THE INFLUENCE OF THE CLUSTERING COEFFICIENT

ON SPOKEN WORD RECOGNITION

BY

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Abstract

The clustering coefficient refers to the proportion of phonological neighbors of a target word that are also neighbors of each other. The influence of the clustering coefficient on spoken word recognition was examined in the present study. In a same-different task, no significant effects of clustering coefficient were observed. In a perceptual identification task, words with a low clustering coefficient (*i.e.,* few neighbors are interconnected) were more accurately identified than words with a high clustering coefficient (*i.e.,* many neighbors are interconnected). In a lexical decision task, words with a low clustering coefficient were responded to more quickly than words with a high clustering coefficient. These findings suggest that the nature of relationships among the neighbors of the target word influences the lexical processing of the target word in the context of spoken word recognition.

Previous Research on the Role of Phonological Neighborhood Structure

Two fundamental questions in research on spoken word recognition and spoken word production relate to the organization of word forms in memory, and how this lexical structure might influence processing. It has been proposed that word forms in the mental lexicon are organized in terms of phonological similarity, with similar sounding words forming a phonological neighborhood (Landauer & Streeter, 1973; Luce & Pisoni, 1998). Phonological neighbors are defined as all those words that differ from the target word by a single phoneme—either substituted, added, or deleted—in any position (Greenberg & Jenkins, 1967; Landauer & Streeter, 1973; Luce & Pisoni, 1998). For example, the word *cat* has phonological neighbors such as _at, scat, mat, cut, cap. Note that *cat* has other neighbors, but only a few were listed for illustration. This metric is adopted in the present study as it is an easy way to operationally define phonological similarity and it was used in many previous studies (Luce & Pisoni, 1998; Storkel, 2004; Vitevitch, 1997, 2002; Vitevitch & Luce, 1999).

Phonological neighborhood density refers to the number of words that are phonologically similar to a target word. Words that have many neighbors, like *cat*, are said to have a ***dense neighborhood*** (e.g., neighbors: at, bat, mat, rat, scat, pat, sat, vat, cab, cad, calf, cash, cap, can, cot, kit, cut, coat), whereas words that have few neighbors, like *dog*, are said to have a ***sparse neighborhood*** (e.g., neighbors: dig, dug, dot, fog). Note that each word has additional neighbors, but only a few were listed for illustrative purposes.

Phonological neighborhood density has been shown to influence the processes of spoken word recognition and spoken word production. A variety of experimental paradigms—auditory perceptual identification of words in noise, auditory lexical decision making, auditory word naming, auditory priming, same-different matching tasks—were used to study spoken word recognition in English-speaking young adults with no history of speech, language or hearing impairment. The influence of neighborhood density is not restricted to young adults with normal hearing. The influences of neighborhood density on spoken word recognition have also been found in young children (Garlock, Walley, & Metsala, 2001), older adults with no history of speech, language or hearing impairment (Sommers, 1996) and adults with a cochlear implant (Kaiser, Kirk, Lachs, & Pisoni, 2003). Results consistently showed that words from dense neighborhoods were recognized more slowly and less accurately than words from sparse neighborhoods (e.g., Cluff & Luce, 1990; Goldinger, Luce, & Pisoni, 1989; Luce & Pisoni, 1998; Vitevitch, 2003; Vitevitch & Luce, 1999). These results support Luce and Pisoni's assumption that words in dense neighborhoods compete with each other in the discrimination process of word recognition (Luce & Pisoni, 1998).

Apart from spoken word recognition, the phonological relationships among words also affect the speech production process of young healthy adults, but with an opposite effect. Whereas words with sparse neighborhoods are *recognized* more quickly and accurately than words with dense neighborhoods, words with dense neighborhoods are *produced* more quickly and accurately than words with sparse neighborhoods. This result has been found in a number of studies using a variety of methodologies. In a series of research projects examining speech errors in a corpus of spontaneously occurring malapropisms (collected by Fay & Cutler (1977)) and in laboratory-induced phonological speech errors (e.g., tongue-twister task, SLIP), more errors were observed in words with sparse than with dense neighborhoods (Vitevitch, 1997, 2002). Words with sparse neighborhoods were also named more slowly than words with dense neighborhoods in picture-naming tasks (Vitevitch, 2002).

The influence of neighborhood density is not restricted to young adults with fluent speech. Influences of neighborhood density on speech production have also been found in children acquiring the production of sounds (Gierut, Morrisette, & Champion, 1999), children who stutter (Arnold, Conture, & Ohde, 2005), older adults with fluent speech (Vitevitch & Sommers, 2003) and individuals with aphasia (Gordon, 2002). It was hypothesized that the processing advantage for words with dense neighborhoods arises from an accumulation of activation spreading from phonologically-related neighbors to the target via shared phonological segments. Thus, words with dense neighborhoods have less susceptibility to error and faster lexical access than words with sparse neighborhoods (Vitevitch, 2002). The findings from both spoken word recognition and spoken word production research suggest that the phonological lexicon is organized according to the similarity among phonological word-forms, and that this structure influences several aspects of spoken language processing

It is important to note, however, that these previous studies only examined how the *number* of neighbors that were phonologically related to a target word, or neighborhood density, influenced spoken language processing. For example, the neighborhood density of the word *cat* is 35, meaning it has 35 phonological neighbors such as *bat, mat, pat, rat, sat, cut* and *can*. To the best of my knowledge, no research has examined how the relationship *among* the phonological neighbors affects the processing of the target word. For example, among the phonological neighbors of *cat*, the words *bat, mat, pat, rat, sat* are also neighbors of each other, but *can* and *bat* are not neighbors of each other. Thus, the proportion of phonological neighbors that are also neighbors of each other could be calculated to represent the interconnectivity among phonological neighbors of a target word. This measure, derived from recent work in network science (Watts & Strogatz, 1998), is referred to as the clustering coefficient. In the case of spoken word recognition, is a word with most of its neighbors that are also related to each other recognized more quickly and accurately than a word with neighbors that are only related to the target word? The present set of studies examined the influence of interconnectivity among phonological neighbors on the recognition of the target word. By examining a different aspect of the lexical structure, namely the interconnectivity of the neighbors (*i.e.*, the clustering coefficient), we can better understand how the structure of the lexicon influences spoken language processing.

Effects of Target Set Size and Interconnectivity on Cued Recall from Long Term Memory

Empirical studies examining the influence of semantic relationships among concepts in long-term memory on cued recall suggest that interconnectivity among phonological neighbors might exert some effects on the processing of the target word (Nelson, Bennett, Gee, Schreiber, & McKinney, 1993; Nelson & Zhang, 2000). Much of the relevant research on semantic relationships on cued recall of words showed a consistent effect of target set size in extra-list cueing tasks (Nelson & Schreiber, 1992; Nelson, Schreiber, & McEvoy, 1992). In an extra-list cueing task, participants study a target word (e.g., *cork*) without the presence of any related words and then are asked to recall the target word in the presence of a related word (e.g., *bottle*) from outside the list. Target set size refers to the number of semantically related associates directly linked to the target word in long term memory (Nelson et al., 1992). For example, the target word, *dog*, has a set size of 5 because it has five semantically related associates, including *animal, cat, puppy, friend* and *house*. Targets words with smaller sets of semantically related associates are more likely to be recalled than those with larger sets of semantically related associates. The target set size effect resembles the neighborhood density effect on spoken word recognition in that the number of entities related to the target influences the processing of the target. Few similar items are processed more quickly and accurately.

In another study, Nelson, Bennett, Gee, Schreiber and McKinney (1993) showed that not only the target set size, but also the connectivity among the associates of the target word affected the target word recall. Connectivity is defined as the mean number of connections among the associates of a target (Nelson & Zhang, 2000). For example, the word *dinner* has high connectivity among its associates (including *food, meal, supper, eat* and *lunch*) as all of its associates are semantically related to each other; whereas the word *dog* has low connectivity among its associates (including *animal, cat, puppy, friend* and *house)* as only some of its associates are semantically related to each other.

In the study by Nelson, Bennett, Gee, Schreiber and McKinney (1993), target words included combinations of target set size (small or large) and target connectivity (high or low). In an extra-list cueing task, it was found that target words with smaller sets of associates and more highly interconnected associates are more likely to be recalled than those having larger sets and those having sparsely connected associates. Furthermore, the effects of target set size and target connectivity were additive, suggesting they represent functionally independent dimensions.

