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LARGE-SCALE NETWORK REPRESENTATIONS OF SEMANTICS IN THE MENTAL LEXICON

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Abstract

The mental lexicon contains the knowledge about words acquired over a lifetime. A central question is how this knowledge is structured and changes over time. Here we propose to represent this lexicon as a network consisting of nodes that correspond to words and links reflecting associative relations between two nodes, based on free association data. A network view of the mental lexicon is inherent to many cognitive theories, but the predictions of a working model strongly depend on a realistic scale, covering most words used in daily communication. Combining a large network with recent methods from network science allows us to answer questions about its organization at different scales simultaneously, such as: How efficient and robust is lexical knowledge represented considering the global network architecture? What are the organization principles of words in the mental lexicon (i.e. thematic versus taxonomic)? How does the local connectivity with neighboring words explain why certain words are processed more efficiently than others? Networks built from word associations are specifically suited to address prominent psychological phenomena such as developmental shifts, individual differences in creativity, or clinical states like schizophrenia. While these phenomena can be studied using these networks, various future challenges and ways in which this proposal complements other perspectives are also discussed.

Introduction

How do people learn and store the meaning of words? A typical American university student knows the meaning of about 40,000 words by adulthood, but even young children know a remarkable number of words (around 3,000 in their spoken vocabulary by the age of 5; Aitchison, 2012). To accomplish this feat, people must extract regularities from the linguistic input they receive and store it in some fashion. In this chapter, our focus is on how this knowledge is organized.

One way to think about word meanings is with the idea of a *mental lexicon*. The mental lexicon can be thought of as a dictionary-like structure, in the sense that it organizes words according to various different properties. This includes semantic properties (meaning) and syntactic properties (e.g. part-of-speech), but might also include perceptual characteristics (e.g. pronunciation) and pragmatic ones (e.g. appropriate usage). However, in other respects the mental lexicon is very different to a typical dictionary. For instance, rather than provide explicit definition for words, the mental lexicon represents meanings in terms of patterns of word use and the connections between words and sensory experiences (Elman, 2009). Similarly, the dictionary metaphor provides a poor guide to thinking about how people retrieve information from the lexicon. Understanding the structure of the mental lexicon helps us explain a variety of phenomena including tip-of-the tongue states (Brown, & McNeill, 1966), learning new words in a second language (deGroot, 1995), and various forms of anomia and aphasia (Aitchison, 2012).

If the mental lexicon is not exactly a dictionary, what kind of organization does it possess? Our goal in this chapter is to discuss how ideas from network science can be used to provide these insights. In particular, we focus on the importance of using *large-scale networks* derived from free association norms. The structure of the chapter is as follows. In the remainder of this section we discuss our approach in some detail and compare it to other perspectives on the problem. In section 2 we illustrate how the study of large networks leads to new predictions that could not be detected in smaller scale studies, and allows us to investigate the structure of the mental lexicon at a global (macroscopic) level, an intermediate (mesoscopic) level, and at the fine-grained (microscopic) level. Finally, in section 3 we discuss how the basic approach can be extended to capture differences between different populations and even among different individuals.

Studying the Mental Lexicon

A cursory review of the literature in psychology, computer science and linguistics reveals that there is a variety of different ways in which the mental lexicon could be studied. It is not our goal to provide an exhaustive survey, but a brief overview is useful for highlighting the manner in which different approaches are useful for addressing different questions.

In psychology there is a long tradition of studying word meaning on the small scale. For example, "feature listing" tasks can be used to empirically measure how meaning is represented in small parts of the lexicon (e.g. De Deyne, Verheyen, Ameel, Vanpaemel, Dry, Voorspoels, & Storms, 2008; McRae, Cree, Seidenberg,

& McNorgan, 2005), and predict measures such as the relatedness between word pairs (Dry & Storms, 2009) and typicality as a member of a category (Ameel & Storms, 2006). On the theoretical side, we can study the semantic properties and relations among a small set of words using connectionist networks (McClelland, & Rogers, 2003) or Bayesian models (Kemp, Tenenbaum, Griffiths, Yamada, & Ueda, 2006). One difficulty with these approaches is the very fact that they are small in scale, and it is not clear which results will generalize when the entire lexicon is considered. Indeed, most psychological studies rely on small sets of concrete nouns (Medin, Lynch, & Solomon, 2000) even though work on abstract and relational words is available (e.g. Recchia, & Jones, 2012; Wiemer-Hastings, & Xu, 2005). Moreover, selection biases also extend towards certain types of relations between these nouns (mostly perceptual properties and categorical relations) and types of task (highlighting relations at the same hierarchical category level), which might render some of the conclusions regarding how the lexicon is structured and represents word meaning premature.

A different approach that emerges from linguistics might be called the "thesaurus" model, and is best exemplified by WordNet (Fellbaum, 1998). WordNet is a linguistic network consisting of over 150,000 words. The basic unit within WordNet is a synset, a set of words deemed to be synonymous. For instance, the word *platypus* belongs to a synset that contains *duckbill*, *duck-billed platypus* and *Ornithorhynchus anatinus*. Synsets are connected to one another via is-a-kind-of relationships, so the *platypus* synset is linked to a synset that consists of *monotreme* and *egg-laying mammal*.[1]

Unlike the traditional psychological approach, WordNet does not suffer from the problem of small scale. Quite the contrary, in fact: The synsets and their connections form an extensive network from which one can predict the similarity of two words, query the different senses that a word may have, and so on. Unfortunately, when viewed as a tool for studying the mental lexicon, WordNet has fairly severe limitations of its own. The fundamental difficulty is that WordNet is not derived from empirical data, and as a consequence it misses properties that would be considered critical when studying human semantics. A simple example would be the fact that it treats the elements of a synset as equivalent. This is highly implausible: While any Australian would have a detailed mental representation for platypus, only a small group of experts would have any representation of the term *Ornithorhynchus anatinus*. Moreover, the meaning of platypus is culture specific and will be much more central within (some) Australian cultures than in American culture (cf. Szalay, & Deese, 1978). Even ignoring culture specific knowledge that differentiates among the members of the synset, the WordNet representation misses important lexical knowledge about the word *platypus* that would be shared among almost all English speakers. To most English speakers, *platypus* is a rare word: The frequency of the word *platypus* (less than one per million words) is just a fraction of that of *duck* (about 25 times per million words), which has a tremendous influence on how quickly people can decide whether it is a real word

(839 ms for *platypus* versus 546 ms for *duck*), or name the animal in question (830 ms versus 572 ms).[2] As this illustrates, the WordNet approach—useful as it may be for its original purpose—is not well suited to the empirical study of the mental lexicon.

