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Authors
Qiu, Mengyang
Castro, Nichol
Johns, Brendan

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Mengyang Qiu (mengyang@buffalo.edu)
Department of Communicative Disorders and Sciences, University at Buffalo
Buffalo, NY 14214 USA

Nichol Castro (nicholca@buffalo.edu)
Department of Communicative Disorders and Sciences, University at Buffalo
Buffalo, NY 14214 USA

Brendan T. Johns (brendan.johns@mcgill.ca)
Department of Psychology, McGill University
Montreal, QC H3A 1G1 Canada

Abstract

Recent studies have applied network-based approaches to analyze the organization and retrieval of specific semantic categories, with a focus on the animal category. The current study extended previous studies by using network science tools to quantitatively investigate the structural differences of noun and verb categories of various levels of specificity. Specific (*animal* and *body movement*) and general noun and verb networks were constructed from four verbal fluency tasks. Common network measures indicated that the two verb networks were more condensed and less modular than the noun networks, supporting that nouns are more well-organized in the mental lexicon than verbs. Comparing the specific and general networks within each lexical category also corroborated lexical semantic studies that nouns have a more clear hierarchical structure. The results of this paper, along with recent semantic network studies, provide converging evidence for the usefulness of network science in semantic memory research.

Keywords: semantic memory; mental lexicon; semantic fluency; network analysis

Introduction

With the advances in network science and graph theory, network-based approaches have become increasingly popular in representing and analyzing complex systems with many interacting components, including human cognitive systems (Castro & Siew, 2020). For example, many studies over the past two decades have conceptualized semantic memory (i.e., the mental lexicon) as semantic networks, where words/concepts are represented as nodes and links/edges between nodes represent certain semantic relatedness (see Figure 1; for a review, see De Deyne, Kenett, Anaki, Faust, & Navarro, 2017).

Semantic networks can be constructed from a variety of sources, such as language corpora (e.g., Wikipedia; Thompson & Kello, 2014), a thesaurus (e.g., WordNet), and human behavioral data (Steyvers & Tenenbaum, 2005). Free association and verbal fluency data are the two most commonly used behavioral data types to create semantic networks. Semantic verbal fluency, in particular, has become the focus of attention in many studies because of its efficiency in estimating networks of specific semantic categories (Zemla & Austerweil, 2018). In a semantic verbal fluency task, individuals produce as many exemplars of a given category as possible within a given time limit.

Most of the network studies of semantic verbal fluency have focused primarily on the animal category. The main advantages of using this specific category include its easiness for participants to understand and its universality across different languages, cultures, and generations (Ardila, Ostrosky-Solís, & Bernal, 2006). However, another semantic/lexical category, namely verbs, though being universal (Hopper & Thompson, 1985), has received far too little attention compared to the animal category or noun-based categories in general. From a lexical semantics perspective, verbs and nouns are distinct in systematic ways. In addition to the differences in semantic content (i.e., 'actions' or 'events' vs. 'entities'), noun-based categories, especially animals, have a clear taxonomic/hierarchical structure, while verb-based categories do not (Graesser, Hopkinson, & Schmid, 1987; Huttenlocher & Lui, 1979).

Several neuropsychological studies compared verb and animal fluency, and it was found that different clinical populations may show different impairments in these two fluency tasks. For example, people with frontotemporal dementia are more impaired in verb fluency, while those with Alzheimer's disease have more problems in animal fluency (Davis et al., 2010). However, these studies only examined the number of correct responses. It would be interesting to further evaluate the pattern of production and the underlying organizational differences in these verbal fluency tasks.

Recently, Qiu and Johns (2021) analyzed the role of word frequency and several types of pairwise similarity in noun- and verb-based fluency tasks. The pairwise similarities include *context* (i.e., word co-occurrence that captures semantic information) and *order* (i.e., relative position of a word that captures simple syntactic information) similarities derived from a semantic space model (BEAGLE; Jones & Mewhort, 2007) trained on a large corpus of fiction and nonfiction books (Johns, Dye, & Jones, 2020), and *perceptual* similarity from sensorimotor norming data (Lynott, Connell, Brysbaert, Brand, & Carney, 2020). In their first experiment, they found significant differences across word frequency and three pairwise similarities between animal and verb fluency. Specifically, verbs produced were of higher word frequency and clustered more on context similarity, while the animal words produced were higher in order and sensorimotor similarities.

