition task. These results suggest that false memories were indeed elicited.

To further examine the nature of the "false memories" for the CIs, we analyzed the false recognition rates for the CIs used as foils in the recognition task (i.e., words that varied in C, but whose neighbors were not presented in the study session). A difference in C was observed for the CIs used as foils in the recognition task, such that more false memories occurred for words with low C (*mean* = .53, sd = .29) than for words with high C (*mean* = .40, sd = .21; t(20) = 2.75, p < .05, *Cohen's d* = .52), even though the neighbors of these CIs had not been presented during the study phase of the experiment. This finding is consistent with the idea that the fluency with which information is retrieved from long-term memory (i.e., the mental lexicon) can influence memory judgments (Benjamin, Bjork & Schwartz, 1998). However, we further observed that the false recognition rates for the CIs whose neighbors had been presented in the study session was greater (*mean* = .57, sd = .17) than the false recognition rates for the CIs whose neighbors had not been presented in the study session (*mean* = .47, sd = .23; t(20) = 2.34, p < .05, *Cohen's d* = .49), indicating that memory for the studied neighbors had an additional influence on the false recognition of the non-studied CIs. These results further suggest that false memories were indeed elicited in the present experiment, and that C not only influences perceptual processes, but memory-based processes as well.

One might also wonder if some other characteristic about the phonologically similar words that were studied (i.e., the neighbors of the CI) influenced the present experiment. We acknowledge the possibility that the lists of phonologically similar words may differ on some psycholinguistic measure.[iv] However, recall that the network science measure known as network density (of the 2-hop neighborhoods) was the same for the two types of words. The network density of the 2-hop neighborhoods assesses the number of neighbors of the phonologically similar words that were studied, as well as the connectivity among those words. Based on our account of the diffusion of activation in the network, and the similarity in the 2-hop neighborhoods of words with high and low C, it is not surprising that no difference was observed in the recognition rates for the studied neighbors of critical items with high (*mean* = .58, sd = .15) versus low C (*mean* = .58, sd = .11; t(20) = .12, p = .90). In

[iii] Note that the values of C for the stimuli used in Sommers and Lewis (1999) were more restricted (lowest C = .214; highest C = .341) than those used in the present experiment (*mean* low C = .218; *mean* high C = .576). We believe the restricted range of C found in the stimuli used by Sommers and Lewis (1999) is a contributing factor in our failure to find a difference that was *statistically significant* in our post-hoc analysis of their stimuli.

[iv] Sommers and Lewis (1999) analyzed the influence that several other characteristics of the phonologically similar words that were studied might have on false recognition rates, and found that none of the additional factors they examined—including the frequency of the CI (which was controlled in the present experiment) and the number of list items that had frequencies higher than the CI—significantly influenced performance either.

other words, it appears unlikely that some characteristic about the phonologically similar words that were studied (or the neighbors of those words) is responsible for the observed difference in false alarm rates for words varying in *C*.

The results of the present experiment demonstrate that the network structure exhibited by phonological word-forms in the mental lexicon influences the long-term memory phenomenon of “retrieving” false memories, not just the on-line production and recognition of spoken words (Chan & Vitevitch, 2009; 2010). It is also interesting and theoretically elegant that (at an abstract level) a common mechanism—the structure of the network—may account for observations made in several cognitive domains, and in social, biological, and technological domains (Newman, 2003).

Experiment 2

In Experiment 1 we demonstrated that activation spreading through lexical networks with different structural characteristics (i.e., clustering coefficient) can differentially influence the activation of non-studied target words, thereby producing more “false memories” for target words with low *C* than high *C*. In the present experiment we wished to further examine how the structure of the lexical network might influence processes associated with long-term memory by demonstrating that network structure would also influence veridical memories of studied target items in an old-new recognition memory task. In the study phase of the present experiment, participants heard a list of words that they were asked to remember. In the test phase, participants were then presented with a list of words that included the items that they had studied, as well as words that they had not studied, and were asked to indicate if the word they heard in the test phase was one of the words from the previously studied list (i.e., old) or not (i.e., new).

If the structure of the lexicon influences subsequent recognition of the target words, we predict that words with low *C* will be better recognized than words with high *C* in the recognition test. Because the words used in the present study (as described in the Methods section) are comparable on a number of other relevant psycholinguistic measures, the initial activation of the target words will be the same. Only *C*, and therefore the amount of activation that feeds back to the target words from the neighbors, differs between the two conditions.

For words with low *C*, like *log* in Figure 2, activation will spread from the target word to the neighbors. Because the neighbors are less interconnected, only a small amount of activation will circulate amongst the neighbors. The rest of the activation will spread from the neighbors back to the target word (resulting in higher activation of the target word), and from the neighbors to other parts of the network. For words with high *C*, like *badge* in Figure 2, activation again spreads from the target word to the neighbors. However, most of the activation will tend to circulate amongst the highly interconnected neighbors, with less activation spreading from the neighbors back to the target word and to the rest of the network. The different amount of activation remaining amongst the neighbors (and therefore the different amount of activation feeding back to the target words) will result in words with low *C* being recognized more accurately than words with high *C*.

Methods

Participants

Forty-four native speakers of Australian-English from the University of Wollongong took part in the experiment. None of the participants reported a history of speech or hearing disorders, or participated in the other experiments reported here.

Materials

Forty monosyllabic words were used as studied items in the present experiment (see Appendix C). Twenty studied items had high C (*mean* = .531, *sd* = .15) and 20 had low C (*mean* = .302, *sd* = .05; $t(38) = 6.26$, $p < .0001$). Although the two sets of words differed in C, they were equivalent (all *p*'s > .10) in word frequency, degree/neighborhood density, concreteness ratings, network density of the 2-hop neighborhood and *imagability ratings* (See Table 2). Forty additional monosyllabic words were selected as distracter items for use in the test phase of the recognition task. The distracter items were comparable to the studied items (all *p*'s > .10) in word frequency, degree/neighborhood density, concreteness ratings, and *imagability ratings* (See Table 3). All stimuli were digitally recorded by a female native Australian English speaker and edited to single word files using ProTools LE software and MBox hardware (Digidesign, Inc.).

Procedure

Participants were tested in groups of up to 5 at a time, on separate computers using the experimental control software SuperLab (Cedrus Corp.). Each participant listened, via headphones, to a different random arrangement of the forty target stimuli and then completed 2 minutes of simple arithmetic as a delay task. The arithmetic problems were presented visually and participants responded on the computer keyboard. Following the delay task participants heard the forty target words randomly mixed with the distracters and responded “old” or “new” by pressing designated keys on the keyboard.