A third tradition, inspired by information retrieval research in computer science, is to study semantic knowledge by analyzing the structure of large text corpora. One of the best known approaches is latent semantic analysis (LSA; Landauer & Dumais, 1997). Using a vocabulary of nearly a hundred thousand words derived from a variety of documents, LSA is able to capture the meaning of words by comparing how similar the contexts are in which two words occur. For example, it infers that *opossum*, *marsupials*, *mammal*, *duck-billed*, *warm bloodedness* and *anteater* are related to *platypus* because these words occur in similar contexts to platypus.[3] In recent years a large number of corpus-based methods have been developed (Recchia, Sahlgren, Kanerva, Jones, & Jones, n.d.). These methods differ in terms of how they define a word's context (e.g. the paragraph, the document, etc.), the extent to which they use grammatical information (e.g. word order), and how the meaning is represented (e.g. latent spaces, mixture models, etc.). Not surprisingly, the choice of text corpus also has a very strong influence on how these models behave, and can even become the determining factor of how well they capture human semantic processing (Recchia, & Jones, 2009).

One of the main selling points to the corpus approach is that it serves as an existence proof for how meaning can be acquired from the world. That is, if the text corpus is viewed as a summary of the statistics of the linguistic environment, then LSA and the like can be construed as methods for extracting meaning from the world (Firth, 1968; Landauer & Dumais, 1997). Without wishing to make the point too strongly, there are some reasons to be cautious about the claim that this is how humans do so. Even supposing that the text corpus is a good proxy for the statistics of the linguistic input available to the human learner, it is not at all clear that the linguistic input presents a good summary of the statistics of the world that children are exposed to. For example, when people are asked to generate associates to *banana*, the word *yellow* is one of the top responses, correctly capturing a relationship that any child acquires from perceptual data. Yet, due to pragmatic constraints on human discourse, we rarely talk about *yellow bananas*. Some studies have looked at this explicitly, by comparing participants who generate ten sentences to a number of verbal stimuli, whereas others generated a closely similar word association task. The results showed that the type of responses, after carefully preprocessing the sentences correlated only moderately (Szalay, & Deese, 1978, $r = 0.48$). Similarly, word co-occurrence extracted from a large text-corpus show only weak correlations with response frequencies from word associations (De Deyne Verheyen, & Storms, 2015). Second, non-linguistic processes contribute to word meaning in the lexicon which are picked up by word associations but not necessarily by text (for the reasons we just mentioned). Evidence comes from a study on the incidental learning of word associations during sentence processing (Prior, & Bentin, 2003). Finally, in contrast to natural discourse where fully grammatical utterances need to be formed, there is less monitoring of the responses in word association tasks. Presumably, the transformation from idea to language is quicker and easier (Szalay, & Deese, 1978).

Limitations notwithstanding, all three methods serve a useful purpose, but each captures a different aspect of the problem. In this chapter we discuss a different approach, one that comes with its own perspective on the problem. Drawing from traditional experimental psychology, we seek to base our study on empirical measures. Much like the corpus approach, we aim to describe the mental lexicon on a large scale in a fashion that is psychologically plausible. Finally, like WordNet, the form of this lexical knowledge can be described using the language of networks.

Using Association Networks to Represent Lexical Knowledge

The approach we take is to construct large-scale semantic networks from word association data. As such there are two key elements to this approach: The reliance on association data, and the use of network representation. In a typical free word association task, a person is asked to write down the first word(s) that spontaneously come to mind after reading a cue word. The important aspect of this task is that it is "free": Unlike tasks such as semantic feature generation, no restrictions are imposed on the answers that are produced.[4] What makes free associations unique and useful is the fact that they are simply the expression of thought, freed from the demands of syntax and morphology (Szalay, & Deese, 1978). If people frequently generate the word *weird* when given *platypus* as a cue, we assume this reflects an association between these words (e.g. people think that platypuses are weird). From this perspective, the word association task is a measurement tool: It is an empirical method for getting access to the semantic representations that people possess. Of course, no empirical measure is perfect (e.g. the relationship between response frequency and associative strength is by no means simple), our view is that the word association task is less problematic than the alternatives.

The second element to our approach is the network representation. Words are represented by nodes, and a directed edge connects *platypus* to *weird* because people generate *weird* in response to *platypus*. This is not the only way in which the empirical data could be described (e.g. we could adopt an LSA-like approach and construct a latent geometric space), but it is one that has a strong justification. At a bare minimum, the network representation can be motivated as a transparent reflection of the word association task: The essence of the task is to generate connections among words, and as such the empirical data are quite naturally described in this fashion. At a more theoretical level, our choice is motivated by the seminal work of Collins & Loftus (1975), who argued that a network representation provides a psychologically plausible way of describing the mental lexicon. Put somewhat crudely, our approach is to use the empirical word association network as an approximation to a latent semantic network. In the next two sections we explain how these two elements are implemented in an explicit network, where the connections between words are derived from human responses in a word association task.

Representation of Semantic Similarity

One important property of the Collins & Loftus (1975) proposal is that the semantic network expresses both semantic similarity and lexical co-occurrence among the pattern of connections among words. The idea, which traces back to the work of Deese (1965) is that two words have a semantic relationship if they are connected to the same words, which in this context is sometimes referred to as having shared "semantic features".

In order for this idea to be reflected in a word association network, it must be the case that free associations are not merely sensitive to simple linguistic collocations (e.g. *ugly*—*duck*), they must also capture a variety of semantic relationships. This is generally thought to be true (Mollin, 2009). Because the generation of associates is "free", it includes a wide range of relations that might also indicate thematic or affective content. To illustrate this, Figure 8.1 shows part of the word association network that is centered on the word *platypus*. The most common associates of *platypus* include *animal*, *duck*, *mammal*, *water*, *bill*, *Australia*, *eggs*, *funny*, *cute*, *beak*, etc. The fact that these connections reflect a variety of taxonomic, thematic and affective properties illustrates how word association networks possess the kind of expressiveness required by a semantic network.

Given the importance of having a network that can capture a broad range of possible relationships, it is worth highlighting how this expressivity is related to the experimental method used to collect word association data. Historically, most studies have used a procedure in which only a single response per cue word is collected (Kiss, 1968; Nelson, McEvoy, & Schreiber, 2004). However, collecting more than a single response is crucial in capturing the distributional properties of the mental lexicon (Aitchison, 2012; De Deyne, Navarro, & Storms, 2013; Hahn, 2008; Kenett et al., 2011). This "continued word association paradigm", in which people provide multiple associates to each cue, offers two advantages over the traditional approach. First, weaker associations can be collected, which is especially important for cues that have very dominant associations (e.g. *blood* and *red*). Second, the resulting network representations are denser (i.e. contain more links between words) and therefore are more suited to capture the distributional properties of meaning compared to the more homogeneous responses in single word associations (typically including just a handful of different responses for a specific cue). This allows us to model human relatedness judgments and test predictions about ways the lexicon is organized, but also allows us to compare groups of speakers, which might represent or process meaning in the lexicon differently (Szalay, & Deese, 1978, cf.).