However, the criterion of verb fluency is more general and imposes little semantic constraint, while animal fluency is more specific and has a clear semantic boundary. To minimize a potential confound of the specificity of category cue, Qiu and Johns (2021) conducted a second experiment that contrasted a general noun fluency task (instruction: *names of any living or non-living things*) and a specific verb fluency task (instruction: *actions that involve your body movement*). Though the category specificity was flipped in the second experiment, they found consistent differences across the four linguistic and perceptual dimensions, signaling the systematic distinctions of the organization of nouns and verbs in the mental lexicon.

The primary goal of the present study is to further investigate the underlying organizational differences of nouns and verbs in the mental lexicon from a network science point of view. Through network analysis of the noun- and verb-based fluency data in Qiu and Johns (2021), it will be shown that the two lexical categories differ quantitatively from each other across common network parameters. This paper also set out to explore how category cue specificity influences the overall network structure within the same lexical category. It will be shown that category cue specificity changes network parameters in a way consistent with the underlying organization of nouns and verbs. The results will point to the importance of including other category cues of various levels of specificity in verbal fluency, in addition to the animal category, to study semantic memory organization, search, and retrieval.

Background

In a semantic fluency task, participants are required to produce as many different words as they can from a given semantic category (e.g., *animals* or *vegetables and fruits*) within a fixed time interval (typically 1 minute). The general pattern of words produced in semantic fluency is called *clustering*; that is, words that are semantically related to each other tend to be produced in succession or close proximity. Semantic relatedness was originally operationalized as word subcategories (e.g., *pets*, *sea animals* and *Australian animals* for the *animal* category; Troyer, Moscovitch, & Winocur, 1997). Hills and colleagues expanded it to local semantic similarities (i.e., pairwise similarity between adjacent words) derived more objectively from natural language corpora. When no semantically proximal word is available in the current cluster, participants will use word frequency to *switch* to a new cluster and start the *clustering* process again (Hills, Jones, & Todd, 2012; Hills, Todd, & Jones, 2015).[1]

Given this cluster-and-switch pattern, one efficient and psychologically plausible way to construct semantic networks from semantic fluency data is to form an edge connecting each pair of successive words.[2] Representing the mental lexicon as semantic networks have a number of advantages. In addition to its visual simplicity and intuitivity, network science has allowed for an explicit examination of the structural properties of semantic networks at micro-, meso-, and macroscopic levels. Common measures of semantic networks include the **degree** (number of edges of a node) and its distribution, **clustering coefficient** (CC; measuring the density of a network by calculating the probability of two neighbors of any random node being connected), **average shortest path length** (ASPL) between pairs of randomly chosen nodes, and **modularity** (measuring the presence of densely connected communities of nodes in a network; De Deyne et al., 2017).

One important global feature of semantic networks, similar to many social and biological networks, is the **small-world** structure, which is mainly characterized by a combination of relatively high CC and low ASPL compared to equally dense random networks (Watts & Strogatz, 1998). Specifically, a small number of words are more densely connected to other words (i.e., having a much higher degree), serving as the hubs to support short path lengths in the networks. The small-worldness in semantic networks may contribute to efficient memory search and retrieval (De Deyne et al., 2017).

Analyzing and contrasting these measures have provided important insights into the organizational differences and changes of the mental lexicon in bilingualism (Borodkin, Kenett, Faust, & Mashal, 2016) and various clinical populations (e.g., children with cochlear implants, Kenett et al., 2013; people with neurodegenerative disorders, Lerner, Ogrocki, & Thomas, 2009). For example, Lerner et al. (2009) and Bertola et al. (2014) employed the aforementioned network estimation method, and constructed separate networks for participants with mild cognitive impairment (MCI) and Alzheimer's disease (AD) and healthy elderly controls from their animal fluency data. Both studies found that network properties start to change (e.g., ASPL decreases and CC increases) from normal aging to MCI, and these changes continue as cognitive impairment worsens. Their results demonstrated the validity of constructing semantic networks directly from verbal fluency data and the usefulness of network science in detecting semantic memory changes.

