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# Network Structure Influences Speech Production

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**Abstract**

Network science provides a new way to look at old questions in cognitive science by examining the structure of a complex system, and how that structure might influence processing. In the context of psycholinguistics, clustering coefficient—a common measure in network science—refers to the extent to which phonological neighbors of a target word are also neighbors of each other. The influence of the clustering coefficient on spoken word production was examined in a corpus of speech errors and a picture-naming task. Speech errors tended to occur in words with many interconnected neighbors (i.e., higher clustering coefficient). Also, pictures representing words with many interconnected neighbors (i.e., high clustering coefficient) were named more slowly than pictures representing words with few interconnected neighbors (i.e., low clustering coefficient). These findings suggest that the structure of the lexicon influences the process of lexical access during spoken word production.

*Keywords:* Computer Science; Linguistics; Psychology; Cognitive Architecture; Complex Systems; Memory

Networks, or systems comprised of interconnected components, have a long and varied history in cognitive science, exemplified in the pioneering work of Rosenblatt (1958) on artificial neural networks, and of Quillian (1967) on semantic networks. The general principles of cognition that emerged from those examples have influenced in some way all areas of cognitive science. Recent developments in mathematics, physics, computer science, and other fields have sparked a ‘‘new’’ science of networks with computational tools that allow researchers to examine the structure of complex systems and explore how that structure might influence processing (Watts, 2004; see also Jasny, Zahn, & Marshall, 2009). Using this approach, words in the mental lexicon can be represented as nodes in a network with links connecting words that are related to each other in some way (see Albert & Barabási, 2002 for examples of how such networks have been used to model social, biological, and

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technological systems). In the present study we examined how the structure of a network representing the phonological similarity among word-forms in the mental lexicon—a complex *cognitive* system—might influence the process of speech production (Vitevitch, 2008; such networks have also been used to model semantic relationships among words: Hills, Maouene, Maouene, Sheya, & Smith, 2009; Steyvers & Tenenbaum, 2005).

There are a number of standard measurements used to describe the structure of a network, but the two measurements most relevant to the present study are *degree* and *clustering coefficient.* Degree refers to the number of links that a node has. In the network of phonological word-forms in the mental lexicon (Vitevitch, 2008), degree corresponds to the number of word-forms that sound similar to a given word. In the psycholinguistic literature, this measure is referred to as *phonological neighborhood density* (Luce & Pisoni, 1998), but we will use the term *degree* to maintain consistency with the network perspective that motivated the present study. Much psycholinguistic research has demonstrated that degree influences spoken word production (e.g., Goldrick & Rapp, 2007; Kittredge, Dell, Verkuilen, & Schwartz, 2008), spoken word recognition (e.g., Luce & Pisoni, 1998), word-learning (e.g., Storkel, Armbruster, & Hogan, 2006), and other language-related processes (e.g., Roodenrys, Hulme, Lethbridge, Hinton, & Nimmo, 2002; Yates, Locker, & Simpson, 2004). Network simulations have also demonstrated that the degree of a node is a good indicator of how important a given node is with regards to information retrieval and navigation within that system (Simsek & Jensen, 2008; see also Griffiths, Steyvers, & Firl, 2007 and Chan & Vitevitch, 2009 for descriptions of similar search mechanisms in the lexicon). Given the robust influence of degree (a.k.a. phonological neighborhood density) on language processing, the present study examined how similarity *among the neighbors*, a measure referred to in network science terms as the *clustering coefficient, C (*Watts & Strogatz, 1998), affects the production of a spoken word.

Note that degree and *C* are two different measures.[1] Fig. 1 shows the words *badge* and *log* as well as the neighbors of each word. Both words have 13 phonological neighbors and thus the same degree. Notice that *bag, bad, bat, back, ban*, and *batch* are not only neighbors of the word *badge* but are also neighbors of each other. Clustering coefficient (in a network of word-forms) measures the extent to which phonological neighbors are also neighbors of each other. A word (like *badge*) with a large number of neighbors also being neighbors of each other is said to have a high *C*, whereas a word (like *log*) with an equal number of neighbors but a smaller number of neighbors also being neighbors of each other is said to have a low *C*.