The measure of target connectivity in the studies by Nelson and colleagues resembles the measure of clustering coefficient in the present study, in that they both measure the interconnectivity among the entities related to the target. These findings and the similarity between target connectivity and clustering coefficient motivated, in part, the present investigation of the effect of clustering coefficient on spoken word recognition.

Graph-theoretic analysis of the Human Lexicon

To better study the interconnectivity among the neighbors in the phonological lexicon, techniques from graph-theory can be used to model and visualize the phonological word-forms in the lexicon (Vitevitch, 2007). The mathematical formalisms of graph-theory have been used in social network research for decades (Milgram, 1967). Graph-theoretic modeling has started to permeate the field of psycholinguistics and has been widely used to model the human lexicon in a large-scale semantic network (Bales & Johnson, 2006; i Cancho & Sol**e**, 2001; Motter, de Moura, Lai, & Dasgupta, 2002; Schweickert, 2007; Steyvers & Tenenbaum, 2005). Recently, Vitevitch (in press) used graph-theoretic techniques to model the phonological word-forms (lexemes) in the mental lexicon. By using the tools from graph-theory, we can estimate the extent to which the neighborhoods of a word are also neighbors of each other.

It is important to note the difference between the measures of phonological neighborhood density and clustering coefficient. The two words *hive* and *wise* are used as an example for low and high clustering coefficient words respectively and the network representations of their respective phonological neighborhoods are displayed in Figure 1. Note that the two target words have the same number of phonological neighbors (15) and thus the same neighborhood density. However, there are fewer interconnections among the neighbors in the network of *hive* than in the network of *wise*. Thus, neighborhood density measures the number of neighbors a target has, whereas clustering coefficient measures the interconnectivity among the neighbors of the target.

As previously mentioned, there have been numerous studies on the relation between phonological neighborhood density and spoken word processing. However, phonological neighborhood density only addresses the relationship between each of the phonological neighbors and the target word. It does not take into account the relationship among the neighbors on the target word. The present set of studies, therefore, is aimed at studying the influence of inter-connective relationships among the phonological neighbors on the processing of the target word by examining the effect of the clustering coefficient on spoken word recognition. The clustering coefficients of the phonological word forms were calculated by a program called Pajek (Batagelj & Mrvar, 1988) that is often used in graph-theoretic analyses. Words that had high clustering coefficients and words that had low clustering coefficients were used as stimuli in the present study. If the clustering coefficient plays a prominent role in spoken word recognition processes, then listeners would respond to words with high and low clustering coefficients differently. Three experiments using the same set of stimuli with 3 different experimental paradigms, including an auditory same-different, an auditory perceptual identification, and an auditory lexical decision task, were conducted to obtain converging evidence for the psychological validity of the clustering coefficient on spoken word recognition.

Experiment 1

The effects of the clustering coefficient on spoken word recognition were first examined by an auditory same-different task. The participants heard pairs of words where the two words were either the same or different. Their task was to respond as quickly and as accurately as possible, indicating whether the word pair was the same or different. The target words in this experiment varied in their clustering coefficient values. The subjective familiarity, word frequency, neighborhood density, neighborhood frequency, and phonotactic probability for these words were equivalent between the two groups. If listeners are sensitive to the clustering coefficient of a word, then listeners should find it easier to make a decision about one group of words than the other (as reflected by shorter reaction times or higher accuracy rates).

Method

Participants*:* Thirty-seven native English speakers were recruited from the pool of Introductory Psychology students enrolled at the University of Kansas. The participants received partial credit towards the completion of the course for their participation. All participants were right-handed with no reported history of speech or hearing disorders. None of the participants in the present experiment took part in any of the other experiments that are reported.

Materials*:* Seventy-six English monosyllabic words were used as stimuli to serve as

SAME pairs in this experiment. All stimuli consisted of three phonemes in a consonant-vowel-consonant structure. Half of the stimuli had high clustering coefficients and half had low clustering coefficients. These stimulus words and their lexical characteristic are listed in Appendix A.1 and A.2 and further described below.

Clustering coefficient: The Clustering coefficient (*CC*) of a network measures the probability that the neighbors of a given node are also neighbors of each other. The clustering coefficient for each stimulus was obtained by using the Pajek computer program (Batagelj & Mrvar, 1988) to analyze the 19,340 lexical entries in Nusbaum, Pisoni, and Davis (1984). The clustering coefficient is calculated with the algorithm in Equation 1 (Batagelj & Mrvar, 1988):

$$CC(v) = \frac{2\,|\,E(G(v))\,|}{\deg(v) \bullet (\deg(v)-1)} \tag{1}$$

where deg (v) stands for the degree of a given node (also called a vertex, v), and E ($G(v)$) is the number of nodes that are one connection away from the target node. CC has a range from 0 to 1; when CC = 0, none of the neighbors of a target node are neighbors of each other; when CC = 1, the network is fully inter-connected, meaning every neighbor is also a neighbor of all the other neighbors of a target word. Words with high clustering coefficients had a mean value of .170 (*SEM* = .003), and words with a low clustering coefficient had a mean value of .119 (*SEM* = .002). The difference between the two groups of stimuli was statistically significant, F (1, 74) = 164.63, $p < .0001$). The items used in this experiment had a relatively narrow and low range (.061-.136 for the low clustering coefficient group and .150 -.221 for the high clustering coefficient group) compared to the theoretically possible range from 0 to 1. The low range for the clustering coefficient may be due to linguistic constraints, such as phonotactic rules and the phonemic inventory of the language, which limit the number of neighbors a word can have and the number of neighbors that cluster together. Although the two conditions differed significantly in clustering coefficient, the two conditions of words were equivalent in subjective familiarity, word frequency, neighborhood density, neighborhood frequency, and phonotactic probability.

Subjective familiarity: Subjective familiarity was measured on a seven-point scale (Nusbaum, Pisoni, & Davis, 1984). Words with a high clustering coefficient had a mean familiarity value of 6.91 (*SEM* = .029) and word with a low clustering coefficient had a mean familiarity value of 6.96 (*SEM* = .015, F (1, 74) = 2.145, p > .05), indicating that all of the words were highly familiar.

Word frequency: Word frequency refers to the average occurrence of a word in the language. Average log word frequency (log-base 10 of the raw values from Kučera & Francis, 1967) was 1.33 (*SEM* = .120) for the high clustering coefficient words and 1.43 (*SEM* = .100) for the low clustering coefficient words (F (1, 74) < 1).

Neighborhood density: Neighborhood density was defined as the number of words that were similar to a target on the basis of the substitution, deletion, or addition of a single phoneme in any position of the target item. The neighborhood density values for the high and low clustering coefficient words were 20.66 (*SEM* = .934) and 21.55 (*SEM* = 1.19) respectively (F (1, 74) < 1).

Neighborhood frequency: Neighborhood frequency is defined as the mean word frequency of the neighbors of the target word. Words with a high clustering coefficient had a mean log neighborhood frequency value of 2.02 (*SEM* = .208) and words with a low clustering coefficients had a mean log neighborhood frequency value of 2.02 (*SEM* = .203, F (1, 74) < 1).

Phonotactic probability: The phonotactic probability was measured by how often a certain segment occurs in a certain position in a word (positional segment frequency) and the segment-to-segment co-occurrence probability (biphone frequency; Vitevitch and Luce, 1998). The mean positional segment frequency for high and low clustering coefficient words were .139 (*SEM* = .005) and .143 (*SEM* = .007, F (1, 74) < 1) respectively. The mean biphone frequency for high and low clustering coefficient words were .006 (*SEM* = .001) and .006 (*SEM* = .001, F (1, 74) < 1) respectively.