Results and Discussion

To examine the ability of participants to discriminate between old and new items we computed d' values for the words with high C and low C for each participant (following MacMillan and Creelman, 2005). This measure combines “hits” (i.e., successfully indicating that a word was indeed from the list of studied words) and “false alarms” (i.e., incorrectly indicating that a word was from the studied list) in discrimination tasks, thereby giving a single, bias-free measure of sensitivity. Larger values of d' indicate that participants were better able to discriminate that a word had indeed appeared on the studied list, and were not simply inclined to indicate that all words had appeared on the studied list (or that a word could be retrieved fluently from long-term memory; Benjamin, Bjork & Schwartz, 1998). d' is the most appropriate measure to use in this instance as it takes into account individual differences in false alarm rates and bias.

Words with low C (*mean* = 1.89, *sd* = .79) had larger values of d' than words with high C (*mean* = 1.74, *sd* = .78; $t(43) = 2.03$, $p < .05$), indicating that participants were more accurate in indicating whether words with low C were (or were not) from the studied list. This finding is consistent with the prediction derived from the verbal framework described in Chan and Vitevitch (2009)—words with low C will be better recognized than words with high C in the recognition test.

These results further suggest that the influence the structure of the phonological network has on processing is not limited to language-related processes such as word recognition (Chan & Vitevitch, 2009) or word production (Chan & Vitevitch, 2010). Rather, as demonstrated in Experiments 1 and 2, the structure of the phonological network influences the retrieval of information from long-term memory as well.

Experiment 3

The present experiment examined how the network structure found in the mental lexicon might influence *redintegration* in short-term memory (Schweickert, 1993). Examining the process of redintegration provides a conceptual bridge from the previous two experiments (which examined certain aspects of long-term memory) to another fundamental domain of cognition: short-term memory. In redintegration, information in *long-term memory* is used to reconstruct degraded representations retrieved from *short-term memory*. In the account of redintegration described by Hulme et al. (1997), an item is retrieved directly from the short-term memory store if its representation is intact. However, if a representation in short-term memory is partially degraded, it will be compared to phonological representations that are permanently stored in long-term memory (i.e., the mental lexicon) to “clean up” the representation in short-term memory. Furthermore, the proposal of Hulme, Maughan & Brown (1991) that verbal short-term memory processes might be considered a by-product of processes involved in speech perception and production makes the process of redintegration an ideal phenomenon to further examine the influence that the structure observed in the mental lexicon might have on other cognitive processes.

A task commonly used to examine short-term memory and the process of redintegration is the serial recall task in which participants hear a list of words and immediately recall them in the order the words were presented. Using this task, Roodenrys et al. (2002) found that lists of words that activated many phonologically similar words in the lexicon (i.e., lists of words with high degree/dense phonological neighborhoods) were recalled more accurately than lists of words that activated few phonologically similar words in the lexicon (i.e., lists of words with low degree/sparse phonological neighborhoods), demonstrating the influence that the number of phonologically similar words stored in long-term memory have on the redintegration of decayed memory traces retrieved from short-term memory.

The results of Experiments 1 and 2 from the present study suggest that the amount of activation that circulates amongst phonological neighbors influences how much activation flows back to the target word, differentially activating target words with low C over words with high C. Therefore, we hypothesized that words with low C would be more highly activated and therefore have more intact representations in short-term memory than words with high C, resulting in lists composed of low C words being recalled more accurately than lists composed of high C words. Furthermore, Hulme et al. (1997) claimed that items that appear later in a list are more likely to become degraded than items that appear earlier in the list. Therefore, we hypothesized that the difference in performance between lists of words with high versus low C would be greatest in the later items in a word-list than in the earlier items in a word-list in the serial recall task.

To test these hypotheses we used a serial recall task as in Roodenrys et al. (2002). However, instead of manipulating degree/the number of phonological neighbors as in Roodenrys et al. (2002), we instead manipulated C. In the serial recall task used in the present experiment, participants heard lists that contained 6 words, such that all the words had high C or all the words had low C. Crucially, the word-lists varying in C were the same in terms of the number of phonologically similar words they would activate in the lexicon (and on a number of other relevant variables), therefore the initial activation of the list of words will be the same. Only C— and the amount of activation that feeds back from their respective neighbors to the words on the list—differs between the two conditions.

Methods

Participants

Forty participants from the same population in Experiment 1 took part in the present experiment.

Materials

Thirty-two words were used in the present experiment (see Appendix D). Sixteen words had high *C* (*mean* = .349, *sd* = .04) and 16 words had low *C* (*mean* = .237, *sd* = .03; $F(1, 31) = 76.01$, $p < .0001$). Although the two sets of words differed in *C*, they were equivalent (all *p*'s > .10) in *familiarity* (measured on a seven-point scale), word frequency (Kučera & Francis, 1967), degree/neighborhood density, neighborhood frequency, neighborhood spread, segment and *biphone frequency*, and *concreteness ratings* (See Table 4).

The words in each condition were pseudo-randomly assigned (such that phonological neighbors could not appear in the same list) to create 16 lists of 6 words in each condition. Creating two different samples of 16 lists, and two different orders of the lists in each condition minimized potential order effects. As there were no statistically significant differences in recall across the various orders, subsequent analyses collapsed across this factor.

Procedure

Participants were presented with the 16 lists in each condition in a counterbalanced order in a single session lasting approximately 30 minutes. The lists were presented over headphones at the rate of approximately 1 word per second using the same equipment as used in Experiment 1. At the end of each list the prompt "Recall" appeared on the screen, and participants recalled aloud the list of words in the order they were presented. Participants were instructed to say "pass" if they could not remember an item in a particular position. Responses were recorded for independent scoring at a later time by two research assistants (reliability = 98.91%). Discrepancies in scoring were resolved by an independent judge.