Chan and Vitevitch (2009) found in a perceptual identification task, where auditorily presented words are mixed with white noise and participants must indicate the word they heard, and in an auditory lexical decision task, where participants decide if what they heard was an English word or not, that words with low *C* were responded to more quickly and accurately than words with high *C*. These results suggest that the structure of the lexical network affects the process of spoken word recognition. Words with low *C* have neighbors that tend to be related to other words elsewhere in the network. This relationship results in activation being broadly dispersed to the rest of the network, allowing the target word to ''stand out'' from its closest competitors. In contrast, words with high *C* have neighbors that tend to be related to other neighbors of the target word. This relationship results in the activation being

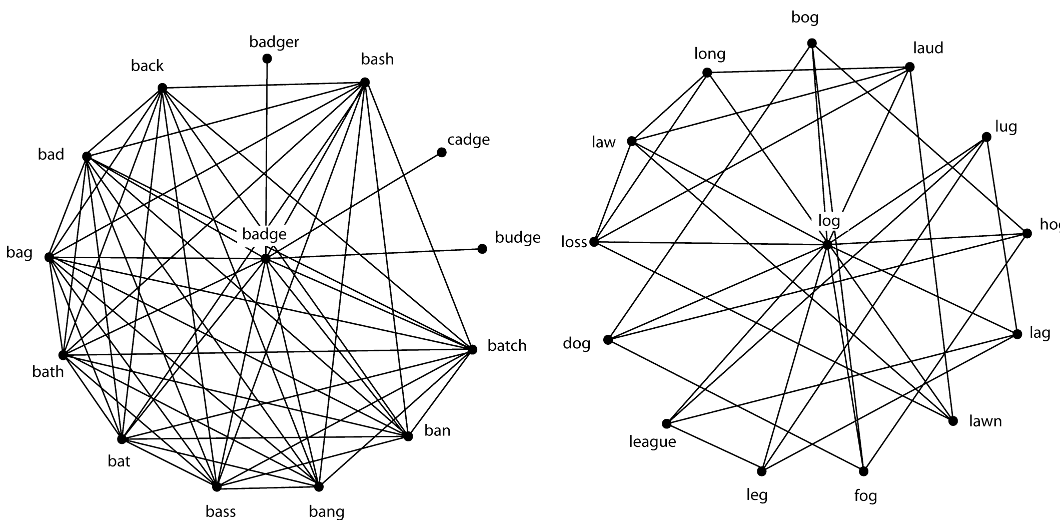


Fig. 1. The left panel represents a word with a high clustering coefficient (*badge*; *C* = .58), whereas the right panel represents a word with a low clustering coefficient (*log*; *C* = .28). Note that both words have the same degree (i.e., number of phonological neighbors).

constrained to a more restricted region of the network, creating a ''reservoir of activation'' among the neighbors, and making it difficult to distinguish the target word from the neighbors.[2]

In the present study, we examined how the dispersal or reservoir of activation found among words varying in *C* might influence the process of spoken word production. It is important to examine the influence of *C* on the production of spoken words in addition to the recognition of spoken words because different effects of degree (i.e., neighborhood density) have been observed in the two processes (*cf*., in English: Luce & Pisoni, 1998; Vitevitch, 2002; *cf*., in Spanish: Vitevitch & Rodríguez, 2005; Vitevitch & Stamer, 2006, 2009), suggesting that the same structure may have different influences on processing during perception versus production.

During speech production, the intended message activates a target word-form that corresponds to the semantic information to be conveyed. In addition to the target word-form being activated, phonologically related words are also activated via the phonological segments that are shared with the target word (see Gordon & Dell, 2001; Vitevitch, 2002).[3] For words with low *C*, the neighbors not only send some activation back to the target word and to the (few) neighbors they are similar to, but they also send activation to other words in the network. With activation spreading to other parts of the network, many representations will become slightly activated, but only one item—the target word—will be highly activated as a result of receiving activation from its phonological neighbors *and* from higherlevel representations (e.g., semantic information). With only the target word being highly activated, retrieval of that item from the lexicon and production of that word will be rapid and efficient.