Method

Verbal Fluency Data

Verbal fluency data were taken from the two experiments in Qiu and Johns (2021).[3] In their study, fifty participants recruited from Amazon Mechanical Turk completed animal and verb fluency tasks, and fifty-six participants completed noun and body movement fluency tasks. The total number of dis-

[1] Although researchers generally agree on the clustering process, there are competing views on the mechanism underlying switching (i.e., whether people use cue switching; Abbott, Austerweil, & Griffiths, 2015; Avery & Jones, 2018).

[2] For a review of other methods with various statistical inferences, see Zemla and Austerweil (2018).

[3] Available at https://osf.io/cgdr2/.

tinct words (i.e., word type) produced and the average number of words produced by a participant in each fluency task are summarized in Table 1.

Table 1: Overall number of word types produced across participants and average number of word types produced per participant in the four verbal fluency tasks in Qiu and Johns (2021).

	Animal	Noun	Body Movement	Verb
Overall	205	492	232	319
Average ($\pm$ SD)	23.10 ± 5.12	25.14 ± 7.53	15.84 ± 5.18	19.52 ± 5.36

Network Construction

Network construction and analyses were performed using the igraph (Csárdi & Nepusz, 2006) and qgraph (Epskamp, Cramer, Waldorp, Schmittmann, & Borsboom, 2012) packages in R (R Core Team, 2020). A semantic network was constructed separately from the pooled responses for each verbal fluency task, with nodes representing every word type produced by at least three participants, and edges connecting words produced in succession, similar to Lerner et al. (2009) and Bertola et al. (2014).

However, since words produced together can either be within the same semantic cluster or a switch from one cluster to another (Hills et al., 2012), networks constructed this way will necessarily include spurious links between unrelated / weakly related words. This problem will be more pronounced when the fluency dataset is very large, which may lead to a fully connected network (Zemla & Austerweil, 2018).

To minimize the presence of spurious links, some studies suggest to use a threshold to only include those adjacent pairs produced certain times (e.g., at least three times; Christensen & Kenett, 2019). In this study, we used two filtering methods. First, we only included the words produced at least three times as the nodes, a weak version of the threshold method. Second, we used each individual's mean inter-item response time (IRT) to filter out the switching pairs. Hills et al. (2012) found that IRTs for switching pairs are typically longer than the mean IRT because it takes extra time to 'give up' the current cluster and look for a new cluster. Therefore, before pooling all the word pairs, we calculated each participant's mean IRT, and removed those pairs with IRTs equal to or great than the mean IRT for each participant. An analysis of similarity values from Qiu and Johns (2021) further confirmed that the removed pairs have significantly lower context and order similarities in all four verbal fluency tasks (Table 2).

Following the conventions of previous studies, we further simplified the networks as undirected (e.g., $cat \rightarrow dog$ is the same as $dog \rightarrow cat$) and unweighted (e.g., multiple occurrences of $cat - dog$ do not increase the strength of connections between the two words) networks. Additionally, all analyses were performed on the giant components (i.e., the largest connected subgraph) extracted from the undirected and unweighted networks. These procedures allow us to capture the essential information in structural comparisons of semantic networks (Borodkin et al., 2016).

Table 2: Mean pairwise context and order similarities (Qiu & Johns, 2021) for word pairs with IRTs below vs. above the mean IRT.