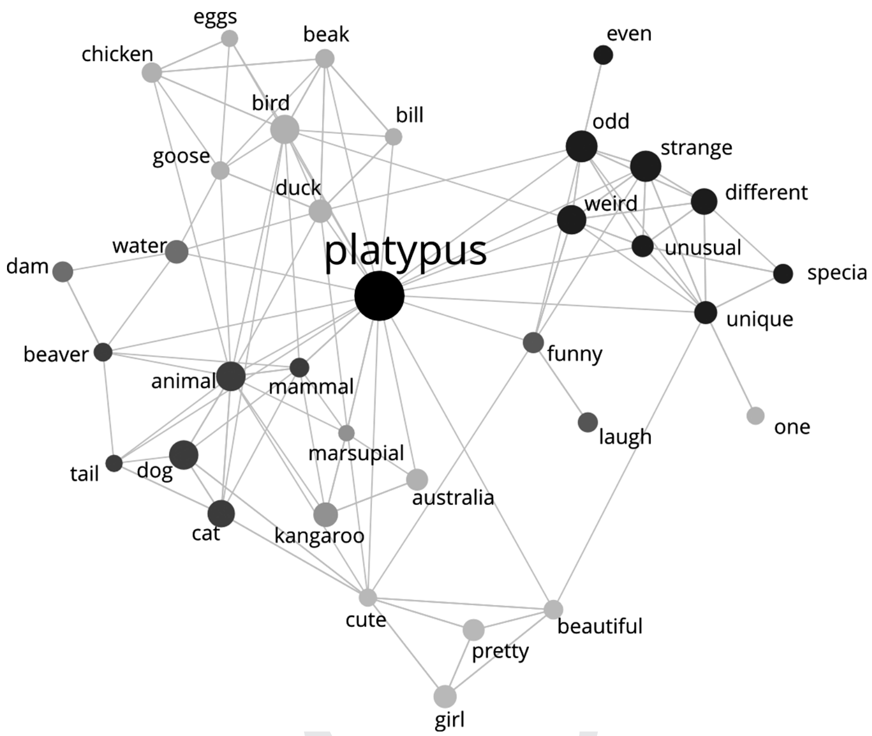

FIGURE 8.1 Portion of the associative network around the word *platypus* showing direct and indirect neighboring nodes.

Spreading Activation

The second key feature of the Collins & Loftus (1975) proposal is the notion of spreading activation. Once a word in the network is activated, activation spreads to other connected words, and quickly dissipates with time and distance (Collins & Loftus, 1975; Den Heyer, & Briand, 1986). This principle has been influential in many psychological theories and models such as the adaptive control of thought theory (Anderson, 1983, 1991), and various connectionist models of semantic cognition (Lerner, Bentin, & Shriki, 2012; McClelland, & Rogers, 2003). Through spreading activation, the meaning of a word in the network is represented by how it is linked to other words and how these are interlinked themselves. In that sense, spreading activation provides a mechanism by which distributed meaning can be extracted from a network.

Formally, spreading activation can be implemented as a stochastic random walk defined over the network. Starting at a particular node, a random walker selects an out-bound edge with a probability proportional to the edge weight and moves across it. Gradually, it will explore more paths around the start node. For many of these walkers the probability of any walker being in on a specific node reaches a state that remains stable after many iterations. In this random walk, the relatedness in meaning between nodes reflects the number and length of the directed paths through the network that connect two nodes. Many short paths between a source and target node allow a random walk to quickly reach the target, which reflects the fact that both nodes are considerably similar in meaning. In the simplest version, a single parameter determines this walk. This parameter governs the decay of activation: It determines the weight of paths of a specific length in such a way that longer paths get less weight than shorter ones, which might be useful depending on the type of task. In recent years, various empirical studies have demonstrated how memory search is governed by a fairly simple random walk over semantic memory (Abbott et al., 2015; Bourgin, Abbott, Griffiths, Smith, & Vul, 2014; Smith, Huber, & Vul, 2013).

To sum up, we propose to construct a mental lexicon as a network derived from word association. This network is a localist representation with nodes corresponding to words.[5] The semantic representations derived from it are functionally distributed, in the sense that the meaning of a word is represented by activation distributed over all edges connected with that word. The scale of the network is crucial: If the network is too small or too poorly connected the spreading activation mechanism becomes biased and lower frequency words like *platypus* might become unreachable (i.e. they will have no incoming links).

The Structure of Semantic Networks

The discussion up to this point has focused on the core ideas behind the network approach, outlining the theoretical basis for the approach and some methodological considerations. We now turn to a discussion of the "payoff" that a network approach brings. That is, what does this perspective tell us about the organization of the mental lexicon? To address this, we can examine the structure of large networks simultaneously at three different levels: macroscopic, mesoscopic, and microscopic (Borge-Holthoefer, & Arenas, 2010b). Depending on the complexity and level of analysis of the network, different functional patterns emerge, which are captured by the phrase more is different (Anderson, 1972). In other words, network science offers a framework that allows the examination of a network at different resolutions or levels, without ignoring qualitative differences between these levels. Each of these levels provides different insights and we discuss some of the findings related to each of these levels in turn.

Insights at the Macroscopic Level

The macroscopic or network level reflects the combined role of all the connections between the nodes of the network. It refers to structural properties of the entire network, rather than any particular part. For example, the network of the mental lexicon exhibits a small world structure. In comparison to random networks, small-world networks are characterized by a high degree of clustering, while maintaining short paths between nodes (Borge-Holthoefer, & Arenas, 2010a; De Deyne & Storms, 2008; Solé, Corominas-Murtra, Valverde, & Steels, 2010; Steyvers, and Tenenbaum, 2005). Similarly, the mental lexicon networks contain a small number of highly connected nodes or hubs, to a much greater extent than would be expected of a random graph. In network terms, these hubs exhibit a *degree* (i.e. number of connected nodes) that is much higher than other nodes. More generally, the connectivity of the network has a characteristic distribution, in which the degree of all nodes in the network follows a truncated power-distribution (Morais et al., 2013).

These properties are not arbitrary: There is evidence that macroscopic level properties such as small-world organization produce networks that are robust against damage and allow efficient information distribution (Borge-Holthoefer, Moreno, & Arenas, 2012). Moreover, small world organization often emerges when a network forms via growth process, as is the case for other dynamic networks such as networks of scientific collaboration, neural networks, and the World Wide Web (Watts & Strogatz, 1998). From this perspective, the observed structure of the semantic network provides insights into how the network grows over time (Steyvers, and Tenenbaum, 2005).