As in the case of a word with low *C*, the intended message will activate the target word-form of a word with high *C*, and the target word-form will activate phonologically related words. The activated neighbors will spread activation back to the target word and to other words in the network. However, in the case of a word with high *C*, the neighbors spread activation among the other phonologically related neighbors of the target word to a greater extent than for a word with low *C*. With the spread of activation reverberating among the neighbors—essentially containing activation within the phonological neighborhood—the target word will no longer ''stand out'' from the neighbors as it did in the case of a word with low *C*, making it difficult to retrieve an item from the lexicon quickly and without error. The present study examined these predictions in a corpus of speech production errors and a picture-naming task.

## 1. Speech error analysis

Fromkin (1971) demonstrated that the analysis of various types of speech errors from a linguistic perspective could provide important insight into the process of speech production. One type of speech error is the malapropism, in which a whole word that is phonologically but not semantically related is substituted for another word, such as saying *octane* instead of *octave* in a conversation about music. A previous analysis of malapropisms (Vitevitch, 1997) found that, compared to randomly sampled words of comparable length and syntactic class, the intended (but erroneously produced) words tended to have low degree (i.e., sparse neighborhoods), suggesting that during speech production such words were more difficult to retrieve than words with high degree (i.e., dense neighborhoods; also see Vitevitch, 2002; Vitevitch & Sommers, 2003).

In the present analysis, we compared the clustering coefficient of 40 malapropisms (i.e., the monosyllabic words from the appendix of Fay & Cutler, 1977) to the clustering coefficient of 10 random samples of 40 words of comparable length and syntactic class (as in Vitevitch, 1997). We predicted that malapropisms would have higher clustering coefficients than randomly sampled words of comparable length and syntactic class if the structure of the lexicon influences speech production. As shown in Table 1, the results confirmed this

Table 1
Mean clustering coefficient (and standard deviation) of the malapropisms and 10 randomly sampled sets of words of comparable length and syntactic class

| | |
|---|---|
| Malapropism | 0.316 (0.122) |
| Sample 1 | 0.254 (0.145) |
| Sample 2 | 0.260 (0.118) |
| Sample 3 | 0.235 (0.139) |
| Sample 4 | 0.291 (0.145) |
| Sample 5 | 0.261 (0.138) |
| Sample 6 | 0.276 (0.157) |
| Sample 7 | 0.285 (0.124) |
| Sample 8 | 0.210 (0.146) |
| Sample 9 | 0.248 (0.150) |
| Sample 10 | 0.253 (0.106) |

prediction: Malapropisms did indeed have higher clustering coefficients than randomly sampled words of comparable length and syntactic class [$F(10, 429) = 2.00$, $p = .03$], suggesting that it is more difficult to retrieve words with high rather than low clustering coefficient.

An alternative analysis comparing the malapropisms to the randomly sampled words (this time treating the randomly sampled words as one large sample) also shows that the malapropisms have higher clustering coefficients than the randomly sampled words [$F(1, 438) = 6.80$, $p = .0094$]. Because of the difficulty in lexical retrieval as a function of clustering coefficient, speakers are more likely to make a speech error on a word with high rather than low clustering coefficient.

## 2. Picture naming experiment

Although much has been learned from analyses of speech errors, and several models of speech production account for speech error data (e.g., Dell, 1986, 1988), Levelt, Roelofs, and Meyer (1999) have argued that:

> Models of lexical access have always been conceived as process models of normal speech production. Their ultimate test...cannot lie in how they account for infrequent derailments of the process but rather must lie in how they deal with the normal process itself. RT studies, of object naming in particular, can bring us much closer to this ideal...[becau-se]...object naming is a normal, everyday activity...[and]...reaction time measurement is still an ideal procedure for analyzing the time course of a mental process...(p. 2)

To further assess how *C* influences the process of speech production, we used an object-naming task (*a.k.a*. picture-naming task; Oldfield & Wingfield, 1965).

## 3. Method

### 3.1. Participants

Thirty native English speakers were recruited from the pool of Introductory Psychology students at the University of Kansas. Participants received credit towards the completion of a course requirement. All participants were right-handed with no reported history of speech or hearing disorders.