	Context			Order		
	IRTs < Mean	IRTs ≥ Mean	t	IRTs < Mean	IRTs ≥ Mean	t
Animal	0.31	0.25	5.69^{***}	0.82	0.80	1.78^{*}
Noun	0.30	0.21	8.97^{***}	0.82	0.78	3.30^{***}
Body Movement	0.36	0.26	6.71^{***}	0.69	0.61	5.14^{***}
Verb	0.37	0.28	4.87^{***}	0.68	0.61	3.19^{**}

$^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$

Network Measures and Comparisons

Common network parameters were calculated as in previous studies (e.g., Borodkin et al., 2016), including the average degree, clustering coefficient (CC), average shortest path length (ASPL), and modularity (Q index). To evaluate the small-worldness, we simulated 1,000 Erdős-Rényi random networks (Erdős & Rényi, 1960) with equal number of nodes and edges to each network independently, and obtained a distribution of CC_{random} and ASPL_{random}. CC and ASPL in each semantic network were compared to the corresponding CC_{random} and ASPL_{random}. If a network has the small-world structure, its CC is much larger than the CC_{random}, and the ASPL is similar to or marginally larger than the ASPL_{random}. A one-sample z-test was also conducted separately for the two parameters to assess whether the semantic networks were significantly different from their corresponding simulated random networks. In addition, the small-worldness index (S), which is based on the trade-off between CC and ASPL (Humphries & Gurney, 2008), was also computed for each semantic network to verify the presence of small-worldness (S value above 1 indicates small-worldness).

Two types of comparisons were carried out among the four semantic networks. First, noun-based and verb-based networks were contrasted to each other while controlling for the category cue specificity. That is, the network from the general noun fluency was compared to the one from the general verb fluency, and the specific noun network (*animal*) was compared to the specific verb network (*body movement*). However, given that most previous neuropsychological studies directly compared animal and verb fluency, this contrast was also included. Second, networks within the same lexical category were contrasted to each other (*animal* vs. *noun* and *body movement* vs. *verb*) in order to examine the effects of category cue on network parameters.

Since the networks have different numbers of nodes, which will in turn affect all the network parameter values, direct comparisons of the networks will likely introduce confounds and lead to alternative explanations (Kenett et al., 2013). Therefore, we used a sub-network bootstrap procedure as in Borodkin et al. (2016) and simulated 1,000 partial networks with a fixed number of randomly selected nodes for each semantic network. The number was computed as half of the