Using Network Structure to Investigate Language Development

In cognitive science, the macroscopic properties of the lexicon have been extensively studied to investigate how new words are gradually incorporated into the mental lexicon. Various growth principles have been proposed to explain the characteristic degree distributions of small world networks. For example, the mechanism of preferential attachment assumes new nodes become connected to the network in proportion to the number of existing connections that they have with neighboring nodes (Steyvers, and Tenenbaum, 2005). Alternatively, growth could also reflect the mechanism of preferential acquisition where new nodes might become preferentially attached to other nodes depending on the structure of the learning environment (Hills , Maouene, Maouene, Sheya, & Smith, 2009). Models of network growth are interesting in their own right, but they also provide constraints to various models of the lexicon and predict a number of interesting phenomena. For instance, the network growth model by Steyvers, and Tenenbaum explains how the age of word acquisition and its frequency in language independently contribute to the ease with which a word is processed.

Recent studies have also correlated macroscopic network properties with the typical and atypical development of the mental lexicon (Hills et al., 2009; Kenett et al., 2013; Steyvers & Tenenbaum, 2005; Zortea, Menegola, Villavicencio, & Salles, 2014, for example). One of these studies compared the development of individual networks in children and found that small world connectivity is indicative of later vocabulary development, whereas children with more cohesive and structured networks are more proficient language learners (Beckage, Smith, & Hills, 2010).

The Relationship Between Creativity and Network Structure

According to the classical associative theory of creativity (Mednick, 1962; Runco, & Jaeger, 2012), creative individuals have a richer and more flexible associative network than less creative individuals. Thus, creative individuals may have more associative links in their network and can connect associative relations faster than less creative individuals, thereby facilitating more efficient search processes (Rossmann & Fink, 2010). Others have suggested that insight problem solving is a result of a successful search throughout the semantic memory network, enabled by either finding "shortcuts" or by the creation of new links between previously unconnected nodes in the network (Schilling, 2005).

A macroscopic analysis to examine creative ability and problem solving might shed new light on these phenomena. Recently, such an analysis revealed that the semantic network of low creativity persons is more rigid than that of high creativity persons (Kenett, Anaki, & Faust, 2014). This higher rigidity was expressed by the degree of structure in the network in terms of tight clusters (as expressed by the network modularity); longer distances connecting words (average shortest path length); and lower small-world-ness (as expressed by a ratio of clustering and distance, see Kenett, Anaki, & Faust, 2014). This macroscopic analysis not only directly verified (modularity), but also extended Mednick's classical theory (Mednick, 1962) in terms of network distance and connectivity.

Structural Differences in Clinical Populations

Structure at the macroscopic scale can not only explain the abrupt emergence of new cognitive functions during development, but also the degradation of these functions with aging or neurodegenerative illness (Baronchelli, Ferrer-i-Cancho, Pastor-Satorras, Chater, & Christiansen, 2013). While network science is widely used to explore the neural aspects of clinical populations (Stam, 2014), a similar methodology aimed at the cognitive level of clinical populations might also be productive in this field. Such network tools can be used to examine the mental lexicon organization of clinical populations suffering from speech, language and thought disorders and provide novel insights to the nature of their deficiencies. Currently, such studies mainly focus on analyzing small-scale representations of lexical category organization (Beckage, Smith, & Hills, 2010; Kenett, Wechsler-Kashi, Kenett et al., 2013; Lerner, Ogrocki, & Thomas, 2009; Voorspoels, Storms, Longenecker, Verheyen, Weinberger, & Elvevåg, 2014), or on the analysis of speech acts (Cabana et al., 2011; Mota, Vasconcelos, Lemos, Pieretti, Kinouchi, Cecchi, Ribeiro, 2012; Holshausen et al., 2014). An example of a recent analysis on the semantic networks is a study on Asperger syndrome. In that study, the semantic network of people with Asperger syndrome was characterized by higher modularity than the network derived from controls, which is argued to be related to rigidity in thought (Kenett et al., 2015). Another example of this is the case of schizophrenia. Here semantic networks could be used to test whether thought disorders can be attributed to a lack of inhibition or an increase in activation spreading through the lexicon. leading to phenomena such as hyper-priming, where semantically related words show larger priming effects compared to normal controls (Spitzer, 1997; Gouzoulis-Mayfrank, Voss, M'orth, Thelen, Spitzer, & Meincke, 2003; Pomarol-Clotet, Oh, Laws, & McKenna, 2008).

Insights at the Mesoscopic Level

The mesoscopic or group level involves the properties of a considerable subset of nodes in the network. The structure at the mesoscopic level in the mental lexicon is informative about the meaning of words. We can investigate structure at this level by computing the distance between a set of words through a set of direct and indirect paths connecting them. These distances allow us to identify closely knit regions or clusters in the network, which are referred to as communities (or modules) in network science.

Apart from clustering, the mesoscopic level also allows us to evaluate whether people infer additional information by using indirect paths when comparing the meaning of two words or mechanisms or retrieving words from memory. This process can be modeled as the stochastic random walk, which we introduced earlier in this chapter, resulting in a measure of relatedness that reflects both the number and the length of paths connecting two nodes in the network. Altogether, the mesoscopic level informs us about (a) the actual content that is activated or accessed in retrieving words and their meaning, which allows us to differentiate between different types of words, and (b) processes and parts of the network that are involved in retrieving word meaning.

Thematic Organization of the Mental Lexicon

Inspecting network structure at the mesoscopic level allows us to better grasp abstract properties at the macroscopic level. Whereas the macroscopic properties of the network summarize the network in terms of its efficiency, growth and global structure, it does not provide any knowledge about the content, qualitative properties or the similarity relationships between words in the lexicon. For example, while we might learn that the lexicon is characterized by a small number of hubs (words like *water*, *money*, *food*, and *car*), understanding how these hubs arise requires investigating how they are embedded in the network. Similarly, a measure of modularity might give us an idea about the degree of clustering for the entire graph, but it does not provide us with any information about the nature of individual clusters.

Looking at the qualitative aspects of specific clusters of words in the lexicon also provides us with a direct way of grasping the principles governing lexical organization at the semantic level. Such principles can be taxonomically or thematically based, an issue which is still debated (Lucas, 2000; Hutchison, 2003). Furthermore, at a higher hierarchical level, larger clusters might also reveal something about neuroanatomical constraints for how words are represented, given that various studies indicate systematic differences between animals or artifacts (Goldstone, 1996; Verheyen, Stukken, De Deyne, Dry, & Storms, 2011) or abstract and concrete words (Crutch & Warrington, 2005; Hampton, 1981).