### 3.2. Materials

Black-and-white line drawings, like those from Snodgrass and Vanderwart (1980), for 56 English monosyllabic nouns consisting of a consonant-vowel-consonant structure were used as stimuli in this experiment (these words are listed in the Appendix, and an example of one

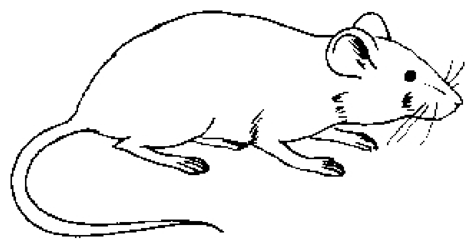

Fig. 2. The black-and-white line drawing depicting the stimulus word *mouse*.

of the images used in the experiment appears in Fig. 2). Half of the line drawings illustrated words with high *C* and the other half illustrated words with low *C*. In each condition, equal numbers of words contained the same initial phoneme.

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 the ratio of the actual number of links existing among neighbors of the target word to the number of all possible links among neighbors if every neighbor was connected (Batagelj & Mrvar, 1988). *C* has a range from 0 to 1. When $C = 0$, none of the neighbors of a target node are neighbors of each other. When $C = 1$, the network is fully interconnected, meaning every neighbor is also a neighbor of all the other neighbors of a target word. Words with high *C* had a mean value of 0.342 ($SEM = 0.012$) and words with a low *C* had a mean value of 0.277 ($SEM = 0.010$). The difference between the two groups of stimuli was statistically significant [$F(1, 54) = 17.13, p < .0001$].

Although the two sets of words differed significantly in *C*, the words were equivalent in subjective familiarity, word frequency, degree (i.e., neighborhood density), neighborhood frequency, phonotactic probability, and a number of other variables. Below we provide a description of each lexical characteristic. Table 2 contains the mean and standard error of the mean for each lexical characteristic.

*Subjective familiarity* was measured on a seven-point scale (Nusbaum et al., 1984); all the stimuli were highly familiar words. *Word frequency* refers to the average occurrence of a word in the language (Baayen et al., 1996; Kučera & Francis, 1967). *Degree* (a.k.a. neighborhood density) refers to the number of words that are similar to a target on the basis of the substitution, deletion, or addition of a single phoneme in any position of the target item (Luce & Pisoni, 1998). *Neighborhood frequency* is defined as the mean word frequency of the neighbors of the target word (Luce & Pisoni, 1998). *Phonotactic probability* was measured by assessing how often a certain segment occurs in a certain position in a word (positional segment frequency) and how often two segments occur next to each other in a certain position in a word (biphone frequency) using the Phonotactic Probability Calculator available via the Internet (Vitevitch & Luce, 2004).

*Spread of the neighborhood* (*P*) refers to the number of phoneme positions in a word that form a neighbor (Vitevitch, 2007). For example, when a single phoneme is substituted into the word *mob*, phonological neighbors are formed in only two phoneme-positions (e.g., *rob*, *mock*); no real word in English is formed when a single phoneme is substituted in the medial

Table 2
Mean (and standard error of the mean) for various lexical characteristics of the stimuli

| Lexical Characteristic | High $C$ | Low $C$ |
|---|---|---|
| Familiarity | 6.97 (.013) | 6.98 (0.011) |
| Frequency of occurrence (K&F $\log_{10}$) | 1.19 (0.02) | 1.34 (0.01) |
| Frequency of occurrence (CELEX) | 0.827 (0.111) | 0.961 (0.090) |
| Degree | 19.93 (1.34) | 20.96 (1.53) |
| Neighborhood frequency (log) | 1.04 (0.040) | 0.99 (0.034) |
| PP positional segment frequency | 0.157 (0.001) | 0.150 (0.001) |
| PP biphone frequency | 0.005 (0.0001) | 0.006 (0.0001) |
| Spread | 2.82 (0.104) | 2.93 (0.050) |
| $N_i$ | 35.5 (3.1) | 37.5 (2.9) |
| $N_m$ | 28.8 (3.1) | 27.5 (3.0) |
| $N_f$ | 35.7 (4.2) | 34.9 (3.1) |
| Imageability | 590 (8.8) | 573 (13.8) |
| Concreteness | 591 (6.0) | 593 (5.9) |
| Picture-name rating | 6.42 (0.073) | 6.36 (0.104) |
| Polysemy | 6.82 (0.997) | 7.11 (0.647) |
| Hypernymy | 8.61 (0.598) | 8.64 (0.464) |

*Notes.* None of the differences between groups were statistically significant (all $p > .05$). Log transformed values were used to reduce the skew typically observed in distributions of word frequency.