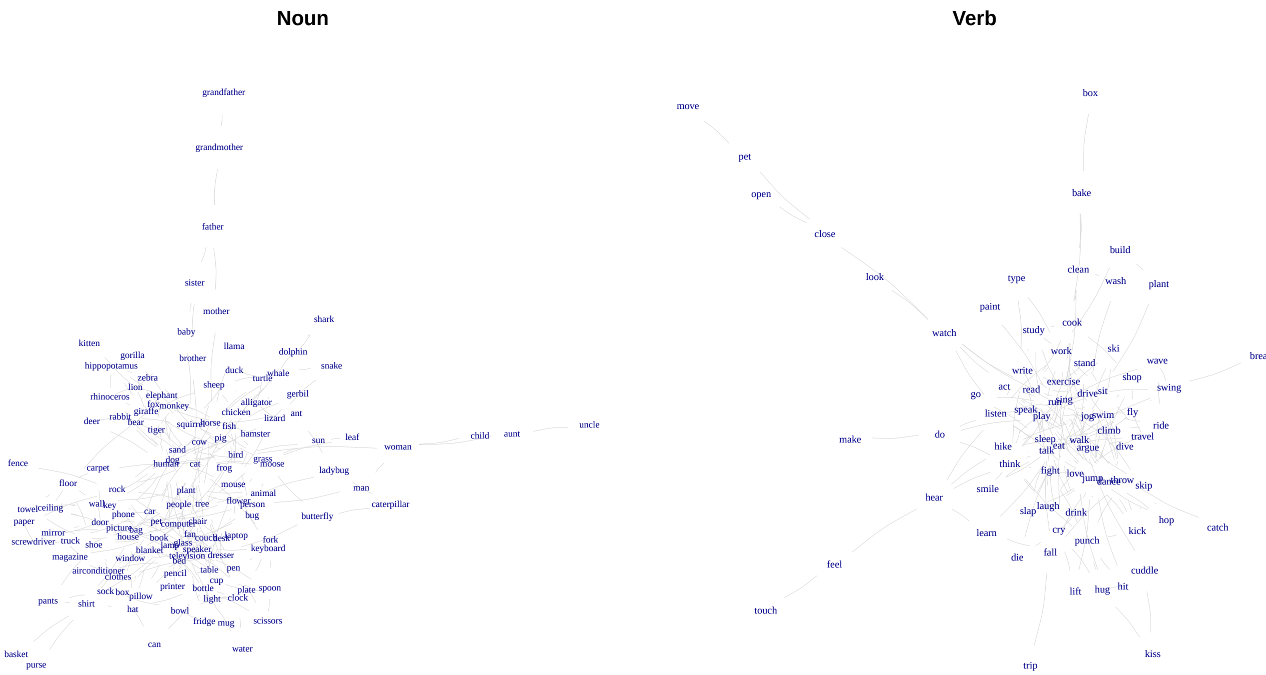

Figure 1: Networks (giant components) constructed from the general noun fluency (left) and the general verb fluency (right).

mean number of nodes across the four networks. The network parameters (CC, ASPL and modularity) of the random partial networks for each semantic network were then compared via independent samples t-tests, with the assumption that any structural differences between the original networks will also emerge in their corresponding sub-networks.

Results

Semantic networks constructed from the general noun and verb fluency tasks are shown in Figure 1. Table 3 presents the parameter values of the four semantic networks. All the four networks were significantly different from the simulated random networks, as revealed by the z-tests between CC and CC_{random}, and ASPL and $ASPL_{random}$ (p's $< .001$). In addition, all the four networks showed small-world properties (i.e., $CC \gg CC_{random}$ and $ASPL \geq ASPL_{random}$), which was further supported by the small-world index values (all $S > 1$).

Parameter values and comparisons of the bootstrapped partial networks are presented in Table 4 and Table 5, respectively. First, between lexical categories, there was a significant difference between noun- and verb-based networks. The CC of the general verb network was higher than that of the general noun network, while the ASPL and the modularity index of the former were smaller than the latter. The comparisons between the two specific networks (*animal* vs. *body movement*) and between the animal and verb networks showed similar patterns. This indicates that compared to nouns, verb organization is more condensed and less modular.

Within the noun category, the ASPL and the modularity index were significantly larger in the general noun network than in the animal network, indicating that the general noun network was more distributed and had more communities. The CC of the general noun network was also significantly lower than that of the animal network, further supporting that the general noun network was more spread out. However, this pattern was not clear in the verb category. The general verb network was more densely connected than the body movement network. However, Cohen's d effect size showed that the differences in ASPL and modularity were small in the two verb-based networks, suggesting that the specific verb network was similar to the general one.

Table 3: Parameters of the four semantic networks.

	Animal	Noun	Body Movement	Verb
Nodes	97	130	79	78
Edges	337	359	260	241
Average degree	6.95	5.52	6.58	6.18
CC	0.21	0.15	0.20	0.24
ASPL	2.61	3.17	2.61	2.85
Small-worldness (S)	1.44	1.86	1.24	1.27
Modularity (Q)	0.35	0.47	0.31	0.33
CC_{random}***	0.07	0.04	0.08	0.08
$ASPL_{random}$***	2.55	3.01	2.50	2.56

$^{***}p < .001$

Table 4: Parameters of bootstrapped partial networks.

	Animal	Noun	Body Movement	Verb
Nodes	48	48	48	48
CC	0.20 ± 0.05	0.14 ± 0.06	0.20 ± 0.05	0.23 ± 0.05
ASPL	3.06 ± 0.31	3.67 ± 0.58	2.78 ± 0.22	2.82 ± 0.25
Modularity (Q)	0.45 ± 0.06	0.59 ± 0.07	0.39 ± 0.05	0.38 ± 0.05

Table 5: Comparisons of bootstrapped partial networks.