Results and Discussion

Consistent with our initial hypotheses, we observed an interaction of *C* and serial position ($F(5, 195) = 7.58$, $p < .0001$, $\eta^2 = .51$), such that large differences in recall performance were observed in the later positions of the lists (~10%; see Figure 3) compared to the earlier positions of the lists. However, in contrast to our initial hypotheses, participants overall recalled more words from lists containing high *C* words (*mean* = 3.15 words out of 6, *sd* = 1.1) than from lists containing low *C* words (*mean* = 2.84 words out of 6, *sd* = 1.4; $F(1, 39) = 15.18$, $p < .0001$, $\eta^2 = .30$). We initially hypothesized that words with low *C* would be more highly activated and therefore have more intact representations in short-term memory than words with high *C*, resulting in lists composed of low *C* words being recalled more accurately than lists composed of high *C* words. As seen in Figure 3, better recall for words with low *C* compared to words with high *C* was observed in the first position of the lists. However, this difference was not statistically significant; it was only observed numerically.

A statistically significant advantage for low *C* words over high *C* words in the initial positions of the list might be observed if the primacy effect was accentuated, perhaps by reducing the length of the list or slowing the rate of presentation. Such well-studied manipulations in a serial-recall task using word lists varying in *C* could provide additional insight into models of STM and on the process of redintegration. However, such manipulations are beyond the scope of the present study, which sought simply to determine if the network structure exhibited among words in the phonological lexicon influenced cognitive processes other than spoken word recognition and spoken word production (Chan & Vitevitch, 2009; 2010).

Although the observed results are not entirely consistent with our initial predictions, the observed results are informative in a number of ways. First, *C* clearly influences short-term memory. Just as the use of phonological neighborhood density (known as *degree* in the network science literature) in studies by Roodenrys et al. (2002) provided new insight to the processes of short-term memory and redintegration, the results from the present study open up a new avenue of investigation for memory researchers. Indeed, if we consider the work of Roodenrys et al. (2002), as well as the account of redintegration described by Hulme et al. (1997), and the spreading-activation account described in Chan and Vitevitch (2009, 2010) the present result hints toward an interesting phenomenon—stochastic resonance—that also warrants future investigation.

Recall that Hulme et al. suggested that items with intact representations are retrieved directly from the short-term memory store. However, if a representation in short-term memory is partially degraded, it will be compared to phonological representations that are permanently stored in long-term memory to “clean up” the representation in short-term memory. Furthermore, items that appear later in a list are more likely to become degraded than items that appear earlier in the list. Moreover, Roodenrys et al. (2002; see also Roodenrys & Hinton, 2002) showed that the number of phonologically similar words in the lexicon (i.e., neighborhood density, or degree) influenced the processes of recall and redintegration. Here we make the same assumptions made by Roodenrys et al. (2002; pg. 1028):

> If we assume that words in a phonological neighborhood are associatively linked in lexical memory, our hypothesis would be that such groups of associated words will all be activated to some extent by the presentation of one word from the neighborhood. A further assumption is that members of a neighborhood form a mutually supportive network of items. Words from large neighborhoods will receive supportive activation from more other words at recall than words from small neighborhoods.

In the present case, representations of the words in the beginning of the lists remained relatively intact, but representations of words at the end of the lists began to decay. For the decaying representations in the later part of the list, phonologically similar representations stored in long-term memory are called upon to “clean up” the representation in short-term memory. That is, redintegration is more likely to take place in the later part of the list than the beginning of the list. As per Roodenrys et al. (2002), redintegration relies on the activation of the target word in long-term memory as well as the activation of the neighbors of the target word.

As per Chan and Vitevitch (2009), activation is thought to circulate predominately amongst the neighbors for words with high *C*, but to disperse to other parts of the network for words with low *C*. Although this pattern of spreading activation is beneficial to performance for words with low *C* in most contexts, in the present case—when phonologically similar representations are needed to “clean up” a representation in short-term memory—the dispersion of activation to the rest of the network provides little support to the decaying representation in short term memory. The lack of support that phonologically similar representations provide in the redintegration of words with low *C* results in poor performance on these words in the latter part of the list in the serial recall task.

However, in the case of words with high *C*, activation tends to circulate amongst the highly interconnected neighbors. The activation in this cadre of phonologically similar representations may provide sufficient information to “clean up” the representations of words with high *C* in short-term memory, resulting in successful redintegration and better performance in the serial recall task for words with high *C*. Although the activation circulating among phonologically similar representations may, in many contexts, produce “noise” in the system and prove detrimental to performance for words with high *C*, in the present context this noise may improve detection of a weak signal (i.e., the decayed representation of the target word with high *C*), much like moderate—but not excessively high or low—amounts of noise can improve signal-to-noise ratios in systems undergoing the phenomenon of stochastic resonance. Stochastic resonance has been observed in neural (e.g., Martínez, Pérez, Mirasso, & Manjarrez, 2007) and perceptual systems (*cf.*, Shepherd & Hautus, 2009). The hint of this phenomenon in a *cognitive* system, as observed in the present experiment (see also Usher & Feingold, 2000), warrants further research. Thus, even though the present result is not consistent with the prediction derived from the computer model in Vitevitch et al. (2011), the result is consistent with other findings in the broader literature on short-term memory and redintegration, and hints towards a new phenomenon—stochastic resonance—to investigate in future research.

Finally, the observed result points to potential limitations of the computational model examined by Vitevitch et al. (2011). The simple model examined by Vitevitch et al. (2011) contained only lexical representations (and connections among phonologically related word-forms), but was able to account for several results observed in studies of spoken word recognition, including the influence of *C* (Chan & Vitevitch, 2009) and the influence of neighborhood density (Luce & Pisoni, 1998) on spoken word recognition. To account for the present result (as well as other results in the literature, as acknowledged in Vitevitch et al., 2011), an additional short-term memory store or an additional level of representation may need to be added to the model. Indeed, a number of studies have demonstrated the role that sub-lexical representations—phonological segments, or sequences of segments—play in spoken word recognition (e.g., Vitevitch & Luce, 2005; Vitevitch, 2003; Vitevitch et al., 2002) and speech production (e.g., Vitevitch, Armbruster & Chu, 2004), two processes that have been implicated in some models of short-term memory and redintegration (e.g., Hulme et al., 1997). The unanticipated results of the present experiment suggest further that the simple computational model examined by Vitevitch et al. (2011) may indeed be too simple.

Although the results of the present experiment did not conform entirely to our initial predictions, the results point to several new avenues of investigation. In addition, the results of the present experiment further demonstrate that network structure not only influences the on-line recognition and production of spoken words (e.g., Chan & Vitevitch, 2009; 2010), but it also influences other cognitive phenomena associated with long-term and short-term memory (i.e., redintegration).