In general these questions can be addressed by identifying clusters or groups of nodes with a higher level of interconnection among themselves than with the rest of the network. There are many ways through which such clusters can be derived (see Fortunato, 2010, for an overview), and some of the more statistical approaches are especially promising. An example is the clustering of a large-scale network of the mental lexicon for over 12,000 nodes derived from word association data (De Deyne Verheyen, & Storms, 2015). In the weighted directed graph to represent the lexicon, the quality of the clusters that are derived are compared with a suitable null model network to see if these groups occur beyond chance levels (Lancichinetti et al., 2011). Inspecting the clusters confirmed that it consistently shows a widespread thematic structure (De Deyne Verheyen, & Storms, 2015), which could also be described as a *free categories organization* principle (Kenett et al., 2011).

An example of how the network could be organized at the mesoscopic level is presented in Figure 8.2. In line with the structure presented in Figure 8.2, a mesoscopic community detection analysis for an extensive lexicon argues against an exclusively taxonomic view of the mental lexicon (Rosch, Mervis, Grey, Johnson, & Boyes-Braem, 1976) but instead shows thematic structure across the hierarchies that were derived from the data grouping. For example, for a typical taxonomic category like birds, it would group together various birds but also words like *beak*, *nest*, *whistle* or *egg*. This converges with recent evidence that highlights the role of thematic representations even in domains such as animals (Lin, & Murphy, 2001).

It is quite likely that a thematic organization is an inherent property of language, where most words are taxonomically related to only a small number of other words, but might occur in a variety of thematic settings. In other words, this illustrates what removing a selection bias towards concrete words does, as the implementation of large-scale networks represents all types of words in language including adjectives, verbs, and nouns.

Predicting Human Judgments of Relatedness

An important test of the structure at the mesoscopic level and the type of processes it supports is the extent to which two nodes are related depending on the direct and

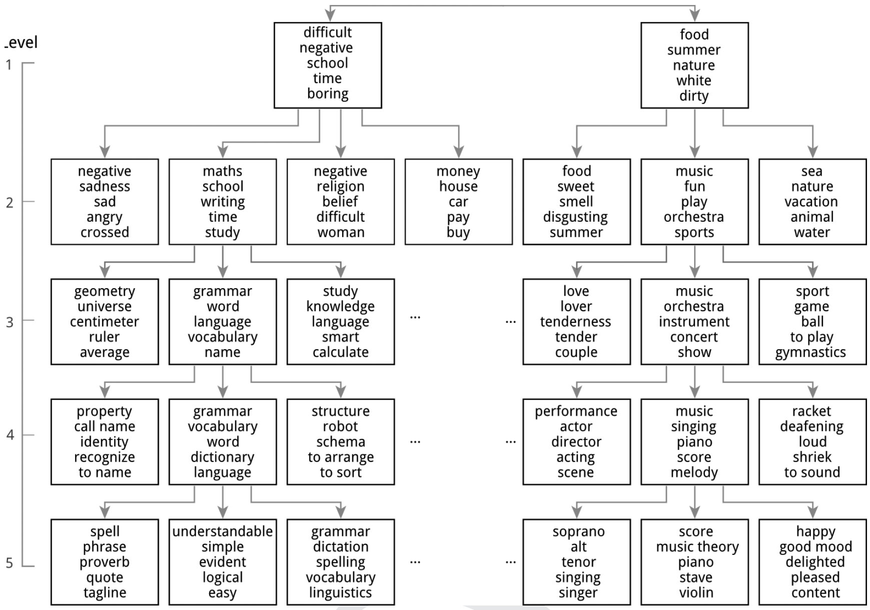

FIGURE 8.2 Hierarchical tree visualization of clusters in the lexicon with five most central members of the mental lexicon adapted from De Deyne Verheyen, & Storms (2015). While the deepest level of the hierarchy shows coherent content, higher levels also convey the relations between smaller clusters and highlight other organizational principles of the lexicon. For example, at the highest level a words connotation or valence tends to capture network structure.

indirect links that exist between them. The idea that the closeness between a pair of nodes in terms of the paths connecting them predicts the time to verify sentences like a *bird can fly* motivated the early propositional network model by Collins & Quillian (1969).

Human relatedness judgments for word pairs like *rabbit—hare*, or *rabbit—carrot* provides a direct way to test various topological network properties at the mesoscopic level and test hypotheses for different kinds of words (e.g. abstract or concrete) and semantic relations. Distinct topological properties of the network affect these predictions. A first one is the role of weak links, where the introduction of weak links through continued responses represents a systematic improvement over networks derived from single-response procedures (De Deyne, Navarro, & Storms, 2013; Hahn, 2008; Kenett et al., 2011). A second factor is the role of indirect links that could contribute to the relatedness of word pairs. Several studies show that incorporating indirect mesoscopic structure using random walks improves predictions of human similarity judgments (Borge-Holthoefer, & Arenas, 2010a; De Deyne Verheyen, & Storms, 2015; Van Dongen, 2000) and can be used to extract categorical relations between words (Borge-Holthoefer, & Arenas, 2010a). A final factor is the directionality of the network. When undirected networks are derived, the density of the network increases as the presence of an undirected link is based on either an in or out-going link. Whereas additional density through continued responses improves prediction, ignoring the directionality actually hampers the prediction of human similarity judgments (De Deyne, Navarro, & Storms, 2013). Altogether, incorporating weak links and considering indirect and directed paths contribute to explaining human semantic cognition.

Capturing Semantic Priming Effects

A quintessential example of the role of processing requirements, directionality, associative strength, and direct and indirect paths is priming. In priming tasks, the processing of a target word is enhanced when it is preceded by a related cue word. In the case of associative priming this involves the presentation of a cue such as *dog*, which facilitates processing of the target *bone*. In network terms, such facilitation might be explained by the presence of an associative link between these words. Even more so, this priming not only reflects the presence of an associative link, but also the strength of the links between nodes (Cañas, 1990).

Closely related is mediated priming, whereby a cue primes a target through a mediated link, as in the example of *stripes—tiger—lion* (Chwilla & Kolk, 2002). This type of priming is of particular theoretical importance, as it allows testing the assumption of spreading activation throughout the network (Hutchison, 2003). Mediated priming also extends to more complex scenarios such as three step priming, where two intervening non-presented concepts exist between prime and target. An example would be where the prime *mane* activates a target *stripes* through the mediators *lion*, *tiger* which are never presented (McNamara, 1992). Using large-scale free association networks, this type of mediated priming can be investigated empirically by considering the paths connecting word pairs (Kenett, Anaki, & Faust, 2015).

