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Openness to experience—the enjoyment of novel experiences, ideas, and unconventional perspectives—has shown several connections to cognition that suggest open people might have different cognitive processes than those low in openness. People high in openness are more creative, have broader general knowledge, and show greater cognitive flexibility. The associative structure of semantic memory might be one such cognitive process that people in openness differ in. In this study, 497 people completed a measure of openness to experience and verbal fluency. Three groups of high ($n = 115$), moderate ($n = 121$), and low ($n = 118$) openness were created to construct semantic networks—graphical models of semantic associations that provide quantifiable representations of how these associations are organized—from their verbal fluency responses. The groups were compared on graph theory measures of their respective semantic networks. The semantic network analysis revealed that as openness increased, the rigidity of the semantic structure decreased and the interconnectivity increased, suggesting greater flexibility of associations. Semantic structure also became more condensed and had better integration, which facilitates open people's ability to reach more unique associations. These results were supported by open people coming up with more individual and unique responses, starting with less conventional responses, and having a flatter frequency proportion slope than less open people. In summary, the semantic network structure of people high in openness to experience supports the

retrieval of remote concepts via short associative pathways, which promotes unique combinations of disparate concepts that are key for creative cognition.

PREVIEW

REMOTELY CLOSE ASSOCIATIONS: OPENNESS
TO EXPERIENCE AND SEMANTIC
MEMORY STRUCTURE

by

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CHAPTER I

INTRODUCTION

Why are open people creative? There's a wealth of research that supports the relationship between the Big Five dimension of openness to experience (hereafter, openness) and creativity. But only a handful of studies have investigated possible processes that facilitate their association. For instance, open people have a general tendency to explore and diversify experiences (DeYoung, 2014), which has been shown to enhance cognitive flexibility—the ability to break old cognitive patterns, overcome functional fixedness, and make novel associations between concepts (Guilford, 1967; Ritter et al., 2012). Moreover, other factors, such as the motivation to learn and obtain broad general knowledge, also contribute to the connections between openness and creativity.

So far, few studies have examined underlying cognitive factors—such as the organization of memory—that might support their association. Recent research has investigated the structure of semantic memory and found that creative people have more flexible, interconnected associations between concepts than people who are less creative (Kenett, Anaki, & Faust, 2014). Given these findings, the structure of semantic memory might be a cognitive factor that is also linked to openness to experience. Thus, the present study compared the organization of semantic associations across high, moderate, and low levels of openness using a computational network approach.

Semantic Networks

Semantic memory is our knowledge about the world, such as word meanings, concepts, and categorization of facts (Jones, Willits, Dennis, & Jones, 2015). The structure of semantic memory was first investigated in a seminal paper by Collins and Quillian (1969), who found semantic memory was organized into hierarchical categories, starting from more general to increasingly specific exemplars. Their ideas set the foundation for semantic memory to be investigated as categorizations of within-level and between-level features, which have connections that extend across an association hierarchy. They proposed that semantic memory could be represented as a sprawling web of highly structured associations between concepts—like a network (Steyvers & Tenenbaum, 2005). Furthermore, Collins and Loftus (1975) theorized that search through semantic memory was the result of activated associations between concepts. Their theory of spreading activation suggests that the organization of associations can affect the efficiency of search and the amount of associations available in memory. Finally, Anderson (1983) proposed the ACT model, which suggests that cognitive units (e.g., semantic concepts) form an interconnected network where retrieval is supported by spreading activation throughout the network. Moreover, the level of activation determines the rate and probability of recall as well as the potential for interference of retrieval. In this way, associative strength and proximity indicate the likelihood a semantic concept will be retrieved from long-term memory.

Despite these pivotal experiments, the complexity of semantic relations has made measuring the structure of semantic memory a difficult problem. The development of

network science and computational graph theory, however, has provided a way to make meaningful inferences into the organization of semantic memory by using web-like graphs to investigate the associations between concepts.