PP, phonotactic probability; $N_i$, percentage of neighbors formed by a substitution in the initial position; $N_m$, percentage of neighbors formed by a substitution in the medial position; $N_f$, percentage of neighbors formed by a substitution in the final position.

position of the word *mob*, giving *mob* a spread of 2. Spread was assessed using *N-Watch* (Davis, 2005). We also used *N-Watch* to assess the *percentage of neighbors formed in each phoneme position* in each word ($N_i$, $N_m$, $N_f$ in Table 2).

*Picture-name agreement* was assessed by a separate group of 20 undergraduate students at the University of Kansas who rated the picture-word pairs on a scale from 1 (the word does not describe the picture well) to 7 (the word describes the picture well). Previous studies have shown that pictures of living objects are named more quickly and accurately than pictures of nonliving objects (e.g., Takarae & Levin, 2001). For the high $C$ condition, there were nine living objects and 19 nonliving objects. For the low $C$ condition, there were 13 living objects and 15 nonliving objects. A two-way chi-square analysis showed that there was no difference between the two conditions with regard to the number of living and nonliving objects, $\chi^2(1, n = 56) = 1.20$, $p > .05$. The words were also comparable with regards to imageability, concreteness ratings (obtained from Coltheart, 1981), polysemy, and hypernymy (obtained from WordNet; Fellbaum, 1998).

Finally, another group of 23 undergraduate students at the University of Kansas took part in an object decision task. In this task, participants decided if the picture they saw was a real object or a nonobject (56 nonobjects were randomly selected from Kroll & Potter, 1984). This task allowed us to assess the potential influence that other factors related to the images themselves (e.g., object complexity, living vs. nonliving, etc.) might have on processing. The average reaction time for pictures with high and low $C$ were 598 ms ($SD = 75.71$)

and 593 ($SD = 73.03$) respectively. This difference was not statistically significant [$F(1, 22) < 1$] and raises doubts that visual or semantic properties of the pictures could account for the differences observed in the picture-naming task.

### *3.3. Procedure*

For the picture-naming task, participants studied a booklet that, on each page, contained a stimulus picture presented centrally along with its identifying name below it. This procedure familiarized the participants with the pictures and their names so as to minimize potential recency effects (i.e., participants respond differently to words as a function of the last time the words were retrieved; Burke, MacKay, Worthley, & Wade, 1991). When participants were confident that they could identify each picture with the given label, they were seated in front of an iMac computer running PsyScope 1.2.5, which controlled the randomization and presentation of stimuli, and collected response latencies. Participants used a headphone-mounted microphone (Beyerdynamic DT 109) interfaced to a New Micros response box, which acted as a voice-keyed switch to terminate a timer with millisecond accuracy.

In each trial, the word ''READY'' appeared on the computer screen for 500 ms. The participants were then presented with a randomly selected stimulus picture that remained visible until a verbal response was detected. The participants were instructed to name the picture as quickly and accurately as possible using the designated picture name (*N.B.*, the word did not appear on the screen). Reaction times were measured from the onset of the stimulus to the onset of the participant's verbal response. Another trial began 1 s after a response was made. The verbal responses were also recorded to aid in the assessment of accuracy. No picture was presented more than once. Prior to the experimental trials, each participant received five practice trials to become familiar with the task. These practice trials were not included in the data analyses.

## 4. Results and discussion

The recorded responses of each participant were scored for accuracy by a trained researcher. Only accurate responses were included in the analysis. Responses other than the given label (e.g., responding with ''rat'' instead of ''mouse'') were counted as errors. Reaction times that were more extreme than two standard deviations from the mean were considered outliers and were excluded from the analysis (accounting for less than 2% of the responses). Responses that triggered the voice-key improperly (e.g., coughing, ''uh'') were not included in the analyses (accounting for less than 1% of the responses).

Participants were highly accurate in naming the pictures. The mean accuracy rate for the high $C$ condition was 93% ($SD = 0.059$) and the mean accuracy rate for the low $C$ condition was 94% ($SD = 0.064$); this difference was not statistically significant [$F(1, 29) < 1$].