General Discussion

Previous network science analyses of phonological word-forms in the mental lexicon found a set of structural characteristics appearing across a variety of languages (e.g., Vitevitch, 2008; Arbesman et al. 2010). Because it is often argued that the structure of a network influences processing in that system (Watts & Strogatz, 1998), Chan and Vitevitch (2009; 2010) used several conventional psycholinguistic tasks to examine how one structural characteristic—clustering coefficient—might influence the production and recognition of spoken words. In the present study, we further examined how the emergent structure of representations in the mental lexicon—that portion of long-term memory devoted to language—might influence phenomena in long-term and short-term memory.

In Experiment 1 we examined processes associated with long-term memory by eliciting false memories for English words that varied in clustering coefficient. Participants studied lists of words that were phonologically similar to non-studied critical items (which varied in clustering coefficient). In a recognition task, participants falsely recognized more non-studied critical items that had low *C* than high *C*. In Experiment 2 we examined recognition memory for events that actually occurred (rather than "false" memories as in Experiment 1). In an auditory old-new recognition task, participants were more accurate recognizing words with low *C* than high *C*. In Experiment 3 we examined the process of redintegration, in which representations in long-term memory are used to reconstruct degraded representations in short-term memory. In a serial recall task, a task commonly used to examine redintegration, participants more accurately recalled word-lists comprised of words with high *C* than with low *C*, especially in the later portion of the word-list.

Despite the different types of memory and different cognitive processes being examined, the network framework described in Chan and Vitevitch (2009) was able to provide an account for the results of all of the present experiments, although it must be acknowledged that the counter-intuitive results of Experiment 3 would require additional assumptions from the short-term memory literature and require further model development. In this framework the mental lexicon is viewed as a small-world network, and lexical retrieval is viewed as a search through that network (e.g., Kleinberg, 2000), much like the PageRank algorithm (Page, Brin, Motwani & Winograd, 1998) searches through the structured network of information that is the World-Wide Web.

A common way to conceptualize search processes in cognitive science is with a spreading activation mechanism. Chan and Vitevitch (2009) described a network with a resource-limited form of spreading-activation. In the case of words with low *C*, activation spreads from the target word to the phonological neighbors. Because the neighbors are less interconnected, only a small amount of activation will circulate amongst the neighbors. The rest of the activation will spread from the neighbors back to the target word, and from the neighbors to other parts of the network. For words with high *C* activation again spreads from the target word to the neighbors. However, most of the activation will tend to circulate amongst the highly interconnected neighbors, with less activation spreading from the neighbors back to the target word and to the rest of the network. The different amount of activation feeding back to the target words (and remaining amongst the neighbors) results in differences in the speed and accuracy with which words varying in *C* are responded to (see Vitevitch et al., 2011 for a network simulation of the word-recognition effects observed in Chan & Vitevitch, 2009).

In the present study, we further examined the framework proposed by Chan and Vitevitch (2009) by presenting participants in Experiment 1 with phonological neighbors, and assessing how much activation spread from the neighbors to the (non-studied) target words, resulting in false memories for those critical items. In Experiment 2 we extended the framework by measuring how the spread of activation influenced the recognition of previously presented words. In Experiment 3 we extended the framework by measuring how activation in long-term memory might influence processes related to retrieval from short-term memory (i.e., redintegration). The results of these experiments suggest that the structure of the lexical network may influence more than just on-line recognition and production of spoken words.

Cognitive scientists have made much use of “networks” to explore human cognition (e.g., artificial neural networks, Rosenblatt, 1958; networks of semantic memory, Quillian, 1967; linguistic nections, Lamb, 1970). However, these earlier approaches should not be confused with the current approach of network science (Jasny, Zahn, & Marshall, 2009; Watts, 2004). Without denying the broad and important influence that spreading-activation/semantic networks and connectionist networks have had on Cognitive Science, the present study examined how the alternative approach of network science might be used to understand certain aspects of cognition. Although the network science perspective has been widely employed in other fields to explore technological, biological, and social systems (e.g., Albert & Barabási, 2002), the network science perspective has been relatively underutilized in the cognitive and neural sciences (see Borge-Holthoefer et al. (2011) and Sporns (2010) as exceptions). The results of the present experiments, as well as the experiments reported in Chan and Vitevitch (2009; 2010), demonstrate how the network science perspective can be used to examine the structure of complex *cognitive* systems, and, more importantly, to test novel hypotheses about cognitive processing.

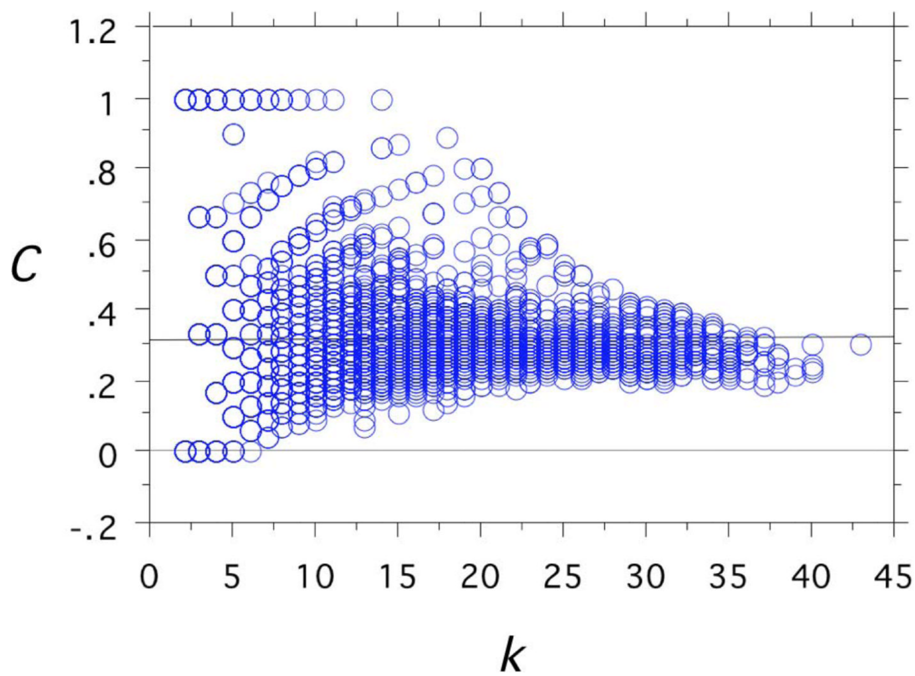
It is not clear how the questions examined in the present experiments regarding the relationship among phonological neighbors, as measured by *C*, could have been posed in the context of current models of long-term memory (e.g., Izawa, 1999) or short-term memory (e.g., Hulme et al., 1997; Lewandowsky, 1999; Roodenrys & Miller, 2008; Schweickert, 1993). Furthermore, it is unclear if any of these current models can account for the influence of *C* that was observed in the present experiments, suggesting that network science might offer psychological science a new perspective on fundamental questions of cognitive processing. Clearly additional work is required to understand how network structure might influence other cognitive processes, providing a potentially fruitful opportunity for collaboration between network and cognitive scientists.