Over the last decade, networks have been used by an expanding number of scientific disciplines to model complex phenomena and to reveal underlying structure in otherwise large, chaotic sets of data (Barabási, 2012; Newman, 2010). In theory, a network is simple. A network is a graph with *nodes*—vertices—connected by *edges*—relations—to other nodes. In an *undirected* network, edges are bidirectional; in a *directed* network, relationships are directional. In addition to direction, edges can be *weighted*, which signifies the strength of a relationship between two nodes. In a semantic network, it's common to represent a node as an exemplar of a category (e.g., an animal) or an association to a target word (e.g., spoon), and edges—undirected and unweighted—as the semantic relatedness between exemplars or word associations (Borge-Holthoefer & Arenas, 2010; De Deyne et al., 2016; Kenett et al., 2013). Connections between nodes in a network form *paths*, a sequence of associations from a *starting* node to an *ending* node, so that distances between nodes suggest relational differences in the network. The number of edges between two nodes is called a *path length*, which has important implications for network structure. Finally, *cliques* are connections between a set of three nodes that form a fully connected subgraph (i.e., a triangle).

There are many different ways to measure network structure that imply quantifiably different meanings. For example, *macro* measures examine organization of the entire network and characterize global features, while *micro* measures investigate the

influence—the connections and positions—of individual nodes in the network (Boccaletti, Latora, Moreno, Chavez, & Hwang, 2006; Borge-Holthoefer & Arenas, 2010). For the purposes of this study, I'll focus on macro measures and interpret their meaning with reference to semantic networks.

The *average shortest path length* (ASPL) is the mean distance between any two nodes in the network. The ASPL is often referred to as *degrees of separation*: lower values suggest greater interconnectivity between all nodes in the network (Watts & Strogatz, 1998). In semantic networks, short path lengths represent smaller distances between category exemplars like *axolotl* and *albatross*, while greater ASPL suggests greater distance between all exemplars (Faust & Kenett, 2014). Another important measure is the *clustering coefficient* (CC), which refers to the extent to which two neighbors of a node will be neighbors themselves—that is, whether two connected nodes will both be connected to a third node. In this way, the CC represents how “cliquish” the network is and indicates finer, more localized organization of semantic information.

Semantic networks range on these two measures of topology (i.e., ASPL and CC) from regular (ordered) to random (chaotic; Faust & Kenett, 2014). *Regular* networks have large clustering coefficients and high ASPL, with connections to their neighbors and their neighbors' neighbors—referred to as a lattice. *Random* networks are poorly clustered (small CC) and mostly have cross-network connections characterized by small ASPL values. Networks that make up the intermediate spectrum are called “*small-world*” networks, which have large CC and small ASPL (Watts & Strogatz, 1998). For visual representation of regular, random, and small-world graphs, see Figure 1. Small-world

networks have been reported in many phenomena, including semantic networks (Borge-Holthoefer & Arenas, 2010; Steyvers & Tenenbaum, 2005). A small-worldness measure can be computed by comparing the CC and the ASPL of the networks generated by the data to an equivalent random graph. The formula for small-worldness is expressed as:

$$S = \frac{\frac{CC}{CC(random)}}{\frac{ASPL}{ASPL(random)}}$$

Networks are considered “small-worlded” when this ratio is greater than one (Humphries & Gurney, 2008). In semantic networks, *small-worldness* (S) measures the degree to which the network has a high clustering coefficient and small ASPL. Higher S allows more flexibility and efficient access to associations in a semantic network, with more shortcuts between localized conceptual relations (Benedek, Kenett, Umdasch, Faust, & Neubauer, 2017; Borge-Holthoefer & Arenas, 2010). An increasing small-worldness measure without structure, however, reflects increasing “chaos” or randomness (Faust & Kenett, 2014; Kenett et al., 2016a). Thus, lower small-worldness suggests decreased flexibility and increased order between associations. Lower small-worldness, specifically higher ASPL, typically means a wider *diameter* (D) because connections are relatively limited in their cross-network connectivity and there is more distance between remote concepts. A small diameter suggests a tight, condensed network, which promotes shorter links between concepts in the network. In general, D, ASPL, and S measures are directly related.