Duration: The duration of the stimulus sound files was equivalent between conditions. The mean overall duration of the sound files for the high clustering coefficient stimuli was 528 ms (*SEM* = 14.42) and for the low clustering coefficient stimuli was 523 ms (*SEM* = 16.7, F (1, 74) < 1). The mean onset duration, including the silence from the beginning of the sound file to the onset of the stimulus, was 11 ms (*SEM* = 1.1) for the high clustering coefficient stimuli and 9 ms (*SEM* = .77) for the low clustering coefficient stimuli, F (1, 74) = 1.427, p > .05. The stimulus duration, measured from the onset to the offset of the stimulus excluding any silence before and after the stimulus in the sound files, had a mean value of 506 ms (*SEM* = 14 ms) for the high clustering coefficient stimuli and had a mean value of 503 ms (*SEM* = 16) for the low clustering coefficient stimuli, F (1, 74) < 1.

In order to assure the participants are really discriminating the stimulus pairs rather than responding 'SAME' all the time, an equal number of filler items served as DIFFERENT pairs. One hundred-fifty-two words with the same phoneme length and the same initial phoneme as the word stimuli were chosen to be filler items. Among these 152 filler words, two words with the same initial phonemes were paired up to form the DIFFERENT pairs, resulting in 76 pairs of filler items with the same initial phoneme as the 76 SAME pairs. For example, a SAME pair, 'bath bath', has one corresponding DIFFERENT pair with the same initial phoneme, 'bad bag'. The 76 filler word pairs are listed in Appendix A.3.

All the stimuli, including the filler items, were spoken in isolation by a male native speaker of American English at a normal speaking rate and loudness in an IAC sound attenuated booth using a high-quality microphone, and recorded to a digital audiotape at a sampling rate of 44.1 kHz. The digital recordings were then transferred directly to a hard-drive via an AudioMedia III sound card and Pro Tools LE software (Digidesign). The pronunciation of each word was verified for correctness. Each word stimulus was edited using SoundEdit 16 (Macromedia, Inc.) into an individual sound file. The amplitude of the individual sound files was increased to their maximum without distorting the sound or changing the pitch of the words by using the Normalization function in SoundEdit 16.

Procedure: Participants were tested individually. Each participant was seated in front of an iMac computer connected to a New Micros response box. PsyScope 1.2.2 was used to control the randomization and presentation of stimuli. The response box contains a dedicated timing board to provide millisecond accuracy for response collection.

In each trial, the word “READY” appeared on the computer screen for 500 ms. The participants then heard one pair of the randomly selected word stimuli or fillers through a set of Beyerdynamic DT 100 headphones at a comfortable listening level. A 500 ms interstimulus interval was used to increase the likelihood that participants will access representations from the lexicon and retain them in memory to perform the discrimination task.

The participants were instructed to respond as quickly and as accurately as possible whether the two items they heard were the SAME or DIFFERENT. If the items were the SAME, they were to press the button labeled ‘SAME’ with the right (dominant) hand. If the items were DIFFERENT, they were to press the button labeled 'DIFFERENT' with their left hand. Reaction times were measured from the onset of the second stimulus in the pair to the button press response. After the participant pressed the response button, the next trial began. Every participant received a total of 152 trials. Half of the stimulus pairs were the SAME pairs of interest and half of the stimulus pairs were the DIFFERENT filler items. The experiment lasted about 15 minutes. Prior to the experimental trials, each participant received ten practice trials to become familiar with the task. These practice trials were not included in the data analyses.

Results and Discussion

Reaction times and accuracy rates were the dependent variables of interest. Only accurate responses for the SAME pairs were included in the analysis. Reaction times that were too rapid or too slow (i.e. below 500 ms and above 2000 ms) were considered to be outliners and were excluded from the analysis. This accounted for less than 6% of the data.

In psycholinguistic research, the current convention is to perform analyses with participants as a random factor (subject analysis) and with items as a random factor (item analysis; however see Clark, 1973 for an alternative analysis). However, there is some debate about the proper use and interpretation of additional item analysis over subject analysis, especially when items are carefully matched or balanced across conditions on important variables correlated with the response measures

(Raaijmakers, 2003; Raaijmakers, Schrijnemakers, & Gremmen, 1999). Although the stimulus items are well-controlled in the present study, and additional item analysis does not seem appropriate or necessary (Raaijmakers, Schrijnemakers, & Gremmen, 1999), they are reported in all of the experiments in this study to be consistent with the conventions of the field.

Repeated measures analysis of variance (ANOVA) was used for the reaction time and accuracy rate measures treating participants as a random factor. There was no significant difference in reaction time between words with high clustering coefficient (mean = 751 ms, *sd* = 96.91) and words with low clustering coefficient (mean = 759 ms, *sd* = 84.54; F (1, 36) = 1.36, $p > .05$). No significant difference was obtained for accuracy rates either (F (1, 36) < 1). Words in each condition were responded to with 92% accuracy.

When collapsed across participants, the items in the high clustering coefficient condition had a mean reaction time of 750 ms (*sd* = 59), whereas items in the low clustering coefficient had a mean reaction time of 761 ms (*sd* = 56). An independent samples *t*-test using stimuli as a random factor was used. The statistical analysis of reaction times failed to show a statistically significant difference between the high and low clustering coefficient conditions (t (74) = .776, $p = .44$). No significant effects were obtained for accuracy rates (t (74) = .173, $p = .863$).

These results failed to show any significant effects of the clustering coefficient on either reaction time or accuracy rate in the same-different task. Although there might be many reasons for obtaining null results, the failure to observe a statistically significant influence of clustering coefficient on processing might be due to the origin of the influence of the clustering coefficient on processing and to the inability of the same-different task to assess that influence.

It was hypothesized that lexical and sublexical representations may be used for spoken word processing (Vitevitch & Luce, 1998, 1999). Lexical representations correspond to whole word forms, whereas sublexical representations correspond to parts of words, such as phonemes or syllables. Like neighborhood density, the clustering coefficient measures the relationships among whole word forms instead of parts of words, and its effects may only be observed in processes involving lexical activation. It was hypothesized that the inter-stimulus interval of 500 ms in this task (Vitevitch, 2003; Vitevitch & Luce, 1999) would encourage the use of long-term (i.e., lexical) representations to perform the task. However, participants might still have performed the same-different discrimination by comparing two low-level (i.e., acoustic or sub-lexical) patterns of the stimuli in memory. Thus, lexical activation may not be necessary to accurately discriminate among pairs of words. Because lexical representations might not have been employed in the task, effects of clustering coefficient were not observed. To test this hypothesis, tasks that involve lexical activation will be used in the following experiments.

Experiment 2

To test the hypothesis that the failure to observe an effect of clustering coefficient on processing in Experiment 1 was due to the failure to sufficiently activate lexical representations of the stimulus words in the same-different task, the same stimuli were used in an auditory perceptual identification task. In the perceptual identification task, participants are presented with a stimulus word against a background of white noise, and are asked to identify it. It was hypothesized that the demands of the perceptual identification task would ensure that lexical representations of the word stimuli would be partially activated, thereby increasing the likelihood of observing effects of clustering coefficient on spoken word recognition. Specifically, if clustering coefficient influences spoken word recognition processes, one group of stimuli should be easier to identify than the other.

Method

<u>Participants</u>: Thirty native English speakers were recruited from the pool of Introductory Psychology students enrolled at the University of Kansas. The participants received partial credit towards the completion of the course for their participation. All participants were right-handed with no reported history of speech or hearing disorders. None of the participants in the present experiment took part in any of the other experiments that are reported.

<u>Materials:</u> The same 76 words stimuli used in Experiment 1 were used in the present experiment. All the stimuli consisted of three phonemes in a consonant-vowel-consonant structure. The consonants in the onset position,

including /b, d, f, g, k, l, m, p, ɹ, s, w/, were balanced in each condition. For the vowels that appeared in the second position of each word, the word with a low clustering coefficient had the following vowels (with the number of occurrence in parentheses), æ (3), ɪ (4), ʊ (1), ʌ (2), ɑ (1), i (3), ɑu (1), e (2), ɔ (5), u (2), ɝ (3), ɑɪ (5), ɛ (5), o (1) and the words with a high clustering coefficient had the following vowels (with the number of occurrence in parentheses), æ (5), ɪ (4), ʊ (3), ʌ (5), ɑ (1), i (8), ɑu (2), e (2), ɔ (2), u (1), ɝ (2) , ɑɪ (3). A chi-square analysis shows that there was no statistically significant difference in the distribution of vowels in the second position of each word between the two conditions (X^2 = 13.71, df = 13, p = .395). As white noise differentially masks fricatives, it is important to carefully balance fricatives that appear in each condition. In the final consonant position, there were 10 fricatives found in the low clustering coefficient condition, and 12 fricatives found in the high clustering coefficient condition. A chi-square analysis shows that the difference was not statistically significant (X^2 = .613, df = 1). Given the high similarities in the distribution of constituent phonemes in the two conditions, it is more likely that any difference observed in the perceptual identification task is due to the difference in the independent variable (*i.e.*, clustering coefficient) than to any difference in the distribution of phonemes in the two conditions.