Acknowledgments

This research was supported in part by grants from the National Institutes of Health to the University of Kansas through the Schiefelbusch Institute for Life Span Studies (National Institute on Deafness and Other Communication Disorders (NIDCD) R01 DC 006472), the Mental Retardation and Developmental Disabilities Research Center (National Institute of Child Health and Human Development P30 HD002528), the Center for Biobehavioral Neurosciences in Communication Disorders (NIDCD P30 DC005803), and an Australian Research Council Grant (DP0663642).

We wish to thank Ryan Taber and Sophie Pohorecki for their assistance collecting the data for Experiment 1, and Elizabeth Cividin for assistance in collecting the data for Experiments 2 and 3.

Appendix



Appendix A Figure.
The scattergram for the 6,281 words with 2 or more neighbors (the minimum number of neighbors required to compute clustering coefficient, *C*) from the network examined in

Vitevitch (2008) illustrating that *C* and degree (*k*) are not correlated. The correlation value for these data is reported in the text and in Chan and Vitevitch (2010).

Appendix B

The words used in Experiment 1. The (non-studied) critical item is in the left column, and the (studied) neighbors are in the right column.

High C	
badge	back, bad, bag, ban, bang, badger, bass, bat, batch, bath
bathe	babe, bail, bait, baize, bake, bane, base, bay, beige, lathe
chair	air, bare, care, check, cherry, fair, pair, rare, share, their,
chill	bill, chin, chip, fill, hill, ill, kill, mil, pill, will,
gear	beer, cheer, dear, ear, fear, gear, hear, mere, pear, rear
hair	air, bare, care, fair, head, hear, hell, pair, share, their
league	lea, leaf, leak, lean, leap, lease, leave, leg, legal, log
leash	lash, lea, leaf, leak, lean, leap, lease, leave, lied, lush
path	bath, math, pack, pad, pal, pan, pass, pat, patch, wrath
robe	aerobe, roar, rob, roe, role, rope, rose, rote, rub, road
shot	chute, got, hot, knot, lot, pot, sheet, shock, shop, shut
siege	cease, cede, sage, scene, seal, seam, seat, seek, seize, serge
thought	aught, bought, caught, fought, naught, sought, taught, thaw, thong, wrought
thug	bug, chug, dug, hug, jug, mug, rug, thud, thumb, tug
vat	at, cat, fat, hat, pat, sat, that, van, vast, vote

Low C	
fray	fry, frail, frame, freight, gray, phrase, pray, ray, tray, bray
glow	blow, flow, glee, gloat, globe, glue, go, grow, low, slow
gut	but, cut, gait, get, got, gum, gun, hut, nut, shut
limb	dim, gym, him, lamb, lid, lime, limp, lip, live, slim
merge	dirge, emerge, midge, mirth, murk, myrrh, purge, serge, urge, verge
ply	fly, lie, pie, play, plea, plight, plough, ploy, pry, apply
pose	chose, hose, nose, pause, peace, pole, poor, pop, rose, those
sauce	boss, cease, loss, moss, saucer, saw, song, sought, souse, toss
serve	curve, nerve, salve, save, search, serf, serge, sieve, sir, verve
side	seed, cite, hide, ride, sad, said, sign, size, tide, wide
sing	king, ring, sick, sin, sink, sit, song, swing, thing, wing
slay	clay, lay, play, say, slate, slave, slow, slain, stay, sway
sly	fly, lie, sigh, sky, slaw, sleight, slice, slide, slow, spy
tree	free, tea, three, tray, treat, trio, trow, troy, true, try
verse	curse, hearse, nurse, purse, vase, verb, verge, vice, voice, worse

Appendix C

The high *C* words, low *C* words, and distracter items used in Experiment 2.

High C	Low C	Distracter items	
badge	bib	bears	noon
beef	boot	boil	pays
beige	bug	cage	pill
born	bush	chap	pine
cough	couch	chart	
dot	deck	chess	porch
gain	goat	dim	raid
gauze	kick	dish	rash
jet	lag	fees	ridge
joke	ledge	fetch	rub
knife	luck	fork	sack
math	lurch	fuss	seal
merge	mile	harsh	shark
morgue	mood	juice	shone
mouse	nerve	lace	shout
nudge	purse	leap	tooth
pub	ripe	lid	toys
thumb	sauce	mate	warn
wash	shove	nail	wit
zip	soup	nod	zone

Appendix D

The high *C* and low *C* words used in Experiment 3.

High C	Low C
bib	bush
bug	boot
dot	gas
gang	goat
gain	gull
gum	cough
case	couch
lag	ledge
look	luck
lose	merge
math	mood
mouse	mile

High C	Low C
ring	sauce
ripe	beach
size	deck
wire	purse

References

Albert R, Barabási AL. Statistical mechanics of complex networks. Review of Modern Physics. 2002; 74:47–97.

Amaral LAN, Scala A, Barthélémy M, Stanley HE. Classes of small-world networks. Proceedings of the National Academy of Sciences. 2000; 97:11149–11152.

Arbesman S, Strogatz SH, Vitevitch MS. The Structure of Phonological Networks Across Multiple Languages. International Journal of Bifurcation and Chaos. 2010; 20:679–685.

Batagelj V, Mrvar A. Pajek - Program for Large Network Analysis. Connections. 1988; 21:47–57.

Benjamin AS, Bjork RA, Schwartz BL. The mismeasure of memory: When retrieval fluency is misleading as a metemnemonic index. Journal of Experimental Psychology: General. 1998; 127:55–68. [PubMed: 9503651]

Borge-Holthoefer J, Arenas A. Categorizing words through semantic memory navigation. European Physical Journal B. 2010b; 74:265–270.