Finally, *modularity* (Q) is a measure of network communities or compartmentalized sections of a network. Greater modularity suggests greater partitioning, which is represented by segregated groupings of nodes in the network (Newman, 2006). In a semantic network, these groupings suggest sub-categories of a larger category. For example, in a network of animals, sub-categories might be pets, neighborhood, and zoo animals. Therefore, modules signify *meso*—mid-level—structure (Borge-Holthoefer & Arenas, 2010). Higher modularity grants greater structure to a semantic network but at the cost of lower flexibility and more rigid categorizations, which is seen in some clinical samples (Faust & Kenett, 2014; Kenett, Gold, & Faust, 2016b). Therefore, modularity measures structural properties of the network as well as the rigidity of associations. In summary, an effective balance of structural (Q and ASPL) and chaotic (S) properties reflects optimal semantic integration between rigidity and randomness (Benedek et al., 2017; Faust & Kenett, 2014; Kenett et al., 2016a).

Semantic networks can help us understand the complex and convoluted organization of semantic memory structure (Borge-Holthoefer & Arenas, 2010; De Deyne et al., 2016; Steyvers & Tenenbaum, 2005). Semantic memory is an important function in human cognition that affects language, how we categorize information about the world, and our ability to recognize situations. Using network models, we can glean valuable inferences about the development of language, second languages, differences in cognition, and psychological disorder (Borodkin, Kenett, Faust, & Marshal, 2016; De Deyne et al., 2016; Kenett et al., 2016b; Steyvers & Tenenbaum, 2005; Vitevitch, Chan, & Roodenrys, 2012). Representing semantic information in networks allows us to ask

many questions: What is the structure of semantic memory? Do semantic networks complement biological networks? Or, as I explore below, how does semantic memory structure relate to personality traits, specifically openness to experience?

Openness to Experience, Cognition, and Semantic Memory

Why would openness to experience be related to semantic memory? One reason is that openness to experience, more than any other personality trait, is linked to several different cognitive abilities such as intelligence, working memory, and creativity (DeYoung, 2014; DeYoung, Quilty, Peterson, & Gray, 2014; Kaufman et al., 2010). Indeed, in an examination of behavioral, affective, and cognitive processes related to Big Five personality traits, openness to experience was found to be epitomized by cognition (Zillig, Hemenover, & Dienstbier, 2002). Moreover, openness has also been linked to memory processes such as the experience and usage of autobiographical recollections (Rasmussen & Berntsen, 2010). The use of autobiographical recall has been shown to support the strategic search of semantic memory, allowing more efficient retrieval from long-term memory (Unsworth, Brewer, & Spillers, 2014).

Finally, there are theoretical connections that suggest there should be significant links between semantic memory and openness to experience (DeYoung, 2014, 2015). For example, semantic memory has been proposed as the root of imagination (Abraham & Bubic, 2015) and central to creativity (Mednick, 1962). These processes—imagination and creativity—are considered to be core characteristics of people high in openness to experience (DeYoung, Grazioplene, & Peterson, 2012; Oleynick et al., 2017; Saucier,

1992). But despite these intermediary connections, the relation between semantic memory and openness to experience have yet to be empirically examined.

The association between crystallized intelligence and openness to experience is a common finding in the personality and individual differences literature. In the Carroll-Horn-Cattell (CHC) model of intelligence, crystallized intelligence is defined by the acculturation of knowledge over time, including language, information, and concepts of a specific culture (McGrew, 2009). The breadth and depth of this knowledge is acquired by formal and informal education as well as general life experiences (McGrew, 2005). For example, open people are more likely to spend their time reading fiction, non-fiction, and fantasy book genres for pleasure (Finn, 1997; Mar, Oatley, & Peterson, 2009; McManus & Furnham, 2006). Thus, they engage with semantic and verbal information more often than people low in openness to experience, making them more likely to accumulate more semantic knowledge. Moreover, because open people have a tendency to engage in a broad diversity of experiences, it's likely that they accrue a lot of general knowledge. Indeed, longitudinal evidence has shown that early stimulation seeking is related to greater general intelligence at later ages (Raine et al., 2002). Raine and colleagues suggest that these curious children create enriched environments for themselves that stimulate cognitive development.

Open people's curiosity and motivation to learn is a hallmark of the trait, which makes them more likely to explore and invest in many knowledge domains (Kashdan, Rose, & Fincham, 2004; Silvia & Sanders, 2010). They also tend to be higher in a cognitive process called *implicit learning*—the ability to unconsciously detect patterns of