A final type of priming that is often considered distinct from the two previous ones is semantic priming. Here, an ensemble of shared features or links rather than a single connection determines whether priming occurs. In contrast with associative priming, semantic priming is considered to be symmetrical, which allows disentangling both types of priming (Thompson-Schill, Kurtz, & Gabrieli, 1998). From a large-scale network perspective, spreading activation over a semantic network may account for various types of priming. First of all, the spreading activation account is often used to explain associative priming, through finding the shortest path between the prime and target (Thompson-Schill, Kurtz, & Gabrieli, 1998). When activation spreads through every possible path connecting two words, it captures different components of meaning where the summed activation reflects semantic similarity. The model spans a continuum going from a singular direct path to an ensemble of paths with arbitrary lengths. At the end of this spectrum, the summed activation over many nodes will start to resemble the activation of semantic features in distributed models (e.g. Plaut, McClelland, Seidenberg, & Patterson, 1996). Thus, a network account provides a flexible, yet well-defined way to understand many of the documented priming effects but also questions certain theoretical predictions, for instance in the case of the symmetric nature of semantic priming.

Memory Retrieval and Search in the Lexicon

Given the large amount of knowledge stored in the lexicon, retrieving information from the lexicon is a formidable challenge. In contrast to directed similarity judgments (which highlights meaning), priming (which allows us to grasp fast, automatic or even unconscious processing), memory and information search studies highlight both aspects of cue salience and meaning during encoding and retrieval. Two experimental paradigms have been developed to assess the underlying structure that would support information retrieval from the lexicon.

A first line of research involves episodic memory effects such as false memories (McEvoy, Nelson, & Komatsu, 1999; Roediger, Balota, & Watson, 2001), recognition and cued recall (Nelson et al., 1998; Nelson, McEvoy, & Bajo, 1988). An interesting property of these tasks is how both direct and indirect paths between words affect the intrusion of non-presented items in false memories and efficiency in cued recall and recognition tasks. In cued recall, for example, participants are required to retrieve words presented earlier when presented with a cue word in a subsequent test phase. Because the cue word is not presented in the experiment, the degree to which it helps retrieval of a studied word depends on the pre-existing connectivity these words have in the lexicon. If the cue word has both many and strong indirect paths connecting with the target word, this significantly increases the probability of correctly recalling it from memory.

A second line of research might provide even more missing pieces of the puzzle as it involves much broader sampling of structure at the mesoscopic level by requiring the integration of many paths between words. Two tasks that leverage on how humans navigate the network are the remote association task (Mednick, 1962) and the more recent remote triad task (De Deyne, Navarro, Perfors, & Storms, 2012). In the first task, participants are shown three cue words (e.g. *falling—actor—dust*) and have to guess which word relates them.[6] In the second task, three words are randomly chosen from a large pool of words (e.g. *Sunday—vitamin—idiot*) and participants have to choose which pair is most related. Both tasks entail the integration of paths connecting words but do this for different ranges (short in the case of the RAT, long in the case of the RTT). Similar to the judged relatedness studies, accessing the deep mesoscopic structure of the lexicon through random walks seems to be key for explaining human performance in the RAT and RTT (Abbott et al., 2015; Capitán, Borge-Holthoefer, Gómez, Martinez-Romo, Araujo, Cuesta, & Arenas, 2012; De Deyne Verheyen, & Storms, 2015; Gupta, Jang, Mednick, & Huber, 2012; Thompson, & Kello, 2014).

Insights at the Microscopic Level

The microscopic or node level of analysis of the network focuses on how a single node is connected with the rest of the network. One example of a network measure of this level is node centrality, expressed as the number different connections (set size) of a word. This type of centrality has been studied quite extensively in psycholinguistics and explains why certain words are processed more efficiently than others (Chumbley, 1986; Hutchison, 2003; Nelson & McEvoy, 2000). However, set size provides a highly impoverished view of how words can be central in a network. Instead, the network view provides a richer hypothesis space by distinguishing weighted and directed relations connecting nodes. The centrality of a node can alternatively be characterized by the number of in and out-going edges (the in and out-degree), the strength of these edges (in and out-strength) or a reciprocal measure that combines in and out-edges. Moreover, centrality measures may reflect some degree of mesoscopic structure as in the cases of eigen-centrality measures like PageRank (Page, Brin, Motwani, & Winograd, 1998). These measures take into account the centrality of the neighboring nodes as well and proved valuable in information retrieval. PageRank, for example, indexes the importance of web pages based on how important the pages that link to it are and analytically closely resembles an implementation of spreading activation based on random walks.

Simple Network Centrality Measures to Explain Word Processing Advantages

At the microscopic level of the mental lexicon, the interconnectivity of a particular node with its neighboring nodes affects how a word is retrieved or processed. The basic concept of interconnectivity is expressed throughout cognitive science. In psycholinguistics, a host of environmental variables have been proposed as to why some words are processed more efficiently, based on word frequency, contextual diversity, age of acquisition, and so on. In the memory literature, network inspired explanations include the fan effect, where the more things that are learned about a word, the longer it takes to retrieve any one of those facts (Radvansky, 1999). Similarly, various studies have found that in semantic tasks, words with many features are processed more efficiently than words with just a few features (Pexman, Holyk, & Monfils, 2003; Recchia, & Jones, 2012).

Mechanistic explanations of how these environmental variables affect structure in the lexicon are often based on the idea that the number of connections a word has in the network influences processing time. In some cases network accounts have been explicitly tested, for instance for explaining the effects of age of acquisition (Steyvers, and Tenenbaum, 2005), contextual diversity and word frequency (Monaco, Abbott, & Kahana, 2007). In the memory literature, the clustering coefficient of a node has been proposed to explain a host of other memory and word processing phenomena including recognition (Nelson, Zhang, & McKinney, 2001) and cued recall (Nelson et al., 1998). However, more often than not a network is only invoked as an explanatory device rather than a full-fledged computational model.

Why should large-scale network representations be used to examine the microscopic organization level of the mental lexicon? The main reason is that large-scale network implementations offer a more complete framework that allows us to explicitly test various ways in which nodes can have a processing advantages. If the network is sufficiently large, it is possible to cover both the number of in and out-going links as well as the number of links that might exist between the neighbors of a node, leading to richer explanations of node centrality than previous proposals. A good example is the concreteness effect, a finding where highly imageable words such as *chicken* will be processed faster and more accurately than abstract ones like *intuition* in word processing tasks like lexical decision (Kroll, & Merves, 1986). According to one hypothesis about the representation of these words in memory, concrete words have smaller associate sets than abstract ones (Galbraith & Underwood, 1973; Schwanenflugel, & Shoben, 1983, and see de Groot; 1989), but such an explanation ignores both the weights and directionality of the links. This goes against evidence suggesting that centrality measures derived from undirected networks do not correspond as much with external centrality measures such as imageability (Galbraith & Underwood, 1973) and age of acquisition (De Deyne & Storms, 2008) or decision latencies in lexical decisions (De Deyne, Navarro, & Storms, 2013) as compared with directed centrality measures. In particular, estimates of in-degree and in-strength rely on how representative the set of cues is to build the network. For example, if, for some reason, the word *water*, which frequently occurs as a response was never presented as a cue, the out-degree or out-strength for many words will be biased as these responses are not encoded in the network.

