Journal of Memory and Language 67 (2012) 30–44

Contents lists available at SciVerse ScienceDirect

Journal of Memory and Language

journal homepage: www.elsevier.com/locate/jml

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

Michael S. Vitevitch[a,*], Kit Ying Chan[a], Steven Roodenrys[b]

[a] Department of Psychology, 1415 Jayhawk Blvd., University of Kansas, Lawrence, KS 66045-7556, United States
[b] School of Psychology, University of Wollongong, Northfields Avenue, Wollongong, NSW 2522, Australia

ARTICLE INFO

Article history:
Received 23 August 2011
revision received 9 February 2012
Available online 16 March 2012

Keywords:
Network science
STM
LTM
Clustering coefficient
Mental lexicon

ABSTRACT

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

Introduction

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

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

* Corresponding author. Address: Spoken Language Laboratory, Department of Psychology, 1415 Jayhawk Blvd., University of Kansas, Lawrence, KS 66045, United States.

E-mail address: mvitevit@ku.edu (M.S. Vitevitch).

0749-596X/$ - see front matter © 2012 Elsevier Inc. All rights reserved.
doi:10.1016/j.jml.2012.02.008

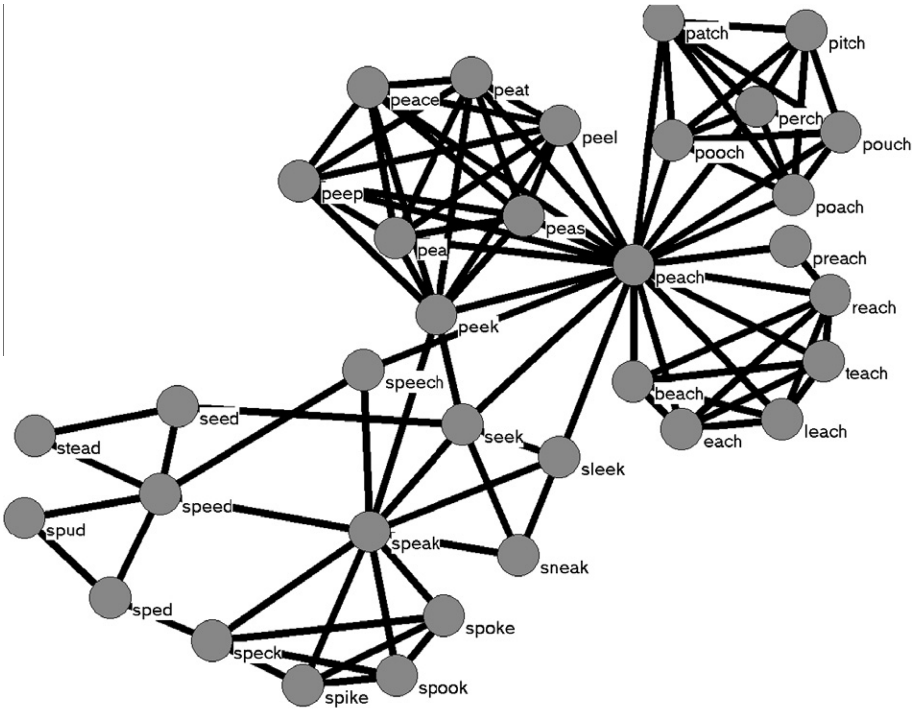

Fig. 1. A sample of words from the phonological network analyzed in Vitevitch (2008). The word "speech" and its phonological neighbors (i.e., words that differ by the addition, deletion or substitution of a phoneme) are shown (i.e., 1-hop neighbors of "speech"). The phonological neighbors of those neighbors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

Maouene, Maouene, Sheya, & Smith, 2009). A sample of words from the network examined by Vitevitch (2008) is shown in Fig. 1.

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

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

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

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

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