Borge-Holthoefer J, Moreno Y, Arenas A. Modeling Abnormal Priming in Alzheimer's Patients with a Free Association Network. PLoS ONE. 2011; 6:e22651. [PubMed: 21829639]

Chan KY, Vitevitch MS. The influence of the phonological neighborhood clustering-coefficient on spoken word recognition. Journal of Experimental Psychology: Human Perception and Performance. 2009; 35:1934–1949. [PubMed: 19968444]

Chan KY, Vitevitch MS. Network structure influences speech production. Cognitive Science. 2010; 34:685–697. [PubMed: 21564230]

Cohen J, MacWhinney B, Flatt M, Provost J. PsyScope: An interactive graphic system for defining and controlling experiments in the psychology laboratory using Macintosh computers. Behavior Research, Methods, Instruments, and Computers. 1993; 25:257–271.

Deese J. On the prediction of occurrence of particular verbal intrusions in immediate recall. Journal of Experimental Psychology. 1959; 58:17–22. [PubMed: 13664879]

Greenberg, JH.; Jenkins, JJ. Studies in the psychological correlates of the sound system of American English.. In: Jakobovits, LA.; Miron, MS., editors. Readings in the psychology of language. Prentice-Hall; Englewood Cliffs, N.J.: 1967. p. xip. 636p. 186-200.

Griffiths T, Steyvers M, Firl A. Google and the mind: Predicting fluency with PageRank. Psychological Science. 2007; 18:1069–1076. [PubMed: 18031414]

Hills TT, Maouene M, Maouene J, Sheya A, Smith L. Categorical structure among shared features in networks of early-learned nouns. Cognition. 2009; 112:381–396. [PubMed: 19576579]

Hulme, Maughan S, Brown GDA. Memory for familiar and unfamiliar words: Evidence for a long-term memory contribution to short-term memory span. Journal of Memory & Language. 1991; 30:685–701.

Hulme C, Roodenrys S, Schweickert R, Brown GDA, Martin S, Stuart G. Word frequency effects on short-term memory tasks: Evidence for a redintegration process in immediate serial recall. Journal of Experimental Psychology: Learning, Memory and Cognition. 1997; 23:1217–1232.

Izawa, C. On human memory: Evolution, progress, and reflections on the 30th anniversary of the Atkinson-Shiffrin model. Lawrence Erlbaum Associates Publishers; Mahwah, NJ, US: 1999.

Jasny BR, Zahn LM, Marshall E. Connections: Introduction to special issue. Science. 2009; 325:405. [PubMed: 19628849]

Kleinberg J. Navigation in a Small World. Nature. 2000; 406:845. [PubMed: 10972276]

Kučera, H.; Francis, WN. Computational Analysis of Present Day American English. Brown University Press; Providence: 1967.

Lamb, S. Linguistic and cognitive networks.. In: Garvin, P., editor. Cognition: A Multiple View. Spartan Books; New York: 1970. p. 195-222.

Landauer TK, Streeter LA. Structural differences between common and rare words: Failure of equivalence assumptions for theories of word recognition. Journal of Verbal Learning & Verbal Behavior. 1973; 12:119–131.

Lewandowsky S. Redintegration and response suppression in serial recall: A dynamic network model. International Journal of Psychology. 1999; 34:434–446.

Luce PA, Pisoni DB. Recognizing spoken words: The neighborhood activation model. Ear and Hearing. 1998; 19:1–36. [PubMed: 9504270]

MacMillan, NA.; Creelman, CD. Detection Theory: A user's guide. Lawrence Erlbaum Associates Publishers; Mahwah, NJ, US: 2005.

Martínez L, Pérez T, Mirasso CR, Manjarrez E. Stochastic resonance in the motor system: Effects of noise on the monosynaptic reflex pathway of the cat spinal cord. Journal of Neurophysiology. 2007; 97:4007–4016. [PubMed: 17428901]

Newman MEJ. Properties of highly clustered networks. Physical Review E. 2003; 68:026121.

Page, L.; Brin, S.; Motwani, R.; Winograd, T. The PageRank citation ranking: Bringing order to the web (Tech. Rep.). Stanford Digital Library Technologies Project; Stanford, CA: 1998.

Quillian MR. Word concepts: A theory and simulation of some basic semantic capabilities. Behavioral Science. 1967; 12:410–430. [PubMed: 6059773]

Roediger HL, McDermott KB. Creating false memories: Remembering words not presented in lists. Journal of Experimental Psychology: Learning, Memory, and Cognition. 1995; 21:803–814.

Roodenrys S, Hinton M. Sublexical or lexical effects on serial recall of nonwords? Journal of Experimental Psychology: Learning, Memory, and Cognition. 2002; 28:29–33.

Roodenrys S, Hulme C, Lethbridge A, Hinton M, Nimmo LM. Word-frequency and phonological-neighborhood effects on verbal short-term memory. Journal of Experimental Psychology: Learning, Memory, and Cognition. 2002; 28:1019–1034.

Roodenrys S, Miller LM. A constrained Rasch model of trace redintegration in serial recall. Memory & Cognition. 2008; 36:578–587.

Rosenblatt F. The perceptron: A probabilistic model for information storage and organization in the brain. Psychological Review. 1958; 65:386–408. [PubMed: 13602029]

Schweickert R. A multinominal processing tree model for degredation and redintegration in immediate recall. Memory & Cognition. 1993; 21:168–175.

Shepherd D, Hautus MJ. Evidence of stochastic resonance in an auditory discrimination task may reflect response bias. Attention, Perception, & Psychophysics. 2009; 71:1931–1940.

Sommers MS, Lewis BP. Who really lives next door: Creating false memories with phonological neighbors. Journal of Memory & Language. 1999; 40:83–108.

Sporns, O. Networks of the Brain. MIT Press; 2010.

Usher M, Feingold M. Stochastic resonance in the speed of memory retrieval. Biological Cybernetics. 2000; 83:L11–L16. [PubMed: 11130587]

Vitevitch MS. Naturalistic and experimental analyses of word frequency and neighborhood density effects in slips of the ear. Language and Speech. 2002; 45:407–434. [PubMed: 12866911]

Vitevitch MS. The influence of sublexical and lexical representations on the processing of spoken words in English. Clinical Linguistics and Phonetics. 2003; 17:487–499. [PubMed: 14564833]

Vitevitch MS. The spread of the phonological neighborhood influences spoken word recognition. Memory & Cognition. 2007; 35:166–175.