After the stimulus sound files used in Experiment 1 were digitalized and normalized, they were degraded by adding white noise with a duration equal to the duration of the sound file using SoundEdit 16. The white noise was 24 dB less in amplitude than the mean amplitude of the sound files. Thus, the resulting stimuli were presented at a +24 dB signal to noise ratio (S/N).

Procedure: Participants were tested individually. Each participant was seated in front of an iMac computer running PsyScope 1.2.2, which controlled the presentation of stimuli and the collection of responses.

In each trial, the word "READY" appeared on the computer screen for 500 ms. The participants then heard one of the randomly selected stimulus words imbedded in white noise through a set of Beyerdynamic DT 100 headphones at a comfortable listening level. Each stimulus was presented only once. The participants were instructed to use the computer keyboard to enter their response (or their best guess) for each word they heard over the headphones. They were instructed to type "?" if they were absolutely unable to identify the word. The participants could use as much time as they needed to respond until they finished by hitting the RETURN key, and then the next trial would begin. Participants were able to see their responses on the computer screen when they were typing and could make corrections to their responses before they hit the RETURN key. The experiment lasted about 15 minutes. Prior to the experiment, each participant received five practice trials to become familiar with the task. These practice trials were not included in the data analyses.

Results and Discussion

For the perceptual identification task, accuracy rates were the dependent variable of interest. A response was scored as correct if the phonological transcription of the response matched the phonological transcription of the stimulus. Misspelling, transpositions, and typographical errors that involve a single letter in the responses were scored as correct responses in certain conditions: (1) the omission of a letter in a word was scored as a correct response only if the response did not form another English word, (2) the transposition or addition of a single letter in the word was scored as a correct response if the letter was within one key of the target letter on the keyboard. Responses that did not meet the above criteria were scored as incorrect.

The mean accuracy rate for the high clustering coefficient condition was 58% (sd = .084) whereas the mean accuracy rate for the low clustering coefficient condition was 72% (sd = .082). Repeated-measures analysis of variance (ANOVA) was performed for accuracy rates between the clustering coefficient conditions. The words in the low clustering coefficient condition had a significantly higher accuracy rate than the words in the high clustering coefficient condition, F (1, 29) = 50.93, p < .0001. This observed difference is considered an effect of large size (d = 1.57) and has a high probability of being replicated (p_{rep} = .996; Killeen, 2005).

To maintain the conventions of the field items analyses are also reported. When collapsed across participants, items in the high clustering coefficient had a mean accuracy rate of 58% (sd = .29), whereas items in the low clustering coefficient had a mean accuracy rate of 72% (*sd* = .28). An independent samples *t*-test using stimuli as a random factor was used. As in the analysis treating participants as a random factor, the difference between the high and low clustering coefficient conditions was statistically significant (t (74) = -2.135, p = .036).

Contrasted with the results of Experiment 1, the results of Experiment 2 showed a robust effect of clustering coefficient on spoken word identification. These findings are consistent with the hypothesis that the effect of clustering coefficient is reflected in a task that emphasizes lexical processing of the spoken stimuli. This lends some support to the hypothesis that lack of lexical activation in the same-different task may have contributed to the failure to observe a significant influence of clustering coefficient on processing in Experiment 1.

More important, the results of the present experiments suggest that the clustering coefficient influences some aspect of spoken word recognition. In the perceptual identification task, words with fewer interconnected neighbors (*i.e*., a low clustering coefficient) were identified more accurately than words with the same number of neighbors, but with more of those neighbors being interconnected with each other (*i.e.,* a high clustering coefficient). The present results support the hypothesis that listeners are sensitive to the clustering coefficient of target words, a measure derived from graph-theoretic analyses of phonological word-forms in the mental lexicon. This demonstrates the psychological validity of the clustering coefficient in the context of spoken word recognition.

In addition to the *number* of phonological neighbors, the present findings show that the *nature* of the relationship among the neighbors also influences the processing of a target word. More specifically, not only the structural relationship between each of the phonological neighbors and the target word, but also the structural relationships among the neighbors of the target word influence the processing of the target word. This further demonstrates the importance of understanding how the structural organization of phonological word-forms in the lexicon can influence language processing.

Experiment 3

Although Experiment 2 provided evidence on the nature of the effects of clustering coefficient in the recognition of spoken words, a final experiment was performed to place these findings on a firmer empirical foundation. The purpose of this experiment was to further examine the effects of the clustering coefficient on spoken word recognition by employing another task that emphasizes the activation of lexical representations in memory—the auditory lexical decision task. The auditory lexical decision task has been proven quite useful in examining the effect of many variables—including phonological neighborhood density, phonotactic probability, and neighborhood frequency—on spoken word processing (Luce & Pisoni, 1998; Vitevitch, 2002; Vitevitch & Luce, 1999).

In the lexical decision task, participants are presented with either a word or a nonword (without any white noise) over a set of headphones. Participants are asked to decide as quickly and as accurately as possible whether the given stimulus is a real word in English or a nonsense word. Thus, the lexical decision task uses stimuli that are not degraded (Luce & Pisoni, 1998). Although the degraded stimuli in the auditory perceptual identification task is close to the input we normally get in the real world (*i.e.*, a signal produced by an interlocutor that is imbedded in background noise), it is important to demonstrate that the clustering coefficient effect could be generalized to stimuli that are not degraded in any way. The use of stimuli without degradation could minimize the possibility that the participants respond to the stimuli using some sort of sophisticated guessing strategy, which might occur in tasks using degraded stimuli (Catlin, 1969; Hasher & Zacks, 1984). Moreover, the lexical decision task allows reaction time data to be collected. Reaction times provide us with a means for investigating the time course of spoken word recognition, and may reveal an effect of the clustering coefficient on the temporal aspect of spoken word recognition.

It is predicted that the results of this experiment will replicate those of Experiment 2. That is, words with a high clustering coefficient should be responded to less accurately than words with a low clustering coefficient. Furthermore, it is predicted that words with a high clustering coefficient should be responded to more slowly than words with a low clustering coefficient.

Method

Participants*:* Forty-five native English speakers were recruited from the pool of Introductory Psychology students enrolled at the University of Kansas. The participants received partial credit towards the completion of the course for their participation. All participants were right-handed with no reported history of speech or hearing disorders. None of the participants in the present experiment took part in Experiment 1 or 2.

Materials*:* The same 76 word stimuli that were used in Experiment 1 were used in the present experiment. A list of 76 phonotactically legal nonwords with the same phoneme length as the word stimuli was constructed by replacing the first phoneme of a real word with another phoneme. For example, the nonword ‘baith’ /beθ/ was formed by replacing /f/ in ‘faith’/feθ/ with /b/. The base words from which the nonwords were created were not words in the stimulus list. The phonological transcriptions of the nonwords are listed in Appendix B.

The nonwords were recorded by the same male speaker in the same manner and at the same time as the real word stimuli that were used in Experiment 1. The same method for digitizing the word stimuli was used for the nonwords in the present experiment. This eliminated possible cues to lexical status of the stimuli that might be induced by different recording characteristics and procedures for the words and nonwords.

Duration: The duration of stimulus sound files was equivalent between conditions. The mean overall duration of the sound files for the nonword stimuli was 536 ms (SEM = 10.28, F (1, 150) < 1). The stimulus duration, measured from the onset to the offset of the stimulus excluding any silence before and after the stimulus in the sound files, had a mean value of 520 ms (*SEM* = 10) for the nonword stimuli. The word and nonword stimuli did not different in the stimulus duration, F (1, 150) = 1.07, $p < .05$.

Procedure: Participants were tested individually. Each participant was seated in front of an iMac computer connected to a New Micros response box. As in Experiment 1, PsyScope 1.2.2 was used to control the randomization and presentation of stimuli. The response box contains a dedicated timing board to provide millisecond accuracy for response collection.