Reverberatory and Other Complex Network Centrality Measures

Besides incorporating edge weights and directionality, recent studies indicate that centrality might reflect even richer structure. Taking into account how central the neighbors of a node are as well tends to result in better predictions than measures that are based on the centrality (in terms of degree for instance) of a particular node. For example, in the phonological fluency task, in which participants generate as many words starting with a specific letter, the PageRank measure was able to account for more of the variance than word frequency (Griffiths, Steyvers, & Firl, 2007). In other words, a network perspective provides a way to test how reverberatory or feedback effects could contribute to how efficiently words are retrieved.

Similarly, other studies have also found that centrality measures that capture some of the mesoscopic or macroscopic properties might explain additional variance in word processing. One example of such a measure is the word centrality measure (Kenett et al., 2011). This measure examines the effect of each node on the general structure of the network. This is achieved by removing a node and examining the effect of the node removal on the average shortest path length (ASPL) of the network without that node. In a study analyzing the Hebrew mental lexicon, Kenett et al. (2011) found that some nodes greatly increase the ASPL of the network once they are removed, thus indicating that these facilitative nodes enhance the spread of activation within the network. The authors also found that some nodes greatly decrease the ASPL of the network once they are removed, thus indicating the presence of inhibitive nodes that hamper the spread of activation within the network.

Altogether, more complex centrality measures based on the reverberatory spread of activation of a node or ASPL highlight how interpreting the complexity at each of the three levels provides a richer explanation for word processing effects.

Discussion

In this chapter we have shown how a large-scale network representation of the mental lexicon and the processes operating on it can account for a large diversity of cognitive phenomena. At the macroscopic level these include language development, creativity, and communication and thought disorders in clinical populations. At the mesoscopic level they include the analysis of lexicon organization principles, semantic relatedness, semantic priming and word retrieval processes. At the microscopic level they include explanations for word processing advantages for environmental variables such as concreteness, age of acquisition or word frequency, but also an overarching framework for memory-based explanations including the fan effect and potentially other measures of semantic richness of words. These studies gradually depict a larger, broader picture of the role of lexicon structure in a wide variety of cognitive phenomena. It can be expected that applications of network theory to studies of the lexicon will continue to grow in the years to come (Baronchelli, Ferrer-i-Cancho, Pastor-Satorras, Chater, & Christiansen, 2013; Faust & Kenett, 2014).

From a modeling perspective, looking at different scales of the network provides us with a rich way of evaluating and contrasting different proposals. In particular, any model of semantic processing can now be evaluated in terms of the type of macroscopic structure it exhibits, which can be achieved by looking at degree-distributions or global modularity indices. At this level, models are expected to be robust against damage and promote efficient diffusion of information. At the mesoscopic level, models should be able to account for the relatedness in meaning between words both in offline and online tasks. Contrasting different tasks such as overt relatedness judgments and semantic priming allows us to investigate issues such as the time course of information retrieval from the lexicon, potential asymmetric semantic relations and the interaction between the centrality of a node and how its meaning is accessed. Finally, at a microscopic level, the network based account indicates that word processing advantages can be the result of distinct connectivity patterns in directed networks, which are equally likely to affect the predictions of language-based tasks (e.g. production or retrieval; online or offline) in different ways. At each of these three levels, various studies have provided valid accounts, but only a few studies have integrated evidence to capture the multilevel structure of the lexicon (Griffiths, Steyvers, & Tenenbaum (2007) is a notable exception). Adapting this approach limits the possible models but also forces models to be comprehensive from the start. Ultimately, both factors should provide us with a more accurate appraisal of how knowledge is represented throughout the lexicon.

The application of a multilevel network view might even go further than providing a general framework upon which several empirical hypotheses and predictions can be examined simultaneously via quantitative means. It might also inspire new theoretic views. One example of how large-scale mental networks are starting to shape theories in cognitive science is a novel proposal which relates lexicon structure to typical and atypical semantic processing (Faust & Kenett, 2014). This theory proposes a cognitive continuum of lexicon structure. On one extreme of this continuum lies rigid, structured lexicon networks, such as those exhibited in individuals with Asperger syndrome (Kenett et al., 2015). On the other end of this continuum lies chaotic, unstructured lexicon networks, such as those exhibited in individuals with schizophrenia (Zeev-Wolf, Goldstein, Levkovitz, & Faust, 2014). According to this theory, efficient semantic processing is achieved via a balance between rigid and chaotic lexicon structure (Faust & Kenett, 2014). For example, in regard to individual differences in creative ability, as the mental lexicon structure is more rigid, it is *less creative*, even to the point of a clinical state. On the contrary, as the mental lexicon structure is more chaotic, it is *more creative*, again producing a clinical state in the extreme case (see also Bilder, & Knudsen, 2014). This theory demonstrates how network analysis of the mental lexicon can provide a general account for a wide variety of cognitive phenomena. In this regard, large-scale representations of the mental lexicon are crucial to advancing such network analysis in cognitive science. As stated above, uncovering larger portions of the mental lexicon, via large-scale representations, will advance examination of cognitive phenomena at all network levels.

Extending the Models to Specific Groups and Individuals

In the introduction to this chapter we have argued that a mental network derived from word associations captures the mental properties of meaning that so far have not been available in linguistically inspired expert models or text corpus-based models. One of the assets of this framework is that it easily extends to homogeneous subpopulations of language users or even individuals.

One obvious way to extend this work is by looking at developmental patterns in order to obtain a more integrated view of why abrupt developmental changes in the lexicon occur. In children, this would primarily include the syntagmatic-to-paradigmatic shift (Ervin, 1961) around the age of six, or the thematic-to-taxonomic shift around the age of nine (Waxman & Gelman, 1986). In older adults, a similar explanation might account for a reverse shift towards syntagmatic responses in Alzheimer patients (Baker & Seifert, 2001), which potentially generalizes to the geriatric lexicon in general. Again, the issue of network size should be considered as some of these shifts might indicate a transition simply caused by increased size or connectivity.