	CC		ASPL		Modularity (Q)	
	t	Cohen's d	t	Cohen's d	t	Cohen's d
Between lexical categories						
Animal vs. Body Movement	0.31	0.01	22.78^{***}	1.02	27.25^{***}	1.22
Animal vs. Verb	-14.67^{***}	0.66	18.49^{***}	0.83	27.28^{***}	1.22
Noun vs. Verb	-35.75^{***}	1.60	42.38^{***}	1.90	75.54^{***}	3.38
Within lexical category						
Animal vs. Noun	22.77^{***}	1.02	-29.23^{***}	1.31	-49.73^{***}	2.22
Body Movement vs. Verb	-15.50^{***}	0.69	-3.87^{***}	0.17	1.85	0.08

$^{***}p < .001$

Discussion

The goal of this article was to employ network science tools to quantitatively assess the organizational differences in nouns and verbs. We constructed specific (*animal* and *body movement*) and general noun and verb networks from the four verbal fluency tasks in Qiu and Johns (2021). Results of the network analysis revealed systematic differences in the global network structure of the two lexical categories.

All four networks showed small-world properties, including much larger clustering coefficient (CC) and similar average shortest path length (ASPL) compared to random networks. However, the small-worldness index (Humphries & Gurney, 2008) revealed that there was a decrease in small-worldness in the two verb networks, suggesting that verbs are less well-organized than nouns.

This was further supported by the parameter comparisons of the bootstrapped partial networks. Common network measures, particularly the ASPL and the modularity index, showed that noun networks, regardless of specific or general, were less condensed and had a more clear community structure. These differences between the noun and verb networks resembled those between the animal networks from healthy controls and people with neurodegenerative disorders (Lerner et al., 2009). The less well-organized structure of verb networks may explain why verb fluency can be differentially impaired than animal fluency in people with mild cognitive impairment (Östberg, Fernaeus, Hellström, Bogdanović, & Wahlund, 2005).

Comparisons of the specific and general networks within the noun category also showed patterns consistent with its hierarchical structure. That is, the more general the category is, the more subordinating categories it may contain (Miller, 1998). The significant increase of the ASPL and the modularity index and decrease of the CC from the specific animal network to the general noun network (all Cohen'$d > 1$) indicated the general noun network was more distributed and contained more subordinating communities. A clear separation of living and non-living things and their sub-categories can be seen in the general noun network (Figure 1). No such pattern was found within the verb category, which is also consistent with the more flat organization of verbs (Fellbaum, 1998). The results of these within-category comparisons also corroborated the findings in Qiu and Johns (2021) that participants may engage in more global switching in noun fluency tasks as nouns have more natural category structures. Future work could examine noun fluency with various levels of category cue specificity (e.g., $organism \rightarrow animal \rightarrow fish$, or $object \rightarrow artifact \rightarrow tool$), which may shed additional light on semantic memory organization and search, and may potentially provide diagnostic information for people with various levels of cognitive impairment.

The present study used a two-step network filtering method, namely, a traditional method based on word co-occurrence thresholds with an additional inter-item response time (IRT) filtering. Different IRT patterns for within- and between-cluster pairs have been reliably observed in previous verbal fluency studies (Wixted & Rohrer, 1994; Hills et al., 2012). The present study directly utilized this information in network construction. Future work could compare this filtering method with other advanced group-level semantic network estimation methods (e.g., community network with statistical inferences of word co-occurrences, Goñi et al., 2011; correlation-based network, Kenett et al., 2013) to see if similar structural differences of noun and verb networks could be observed.

Conclusion

Although the organizational differences of nouns and verbs have been well documented in theoretical linguistics, and have been discussed extensively in the psycholinguistic and neurolinguistic literature (Vigliocco, Vinson, Druks, Barber, & Cappa, 2011), we showed here that by examining the network measures, these qualitative differences can be quantitatively compared and contrasted. Moreover, the quantitative differences derived from the network measures fit well in the general framework of lexical semantics of nouns and verbs. The results contained in this paper, along with recent semantic network studies, demonstrate the validity of network-based approaches in semantic memory research.

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