In each trial, the word "READY" appeared on the computer screen for 500 ms. The participants then heard one of the randomly selected words or nonwords through a set of Beyerdynamic DT 100 headphones at a comfortable listening level. Each stimulus was presented only once. The participants were instructed to respond as quickly and as accurately as possible whether the item they heard was a real English word or a nonword. If the item was a word, they were to press the button labeled 'WORD' with their right (dominant) hand. If the item was not a word, they were to press the button labeled 'NONWORD' with their left hand. Reaction times were measured from the onset of the stimulus to the onset of the button press response. After the participant pressed a response button, the next trial began. The experiment lasted about 20 minutes. Prior to the experimental trials, each participant received ten practice trials to become familiar with the task. These practice trials were not included in the data analyses.

Results and Discussion

Reaction times and accuracy rates were the dependent variables of interest. Only accurate responses for the word stimuli were included in the analysis. Reaction times that were too rapid and too slow (i.e. below 500 ms and above 2000 ms) were considered to be outliners and were excluded from the analysis; this accounted for less than 1% of the data. Although item analyses may not be appropriate for the current experimental design, such analyses are reported to maintain the current convention of psycholinguistic research.

Repeated measures analysis of variance (ANOVA) was used for the reaction time and accuracy rate measure treating participants as a random factor. For the reaction times, the analyses showed that the clustering coefficient significantly influenced processing (F (1, 44) = 6.47, p = .015). The observed difference is considered an effect of small size (d = .142), but has a high probability of being replicated (p_{rep} = .938; Killeen, 2005). Words with a high clustering coefficient (mean = 900 ms, sd = 86.64) were responded to more slowly than words with a low clustering coefficient (mean = 888 ms, sd = 82.13).

An independent samples t-test was also used to analyze the data treating items as a random factor. The items in the high clustering coefficient condition had a mean reaction time of 908 ms (sd = 83), whereas items in the low clustering coefficient had a mean reaction time of 890 ms (sd = 93; t (74) = -.878, p = .383). Although the analysis treating items as a random factor is not statistically significant, it is important to note that the means in the items analysis are in the same direction as those in the analysis treating participants as a random variable.

For the accuracy rates, the influence of clustering coefficient approached significance (F (1, 44) = 4.037, p = .051). Words with a high clustering coefficient were correctly responded to 91.6% of the time (sd = .057) whereas words with a low clustering coefficient were correctly responded to 93.3% of the time (sd = .042). In an analysis treating the items as a random variable, items in the high clustering coefficient condition had a mean accuracy rate of 91.6% (sd = .11), whereas items in the low clustering coefficient condition had a mean accuracy rate of 93.3% (sd = .10). The observed difference was not significant (t (74) = .748, p = .457), but is in the same direction as that observed in the analysis treating participants as a random variable.

The results of the present experiment revealed significant effects of clustering coefficient on lexical decision time. Words with more interconnected neighbors (i.e., a high clustering coefficient) were responded to more slowly than words with fewer interconnected neighbors (i.e., a low clustering coefficient). Although the effect of clustering coefficient was not significant in the accuracy rate of lexical decision in the present experiment, a trend in the predicted direction was observed. Words with fewer of their neighbors also being neighbors of each other tend to be recognized more accurately than words with many interconnected neighbors. In this task, the lexical representation of the word in memory must be activated to make a lexical decision. Thus, this result from the lexical decision task supports the hypothesis made from Experiment 1 that the clustering coefficient influences processing of the lexical representations, but not of acoustic or sub-lexical representations. That may explain why a significant effect of clustering coefficient was not observed in the same-different task (in Experiment 1) in which lexical processing most likely was not involved.

Furthermore, the results of Experiment 3 suggest that clustering coefficient not only affects the accuracy of word recognition, but also the *time-course* of lexical access. This is important because accuracy rates only reflect the end product of the spoken word recognition process and could be biased by postperceptual guessing strategies (Marslen-Wilson, 1987). Instead, the lexical decision time is an immediate measure of processing activities, which may be less susceptible to postperceptual biases. Thus, the significant result on lexical decision time in this experiment shows that the effect of clustering coefficient is quite robust and could not be attributed to postperceptual biases. In addition, results from the present experiment showed that the effects of the clustering coefficient on spoken word recognition are not restricted to degraded stimuli. Therefore the influence of clustering coefficient on spoken word recognition is not likely to be due to participants' simply using a sophisticated guessing strategy when presented with degraded stimuli.

General Discussion

The goal of the present study was to examine how the interconnective relationships among the phonological neighbors of the target words influence the recognition of the spoken target word. The clustering coefficient of the stimuli, which measures the proportion of phonological neighbors of a target word that are also neighbors of each other, was examined. It was hypothesized that if the clustering coefficient of the stimulus word influences spoken word recognition, then participants should differ in the speed and accuracy of their responses to words varying in the clustering coefficient.

In Experiment 1, a significant effect of clustering coefficient on the reaction time or accuracy rates of discriminating whether two stimulus words were the same or different was not found. It was hypothesized that the lack of an effect in this simple discrimination task could be due to the lack of lexical processing in the same-different task. In Experiment 2, an auditory perceptual identification task—a task that does require lexical processing—was used. In this case it was found that words with a low clustering coefficient (i.e., few interconnected neighbors) were more accurately identified than words with a high clustering coefficient (i.e., many interconnected neighbors). In Experiment 3, the effect of clustering coefficient was observed in a lexical decision task such that words with a low clustering coefficient were responded to more quickly than words with a high clustering coefficient. Thus, the clustering coefficient influences the accuracy as well as the speed of spoken word recognition.

The findings in the latter two experiments using tasks that require lexical processing of the stimuli supported the hypothesis that the effect of clustering coefficient may rely on the lexical level of processing during spoken word recognition. These results suggest that in addition to the number of phonological neighbors, the nature of the relationship among the neighbors also influences the processing of spoken words. Although current models of spoken word recognition can account for the influence of the number of phonological neighbors on processing, it is not clear if they can also account for the influence that the relationship among the neighbors (i.e., clustering coefficient) has on spoken word recognition.

The TRACE model of spoken word recognition was a connectionist model designed by McClelland & Elman (1986) to account for lexical effects on phoneme recognition and speech segmentation. In TRACE, there are several levels of nodes, or individual processing units, that represent features, phonemes, and words in a hierarchy. Nodes between adjacent levels are connected so that features nodes are connected to phonemes nodes, and phoneme nodes are connected to word nodes. Also, all the nodes at the same level are interconnected. Connections between levels are facilitatory and bidirectional, whereas connections within levels are inhibitory. TRACE is constructed within an interactive activation framework, so that nodes at different levels or within the same level influence each other in proportion to their activation levels and the strengths of their interconnectivity. When input is presented to TRACE, activation levels of consistent units increase through the excitatory connections between layers of nodes. Activation levels of competing units are inhibited in proportion to the degree of overlap through the inhibitory connections within the same layer. The greater is the overlap, the greater is the inhibition. This competition among words results in the word with the highest activation winning out for recognition.

Based on the top-down feedback characteristic of TRACE, it appears to have the requisite architecture to account for the clustering coefficient effect. After the phonemes of the target word get activated from the auditory input, these target phonemes send activation to both the target and neighbor words in the word level. Thus, both target and neighbor words are activated and in turn they send excitatory feedbacks down to the corresponding phoneme nodes that they contain. Assuming that there are two target words with the same number of neighbors, but one has many of its neighbors interconnected, like *cat* (its neighbors include *cap, sat, mat, rat, pat*) and the other one has few of its neighbors interconnected, like *dog* (its neighbors include *dig, dug, dot, fog, cog*). Note that in reality, the word *cat* has many more neighbors than the word *dog*, but here it is assumed that they just have the neighbors listed in parentheses in order to illustrate how TRACE might account for the observed clustering coefficient effect. Figure 2 shows the interaction between the word and phoneme level of the two example words, *cat* and *dog*. For a word with a high clustering coefficient, some of the target phonemes are widely shared among the highly interconnected neighbors, like /æ/ and /t/ in *cat* being shared by the neighbors *sat, mat, rat* and *pat*. Note that the number under each target phoneme in Figure 2 reflects the number of words at the lexical level sharing that particular phoneme. Thus, the widely shared phonemes (/æ/ and /t/ in the example) would get relatively more feedback activations from these interconnected neighbor words at the lexical level than those phonemes which are not widely shared (/k/ in the example). For a word with a low clustering coefficient, the target phonemes were more evenly shared by the neighbors. Activated phonemes again will send activation to the lexical level and the activation would bound to and fro between the word and the phoneme level. Therefore, the interconnected neighbors of a high clustering coefficient target word would receive a high level of activations compared to those neighbors of a low clustering coefficient word due to activation from those highly activated widely shared target phonemes. As a result, the high clustering coefficient target word would be recognized more slowly or less accurately against the noisy background activation of its neighbors. This prediction is consistent with the present findings.