A second possible extension of the large-scale network representation model is towards examining individual semantic networks. While most lexicon networks are collected from many individuals, some studies have tried to look at network structure within specific individuals. To date, only few studies have investigated the macroscopic properties of the semantic networks of different individuals. One such study was conducted by Morais et al. (2013). Similar to aggregated networks, the individual networks showed short average distances and a high degree of clustering between nodes. Moreover, the degree-distribution also followed a truncated power law just like the aggregated counterparts. One of the interesting observations in this study was the variability in the network sizes for different individuals, with some networks consisting of just over 5,000 links and others over 27,000 links. Potentially, this relates to other individual differences, such as executive functions, intelligence, attention, etc. On the other hand, these differences might also reflect task-effects such as sensitivity to semantic satiation or the effect that stimuli temporarily lose their meaning, which potentially occurs in prolonged tasks (Cramer, 1968; Szalay, & Deese, 1978). More research is needed to establish ways to minimize task effects specific to individuals, groups of people and assessments over prolonged periods. Altogether, investigating network structure at the individual level might be feasible and many of the implications of individual differences are yet to be explored.

A final extension of large-scale network representations is towards the study of clinical populations. While investigations into the cognitive aspects of clinical populations from a network scientific perspective are just beginning to take off, a few studies so far prove the feasibility (Cabana et al., 2011; Holshausen et al., 2014; Kenett et al., 2015, 2013; Mota et al., 2012). Conducting large-scale network representation studies in clinical populations could greatly contribute by providing quantitative measures related to clinical deficiencies. Furthermore, such research can be used in clinical diagnostics, by examining lexicon structure during clinical treatment.

Challenges

Recently, Griffiths (2015) presented a manifesto for a computational cognitive revolution at the era of Big Data. In line with his view, we advocate in this chapter the significance of investigating the mental lexicon from a multi-level, Big Data, association based approach. So far we have mainly focused on the representation of word meanings, without saying much about other factors that affect semantic processing and memory retrieval. Various studies provide indirect evidence that executive functions, working memory, attention, mood and personality traits all contribute to how we process and retrieve meaning in the lexicon (Bar, 2009; Beaty, Silvia, Nusbaum, Jauk, & Benedek, 2014; Benedek, Franz, Heene, & Neubauer, 2012; Benedek, Jauk, Sommer, Arendasy, & Neubauer, 2014; Heyman, Van Rensbergen, Storms, Hutchison & DeDeyne, in press). To advance the application of large-scale representation of the mental lexicon, such application must account for the effect of these variables.

A further challenge is elucidating the relation between the phonological network (Arbesman, Strogatz, & Vitevitch, 2010), which serves as the gateway into the mental lexicon, and the semantic network. This relation can be studied from a network of networks perspective (Kenett et al., 2014), that provides a way to analyze networks which are related to each other and the interaction between them. Such an approach will enable quantitative analysis of broader linguistic issues.

Besides the challenges in further integrating psychological factors and other aspects of word representations, the use of network analysis also raises some methodological challenges. The picture drawn so far still only covers a small portion of how network science for large graphs can contribute to many psychologically interesting phenomena. At the moment, many methods and ideas in network science are just recent developments and continue to improve. Only a few years ago, using binary undirected networks was conditional on the lack of methods for weighted directed graphs. Similarly, the statistical underpinnings for identifying clusters in these types of networks (Lancichinetti et al., 2011) or comparing different networks have only very recently become available. Currently, developing statistical models that allow us to test hypotheses for comparing networks remains a major challenge for applying network science in empirical research. This is mainly due to difficulties in estimating or collecting a large sample of empirical networks and only few statistical methods to compare between networks (Moreno & Neville, 2013). In these cases, bootstrapping methods over comparable networks might be a solution (Baxter, Dorogovtsev, Goltsev, & Mendes, 2010). A similar approach is used in more advanced applications of community detection for large-scale directed weighted networks, where the cluster membership is determined by evaluating the likelihood of this event in a comparable random network (Lancichinetti et al., 2011).

Perhaps an even bigger challenge is the need to implement dynamic properties in the networks, which might be needed to address the dynamic nature of semantic processing over the mental lexicon and growth and evolution over the lifespan. Such a dynamic time-course process of semantic retrieval within an individual might involve the availability of different types of semantic information. In these cases it might be important to distinguish qualitatively different types of links between nodes, which would lead to a multiplex network, where the contribution of different types of information (be they thematic, taxonomic, language or imagery-based) is time-dependent.

While studying network dynamics together with labeled semantic relations could help us better grasp developmental changes throughout our lives, it doesn't explain how episodic experiences eventually becomes encoded as part of the semantic knowledge represented in the lexicon. This brings us to a last issue of a more theoretical nature. While the properties of the linguistic environment are an important key to the puzzle of where semantic representations come from, and text-corpus models do indicate that this linguistic input is richly structured, it remains unclear how to arrive at mental models that operate on this input. Similarly, it is unclear to what extent input from the linguistic environment in itself suffices to capture the richness in meaning of the mental lexicon. In previous research (De Deyne et al., 2015; De Deyne Verheyen, & Storms, 2015), we found only limited agreement between textual-corpora based and word association based networks, which adds empirical support to the idea that the association task does not rely on the same properties as common language production, but should rather be seen as tapping into the semantic information of the mental lexicon (Mollin, 2009; McRae, Khalkhali, & Hare, 2011). Of course, humans do encode structure from the languages they are exposed to and in many cases this structure can even mimic properties that are considered to be non-linguistic in the first place (Louwerse, & Connell, 2011). This suggests that text corpus data can provide us at least a partial answer of how language shapes the mental lexicon but large-scale word association networks might give us a more privileged view into the structure, dynamics and processes of the mental lexicon.

The above makes clear that different approaches to study word meaning are complementary to each other. Whether derived from text corpora or from more direct word associations, they highlight the valuable role of Big Data to understand how words are acquired and represented typically and in atypical cases such as psychiatric or neurological disorders. In doing so, there is not a single preferred level of analysis, and just like the qualitative properties of the data, considering different levels of complexity in these data will be important to constrain future theories and understand a large diversity of empirical findings in this field.

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Notes

1 Information retrieved from http://wordnet.princeton.edu/wordnet/man/wnstats.7WN.html.
2 Results were retrieved from the English Lexicon project website, see http://elexicon.wustl.edu.
3 For similar examples, try deriving neighbors using the LSA website at http://lsa.colorado.edu.
4 Some researchers do ask participants to give "meaningful responses" (Nelson, McEvoy, & Dennis, 2000), in all studies of our own, we have stuck to a true free task.
5 The idea that each word maps onto exactly one node is most likely an unrealistic assumption about how words are actually represented in the brain. However, this simplification offers us both the flexibility needed to integrate key findings in word processing and the ability to understand explicitly how information is retrieved as the state of the network is interpretable by looking at which nodes are activated.
6 In this easy example, the related word is *star*.

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