Vitevitch MS. What can graph theory tell us about word learning and lexical retrieval? Journal of Speech Language Hearing Research. 2008; 51:408–422.

Vitevitch MS, Armbruster J, Chu S. Sublexical and lexical representations in speech production: Effects of phonotactic probability and onset density. Journal of Experimental Psychology: Learning, Memory and Cognition. 2004; 30:514–529.

Vitevitch MS, Ercal G, Adagarla B. Simulating retrieval from a highly clustered network: Implications for spoken word recognition. Frontiers in Psychology. 2011; 2:369. doi: 10.3389/fpsyg.2011.00369. [PubMed: 22174705]

Vitevitch MS, Luce PA. A web-based interface to calculate phonotactic probability for words and nonwords in English. Behavior Research Methods, Instruments, and Computers. 2004; 36:481–487.

Vitevitch MS, Luce PA. Increases in phonotactic probability facilitate spoken nonword repetition. Journal of Memory & Language. 2005; 52:193–204. [PubMed: 18797517]

Vitevitch MS, Pisoni DB, Kirk KI, Hay-McCutcheon M, Yount SL. Effects of phonotactic probabilities on the processing of spoken words and nonwords by postlingually deafened adults with cochlear implants. Volta Review. 2002; 102:283–302. [PubMed: 21637721]

Vitevitch MS, Stamer MK. The curious case of competition in Spanish speech production. Language & Cognitive Processes. 2006; 21:760–770. [PubMed: 18802492]

Vitevitch, MS.; Stamer, MK. Spoken Language Laboratory Technical Report. Vol. 1. KU ScholarWorks; 2009. The influence of neighborhood density (and neighborhood frequency) in Spanish speech production: A follow-up report. University of Kansas; p. 1-6.http://hdl.handle.net/1808/5500

Watts DJ. The “new” science of networks. Annual Review of Sociology. 2004; 30:243–270.

Watts DJ, Strogatz SH. Collective dynamics of ‘small-world’ networks. Nature. 1998; 393:440–442. [PubMed: 9623998]

Highlights

- Previous studies suggest the mental lexicon has a small-world network structure.
- Furthermore, this structure influences certain language-related processes.
- The present study examined how network structure influences LTM and STM.
- The results are accounted for in the complex network framework.

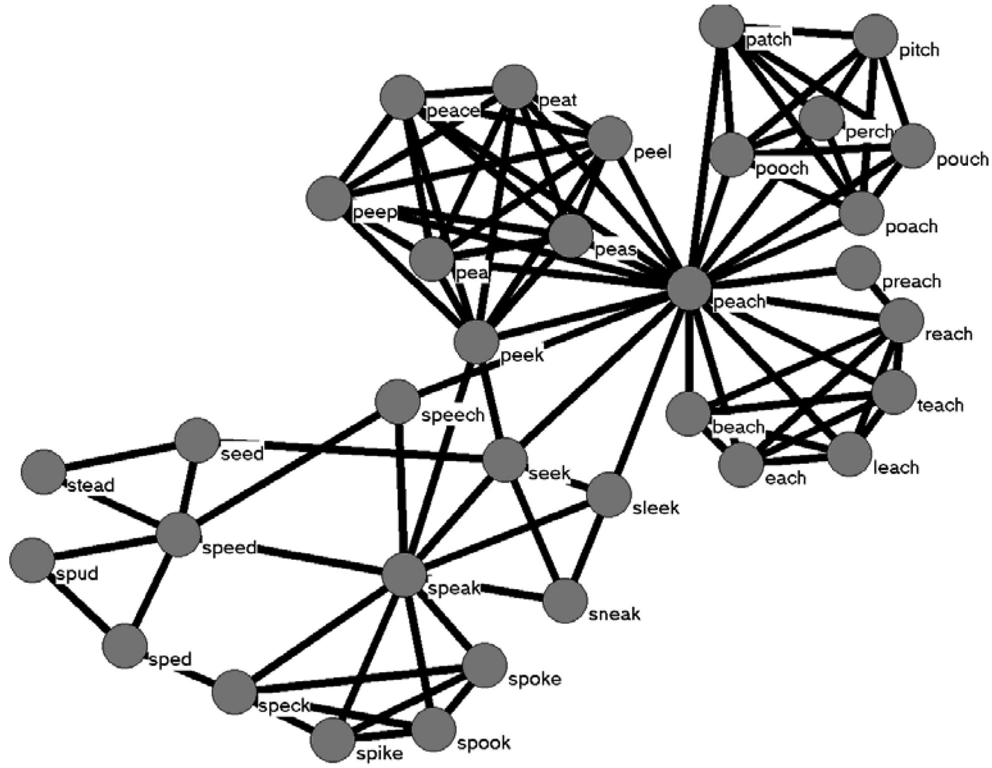


Figure 1.

A sample of words from the phonological network analyzed in Vitevitch (2008). The word "speech" and its phonological neighbors (i.e., words that differ by the addition, deletion or substitution of a phoneme) are shown (i.e., 1-hop neighbors of "speech"). The phonological neighbors of those neighbors are also shown (i.e., 2-hop neighbors of "speech").

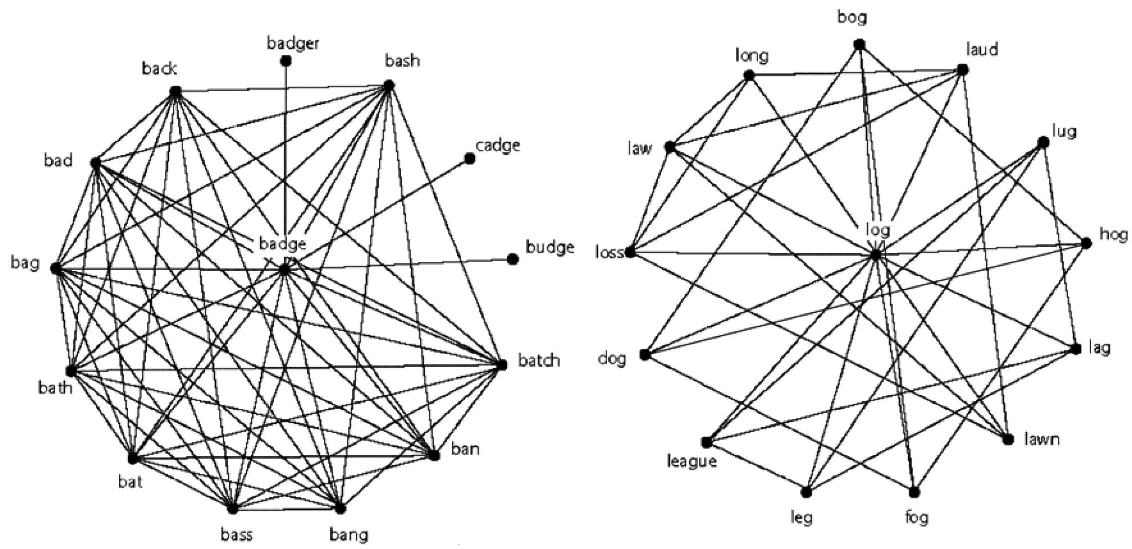


Figure 2.