However, when the characteristic of inhibition within a level is taken into consideration, TRACE may predict a clustering coefficient effect in a direction opposite to the present findings— high clustering coefficient words are recognized faster and more accurately than low clustering coefficient words. Using the same example mentioned before, the target words *cat* and *dog* each is assumed to have 4 phonological neighbors. Figure 3 showed the word level of these two words. In the word level, each target word would receive inhibition from the 4 neighbor words, which each share two phonemes with them, as shown by the black links between the target and the neighbors in Figure 3. However, there would be much more inhibition among the neighbors of a target word with a high clustering coefficient compared to those of a target word with a low clustering coefficient. Therefore, there is more inhibition as shown by the red links in Figure 3 among just the neighbor words themselves in the case of *cat* than in the case of *dog*. The neighbors of a high clustering coefficient target word would have a relatively lower activation compared to those of a low clustering coefficient target word. With less competitive neighbors, high clustering coefficient target words would win out more easily than low clustering coefficient words. This prediction is in an opposite direction of the present findings. TRACE is a complex model and verbal exploration of its inner workings is not sufficient to test whether the feedback or inhibition mechanism would win out. Simulation is required to test which proposed mechanism is more tenable (Lewandowsky, 1993), and to determine if TRACE can account for the present findings.

Shortlist is another connectionist model of continuous speech recognition. It was designed by Norris (1994) to address the deficiencies of TRACE, including the over-emphasis on the importance of top-down feedback and time-shift invariance problems. Thus, Shortlist is very similar to TRACE except that it has an entirely bottom-up architecture with a recurrent network generating a set of candidate words which are roughly consistent with the bottom-up inputs (Norris, 1994). As in TRACE, in the lexical level of Shortlist, overlapping words inhibit each other in proportion to the number of phonemes they have in common, and they compete with each other for recognition. Likewise, in Shortlist, the neighbors of high clustering coefficient words would have relatively lower activations compared to the neighbors of low clustering coefficient words due to the mutual inhibition among themselves. Therefore, Shortlist predicts that high clustering coefficient words would be recognized faster and more accurately than low clustering coefficient words. This clustering coefficient effect is in the opposite direction from the present findings. The other proposed mechanism in TRACE that involves feedback from the word level is not possible in Shortlist as it has an entirely bottom-up architecture and top-down feedback is not allowed in the model. Thus, Shortlist probably could not account for the present findings.

Luce and Pisoni (1998) developed the neighborhood activation model (NAM) to account for the influence of the structural organization of the representations in the mental lexicon on spoken word recognition. In NAM, spoken input activates a set of acoustic-phonetic patterns in memory according to the degree of similarity between the spoken input and the patterns. The more they are similar, the higher the level of activation is. Then the acoustic-phonetic patterns that correspond to words in memory activate a system of word decision units which monitor several sources of information including the acoustic-phonetic pattern activation to which the units correspond (i.e. activation of the target word), the overall level of activity in the system of units (activation of the target and all its neighbors), and higher levels of information (e.g., frequency of the target and neighbor words). As the processing of spoken input continues, the decision units continuously compute decision values based on the neighborhood probability rule to determine the probability of identification of the stimulus word. Once the decision value surpasses the criterion, the word is recognized. The neighborhood probability rule (Equation 2)

$$\left(\frac{SWP * Freq_s}{(SWP * Freq_s) + \sum(NWP_j * Freq_{N_j})}\right) \tag{2}$$

takes into account the activation level of the acoustic-phonetic pattern (SWP), the sum of neighbor word probabilities (NWPjs, *i.e.*, the overall level of activity in the decision system) and the frequency information. Neighborhood density and word frequency effects lay in the decision stage of processing in NAM via the neighborhood probability rule. When the input word has a high number of confusable and high frequency neighbors, the sum of neighbor word probabilities ($\sum(NWP_j * Freq_{N_j})$) would be high and thus the probability of recognizing the input word would be low. In contrast, when the input word has a small number of confusable and low frequency neighbors, the sum of neighbor word probabilities would be low and thus the probability of recognizing the input word would be high.

However, the neighborhood probability rule does not take the clustering coefficient into account. That is, there is no variable in Equation (2) that represents the interconnectivity among the neighbors. Like TRACE and Shortlist, NAM has a two stage process of activation and decision. However, in NAM, the competition among lexical candidates does not involve any inhibitory links among them. This means activation of one decision unit will not affect the activation of another decision unit directly, but it will influence the output decision through its influence on the overall activation of the whole decision system. Thus, in order for NAM to account for the clustering coefficient effect found in this study, a variable representing the interconnectivity among the neighbors may need to be added to the sum of neighbor word probabilities ($\sum (NWP_j * Freq_{N_j})$) in the neighborhood probability rule so that the total activation of the system would increase with higher interconnectivity among the neighbors. This will slow the time for the decision unit to reach criterion when the input stimulus has a high clustering coefficient. However, the detail of what variable to add in the rule and whether the modified NAM would be able to produce the results observed in the present study is at present unclear.

The results from the present study suggest that the clustering coefficient affects the time course and accuracy of spoken word recognition. This implies that in addition to the number of phonological neighbors a target word has, the interconnectivity among the phonological neighbors also exerts an influence on the processing of the target word. Current models of spoken word recognition, including TRACE, Shortlist and NAM, were considered. Based on the characteristics of feedback from word level and inhibition within level, simulation is required to find out whether TRACE could account for the present findings. Shortlist seems to fail to produce a clustering coefficient effect in the same direction as that observed in the present study due to the inhibitory links among the words on the lexical level. Another spoken word recognition model, NAM, does not take clustering coefficient into account in the decision rule. Modification of NAM may be required to account for the clustering coefficient effect observed in the present study.

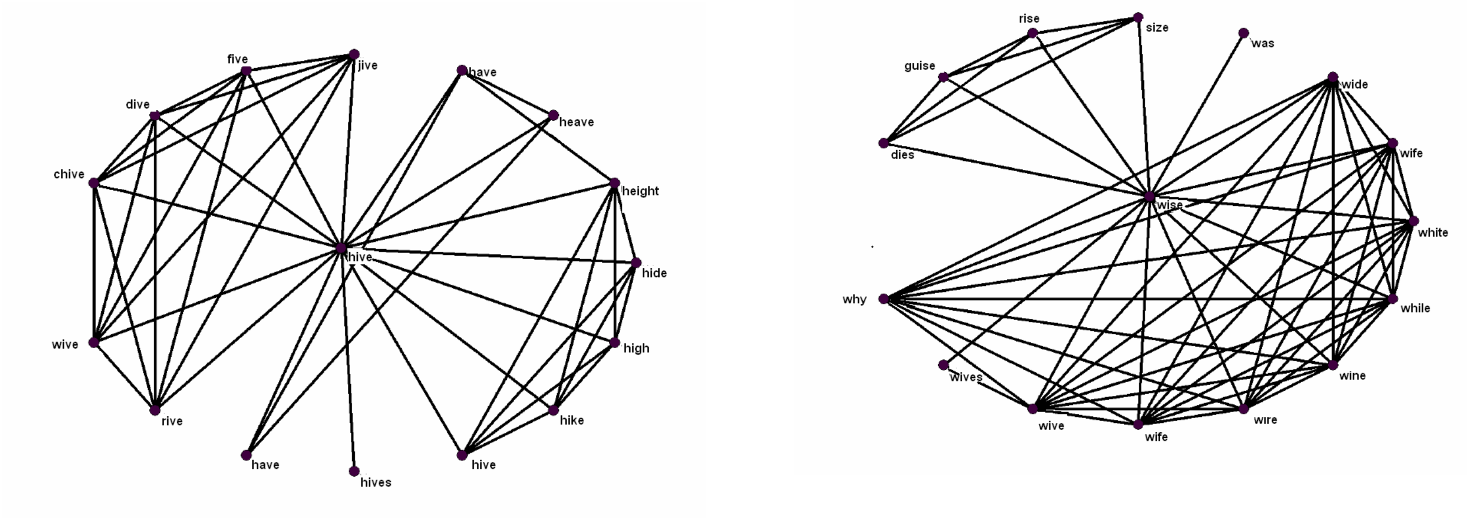

Figure 1.The left graph represents a word with a low clustering coefficient (hive), whereas the right graph represents a word with a high clustering coefficient (wise). Note that both words have the same number of phonological neighbors (same neighborhood density).