However, participants named words with high $C$ ($M = 772$ ms, $SD = 115.07$) more slowly than words with low $C$ ($M = 739$ ms, $SD = 94.77$; $F_1(1, 29) = 14.09$, $p = .001$;

$F_2(1, 54) = 2.58$, $p = .11$).[4] Although the observed difference is considered a small effect ($d = .313$), it has a high probability of being replicated ($p_{\text{rep}} = .986$; Killeen, 2005) and is in the predicted direction (in the subject and item analyses): Words with high *C* were named more slowly than words with low *C*. Consistent with the speech-error analysis, the result of the picture-naming task also suggests that it is more difficult to retrieve words with high rather than low clustering coefficient.

Taken together, the results from the speech-error analysis and the picture-naming task suggest that the structure of the lexical network—as measured by *C*—influences the cognitive processes associated with spoken word production (for influences in spoken word recognition see Chan & Vitevitch, 2009). Regions of the lexical network with high *C* create reservoirs of activation among similar sounding word-forms. With activation concentrated in a handful of similar sounding words, selection of the target word-form becomes more difficult. In contrast, regions with low *C* disperse activation to a wider region of the network, allowing the target word to ''stand out'' from the other candidates, making the process of lexical retrieval rapid and accurate.[5]

Observing such effects in the *cognitive* domain of language processing further expands the scope of the ''new'' science of networks (Watts, 2004). By continuing to examine other aspects of lexical structure—through experiments, corpus analyses, network analyses, and other approaches—we can better understand the structure of the lexicon, and how that structure may influence various aspects of spoken language processing. Just as previous versions of the network metaphor have reshaped and advanced our understanding of various psychological processes in significant ways, the current version of the network metaphor in the form of network science may have much to offer cognitive and neural sciences (e.g., Ferrer i Cancho & Sole, 2001; Sporns, Chialvo, Kaiser, & Hilgetag, 2004).

## Notes

1. Degree and *C* are not only different measures by definition, but empirically these measures are independent of each other. The correlation between degree and *C* for the 6,281 words with two or more neighbors (the minimum number of neighbors required to compute *C*) from the lexical network in Vitevitch (2008) is $r = .005$, $p = .68$.
2. As described in Chan and Vitevitch (2009) this pattern of results is also consistent with the hypothesis that lexical retrieval can be construed as a search through a lexical network in addition to the account based on spreading activation. Although experiments measuring lexical processing may not be able to distinguish between the two accounts, the structural analyses of Vitevitch (2008) and Arbesman, Strogatz, and Vitevitch (in press) favor the hypothesis that lexical retrieval might be better viewed as a search through a lexical network.
3. See Goldrick (2006) for a review of the difficulties that strictly feed-forward models of speech production have in accounting for the influence of phonological neighbors on the speed and accuracy of producing spoken words.

4. For a discussion of ''items analyses'' see Baayen (2004), Cohen (1976), Keppel (1976), Raaijmakers, Schrijnemakers, and Gremmen (1999), Smith (1976), and Wike and Church (1976) among others.
5. It is possible that reservoirs of activation might have a different influence later in processing, or in a different cognitive process. For example, Vitevitch, Chan, and Roodenrys (2009) found that lists comprised of words with high *C* were recalled more accurately than lists comprised of words with low *C* in a serial recall task, suggesting that reservoirs of activation may benefit the reconstructive memory process of reintegration.

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## Appendix

List of the stimulus items used in the picture-naming experiment

| High *C* | Low *C* |
|---|---|
| Badge | Bat |
| Bun | Bed |
| Bib | Beach |
| Book | Bush |
| Bull | Boot |
| Doll | Duck |
| Gun | Goat |
| Keg | Cat |
| Cake | Cup |

Appendix: (Continued)

| | |
|---|---|
| Cane | Cape |
| Cave | Kid |
| Coin | King |
| Cook | Couch |
| Lawn | Lung |
| Mop | Mouse |
| Pig | Palm |
| Pin | Pen |
| Pool | Pearl |
| Pipe | Purse |
| Wreath | Rope |
| Rose | Rice |
| Seal | Soap |
| Sheep | Sheet |
| Tail | Tongue |
| Teeth | Tire |
| Web | Watch |
| Witch | Wedge |
| Wine | Wing |