The word ***badge*** has high *C* and the word ***log*** has low *C*. Both words have the same number of neighbors (*a.k.a.* degree). Connections are placed between words that are phonologically similar. For visual clarity, connections from the neighbors to other words in the network are not shown.

NIH-PA Author Manuscript

NIH-PA Author Manuscript

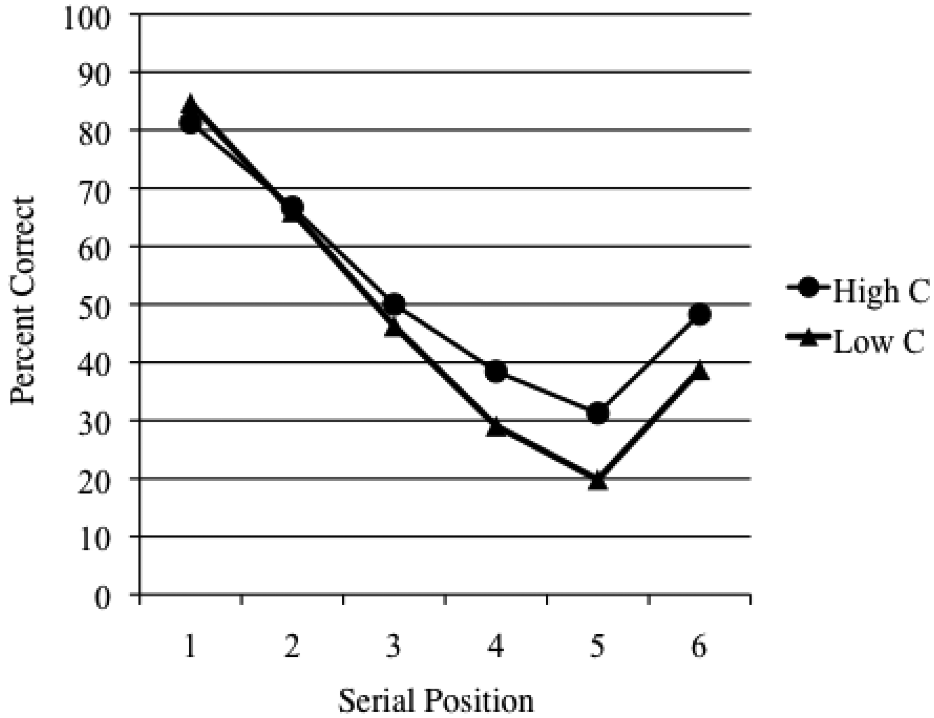


Figure 3.
In the serial recall task participants more accurately recalled words with high *C* than low *C*, especially toward the end of the to-be-recalled list.

Table 1

Mean (and standard deviation) values of the lexical characteristics of the non-studied critical items in Experiment 1.

	High *C*	Low *C*
Familiarity	6.80 (.56)	6.73 (.59)
Word Frequency‡	1.21 (.81)	1.15 (.78)
Degree *(a.k.a.* Neighborhood Density)	17.00 (4.47)	17.00 (4.47)
Neighborhood Frequency‡	1.07 (.30)	.98 (.16)
Spread	2.60 (.51)	2.86 (.35)
Segment Frequency	.134 (.012)	.152 (.009)
Biphone Frequency	.006 (.001)	.008 (.001)
Concreteness Ratings	477.00 (73.60)	499.40 (34.53)
Network Density of 2-hop neighborhood	.06 (.01)	.06 (.01)

Notes:

‡ $\log_{10}$ values of occurrences per million.

Table 2

Summary information of linear multiple regression predicting false alarm rates for words used in Experiment 1 of Sommers and Lewis (1999).

	β	*t*	*p*-value
C	-.42	-1.78	.09
Concreteness	.25	.88	.39
Word frequency	.31	1.28	.22
Segment frequency	-.05	-.16	.87
Biphone frequency	-.16	-.63	.54
Neighborhood frequency	.06	.22	.82
Degree	-.33	-1.19	.25

Table 3

Mean (and standard deviation) values of the lexical characteristics of the studied words in Experiment 2.

	High *C*	Low *C*	Distracter Items
Word Frequency	248.70 (252.38)	284.90 (248.93)	218.85 (94.44)
Degree (*a.k.a.* Neighborhood Density)	19.25 (11.01)	21.00 (8.68)	21.84 (8.91)
Concreteness Ratings	512.08 (115.11)	504.87 (123.71)	518.52 (89.33)
Imagability Ratings	535.00 (91.96)	524.80 (64.75)	530.04 (70.06)
Network Density of the 2-hop neighborhood	.08 (.06)	.06 (.02)	.06 (.03)

Table 4

Mean (and standard deviation) values of the lexical characteristics for the stimuli from Experiment 3.

	High *C*	**Low *C***
Familiarity	6.91 (.16)	6.95 (.10)
Word Frequency‡	1.37 (.71)	1.21 (.49)
Degree (*a.k.a.* Neighborhood Density)	19.38 (5.10)	18.19 (7.42)
Neighborhood Frequency‡	2.02 (.20)	1.91 (.16)
Spread	2.88 (.34)	2.94 (.25)
Segment Frequency	.138 (.03)	.137 (.04)
Biphone Frequency	.006 (.005)	.005 (.003)
Concreteness Ratings	316.88 (239.92)	315.81 (274.85)
Network Density of 2-hop neighborhood	.05 (.01)	.06 (.02)

Notes:

‡ $\log_{10}$ values of occurrences per million.