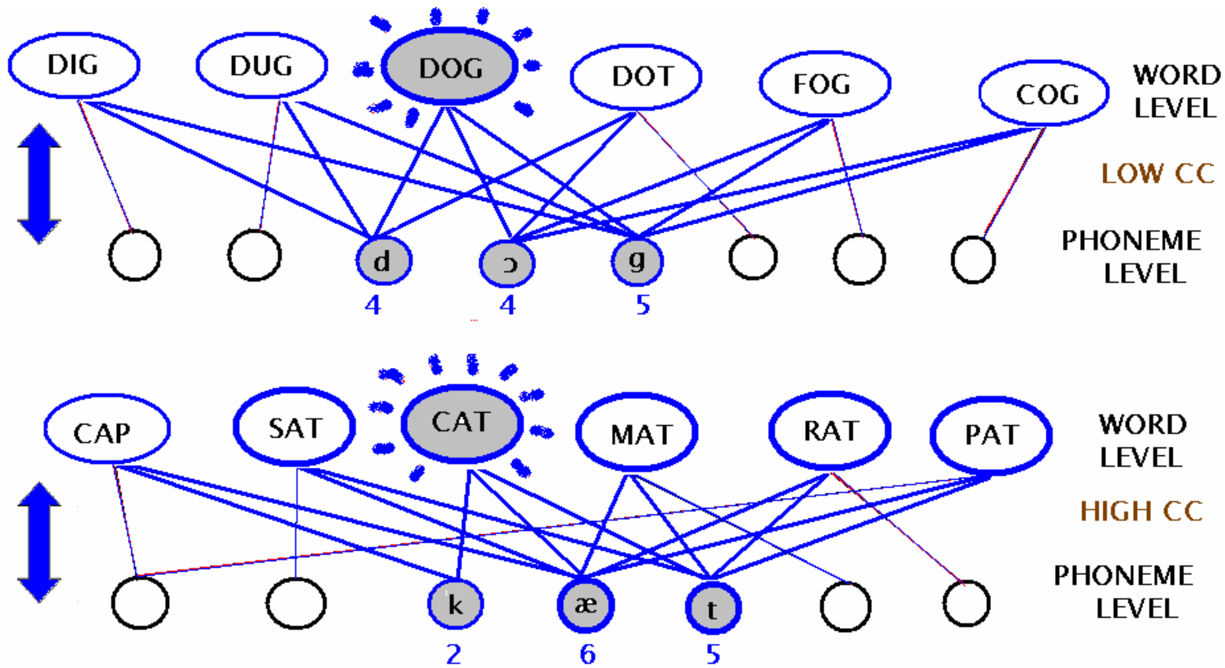

Figure 2. The graphs present the word and phoneme levels for the target word with a low clustering coefficient, *dog* (the upper graph) and the target word with a high clustering coefficient, *cat* (the lower graph).* In both graphs, the target words and target phonemes are highlighted in grey. Words and its constituent phonemes are linked together. The number under the phoneme represents the number of words at the lexical level sharing that particular phoneme. For example, the number 4 under the phoneme /d/ in the upper graph means there are 4 words, including dig, dug, dog and dot, containing the phoneme /d/. The arrows show that the activation could flow bidirectionally between both levels.

* The target words actually have different number of neighbors in reality. But they are assumed to have the same number of neighbors in the example just for illustrating the clustering coefficient effect without being confounded by the neighborhood density effect.

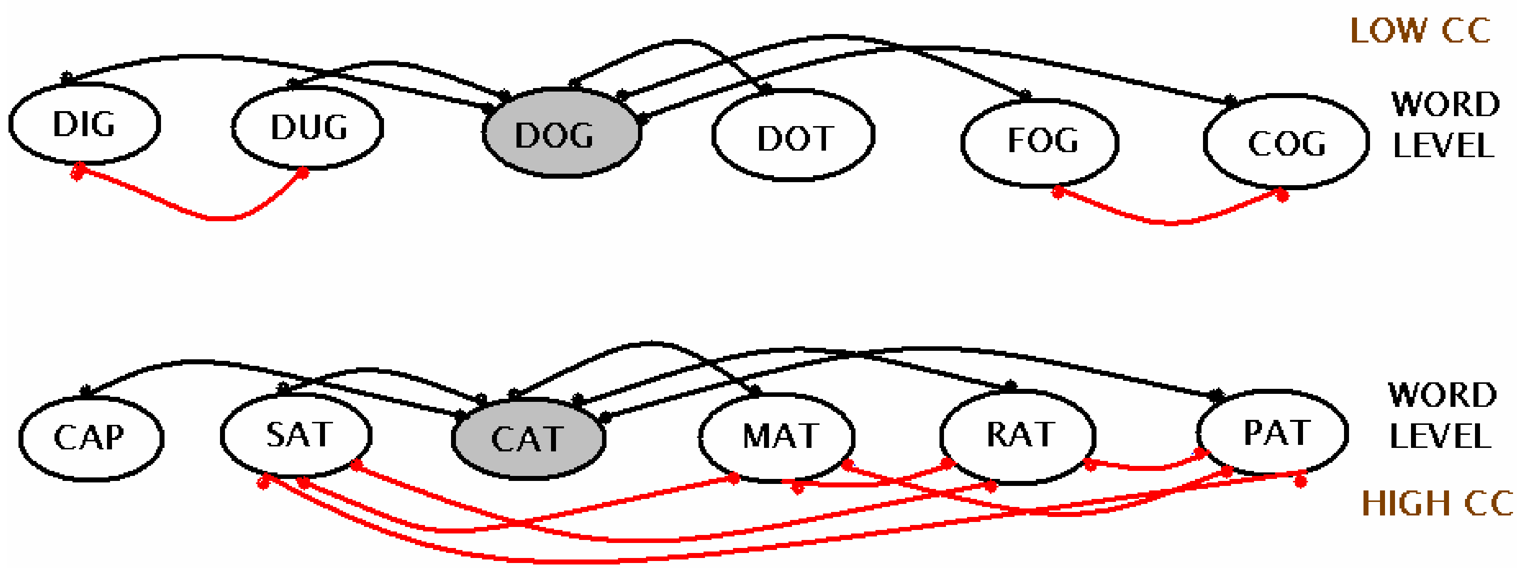

Figure 3. The graphs present the word levels for the target word with a low clustering coefficient, *dog* (the upper graph) and the target word with a high clustering coefficient, *cat* (the lower graph). In both graphs, the target words are highlighted in grey. The inhibition between the target word and its neighbors is represented by the black links between them. As both *dog* and *cat* are assumed to have the same number of neighbors in the example, there are the same numbers of black links in each graph. The inhibition among the neighbors themselves is represented by the red links among them. As many of the neighbors of the target word *cat* are also neighbors of each other, there are much more red links in the graph of *cat* than in the graph of *dog*.

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APPENDIX A.1- High Clustering Coefficient Words

Stimulus Word	Clustering Coefficient	Familiarity	log Word Frequency	ND	log NF	Pos. Seg. Freq.	Biphone Freq.
bash	0.163	6.50	0.00	24	1.82	0.138	0.0079
bath	0.193	7.00	1.42	17	2.26	0.138	0.0069
bib	0.172	6.83	0.30	13	2.25	0.173	0.0064
bull	0.154	7.00	1.15	13	2.43	0.135	0.0031
bug	0.151	7.00	0.60	26	1.80	0.108	0.0047
dot	0.167	7.00	1.11	26	2.06	0.178	0.0050
dig	0.178	6.92	1.00	17	2.19	0.166	0.0187
dish	0.217	7.00	1.20	12	2.22	0.156	0.0164
dug	0.175	7.00	1.20	22	1.83	0.109	0.0037
feel	0.166	7.00	2.33	30	2.06	0.152	0.0046
full	0.221	7.00	2.36	15	2.45	0.131	0.0026
foul	0.196	7.00	0.70	17	2.00	0.130	0.0010
gang	0.193	7.00	1.34	15	1.65	0.117	0.0070
gain	0.180	7.00	1.87	25	2.22	0.151	0.0042
gum	0.206	7.00	1.15	16	1.93	0.115	0.0067
call	0.152	7.00	2.27	26	2.16	0.183	0.0060
case	0.173	6.75	2.56	22	2.14	0.201	0.0050
lag	0.152	6.58	0.48	27	1.73	0.131	0.0073
leaf	0.189	7.00	1.08	25	1.90	0.086	0.0033
leap	0.163	6.83	1.15	30	1.93	0.103	0.0039
lease	0.166	6.92	1.00	27	2.02	0.145	0.0042
leave	0.167	7.00	2.31	26	1.76	0.089	0.0038
look	0.203	7.00	2.60	17	2.21	0.098	0.0013
lose	0.160	6.50	1.76	17	2.00	0.076	0.0031
lull	0.152	6.25	0.30	15	1.66	0.147	0.0064
love	0.156	6.67	2.37	11	1.91	0.097	0.0030
math	0.152	7.00	0.60	15	2.23	0.144	0.0111
mall	0.152	7.00	0.48	24	2.27	0.147	0.0044
meal	0.174	7.00	1.48	28	1.92	0.163	0.0047
mouse	0.169	7.00	1.00	14	1.93	0.146	0.0017
perk	0.150	6.83	0.00	22	1.72	0.163	0.0061
pearl	0.153	7.00	0.95	21	1.98	0.183	0.0045
ring	0.155	7.00	1.69	23	2.04	0.158	0.0203
ripe	0.154	6.92	1.15	20	1.93	0.122	0.0034
seal	0.166	7.00	1.23	31	2.20	0.208	0.0055
size	0.152	7.00	2.14	12	2.29	0.157	0.0041
weak	0.150	7.00	2.49	22	1.93	0.106	0.0030
wire	0.173	7.00	1.62	22	1.86	0.133	0.0035

Note: **ND** is neighborhood density; **NF** is neighborhood frequency; **Pos. Seg. Freq.** is position segment frequency (a measure of phonotactic probability); **Biphone Freq.** is biphone frequency (a measure of phonotactic probability).

APPENDIX A.2- Low Clustering Coefficient Words

Stimulus Word	Clustering Coefficient	Familiarity	log Word Frequency	ND	log NF	Pos. Seg. Freq.	Biphone Freq.
beach	0.127	7.00	1.83	18	2.04	0.091	0.0028
bead	0.110	7.00	0.00	26	2.22	0.121	0.0044
beat	0.117	7.00	1.83	33	2.28	0.149	0.0045
bush	0.061	7.00	1.15	6	1.83	0.069	0.0015
boot	0.118	7.00	1.11	32	1.91	0.139	0.0039
dog	0.133	7.00	1.88	8	1.82	0.086	0.0016
dead	0.133	7.00	2.24	24	2.25	0.163	0.0108
deck	0.136	7.00	1.36	20	2.00	0.178	0.0142
debt	0.129	7.00	1.11	28	2.36	0.191	0.0120
fat	0.131	7.00	1.78	28	2.37	0.192	0.0093
fell	0.131	6.83	1.96	30	2.29	0.193	0.0114
fate	0.131	6.92	1.56	29	2.47	0.142	0.0049
gas	0.122	7.00	1.99	19	1.86	0.184	0.0104
goat	0.118	7.00	0.78	26	1.91	0.141	0.0056
gull	0.111	6.67	0.00	21	1.75	0.139	0.0062
cough	0.121	7.00	0.85	11	2.10	0.129	0.0031
couch	0.092	7.00	1.08	9	1.62	0.110	0.0021
lock	0.113	7.00	1.36	31	1.93	0.148	0.0052
log	0.135	6.73	1.04	13	2.28	0.069	0.0024
lose	0.108	7.00	1.93	19	2.14	0.129	0.0026
ledge	0.114	6.83	0.78	18	1.82	0.118	0.0056
lick	0.108	6.75	0.48	32	2.04	0.184	0.0148
lip	0.122	7.00	1.26	29	1.81	0.167	0.0111
live	0.124	7.00	2.25	15	1.94	0.154	0.0093
lime	0.128	6.92	1.11	23	1.97	0.118	0.0047
luck	0.122	7.00	1.67	26	1.88	0.127	0.0037
miss	0.106	7.00	2.41	23	1.91	0.232	0.0251
merge	0.113	6.92	1.00	11	1.65	0.093	0.0021
mood	0.125	7.00	1.57	17	2.03	0.117	0.0024
mile	0.135	6.75	1.68	28	1.95	0.165	0.0051
pass	0.117	7.00	1.95	24	1.96	0.243	0.0158
purse	0.117	7.00	1.15	19	1.96	0.188	0.0066
rhyme	0.119	7.00	0.60	25	1.94	0.134	0.0031
rise	0.135	7.00	2.01	21	2.05	0.105	0.0029
sause	0.105	7.00	1.30	10	2.25	0.198	0.0022
save	0.129	7.00	1.79	22	2.01	0.155	0.0033
word	0.131	7.00	2.44	19	2.29	0.083	0.0030
wide	0.130	7.00	2.10	26	2.06	0.093	0.0041

Note: **ND** is neighborhood density; **NF** is neighborhood frequency; **Pos. Seg. Freq**.

is position segment frequency (a measure of phonotactic probability);
Biphone Freq. is biphone frequency (a measure of phonotactic probability).

APPENDIX A.3- Filler pairs used in Experiment 1

bad	bag
back	ban
bud	buff
balm	bar
ball	boss
bell	bet
bait	beige
big	bit
bone	boat
booth	boom
duck	dull
dock	doll
deaf	den
ditch	dill
death	deal
dean	deep
dip	dim
doom	dune
fad	fan
fetch	fame
fig	fill
faith	faze
fin	fit
faille	fight
gag	gap
gun	gush
gone	gauze
gage	Gael
gait	gaze
goal	give
calf	cap
cache	cat
cod	cock
con	cop
lad	laugh
lac	lamb
lap	lash
lung	lush
lob	lodge
long	lawn
loop	learn
lead	leg
lake	lame
lain	lace
lid	limb
leak	lean
lied	lit
lobe	load
loaf	loan
loose	loot
like	line
lice	light
mad	man
mass	mat
moss	moth
made	make
mail	main
mil	myth
moon	move
mike	mice
pad	pack
pan	pat
pod	pop
par	pot
rash	rat
raid	red
rib	rich
ride	writhe
sake	sane
seat	scene
soak	sol
side	cite
wick	win
work	worm
wife	wine
wipe	wise

APPENDIX B –International Phonetic Alphabet (IPA) Transcription of the Nonwords used in Experiment 3

bɛf	faʤ	laɪl	mlp
bɪm	fam	lot	mlɹ
bɛtʃ	fɛd	loɪz	mɝs
beθ	fig	luz	pʌm
bɔz	fætʃ	lɑm	pɑuθ
blv	gls	lel	pɛʃ
bæf	gaɪl	loɹ	pæf
bem	gaɪz	lɛl	ɹɑʤ
bɔn	gɑk	lɝtʃ	ɹæk
bɝm	glk	lɑuθ	ɹoɪn
dʊk	gls	lɝm	ɹɑud
det	kɑun	lɔk	sʌd
ditʃ	kɝl	llʃ	sud
dɝd	kus	lev	saɪs
dɝθ	klʃ	mɝl	soɪz
dɛs	lɝv	moɪn	wʌd
dɔz	loɪl	mɔn	wed
dis	loɹ	mem	witʃ
fɑt	lɝʤ	maɪf	wɝtʃ