Investigating the Impact of Vocabulary Size on Lexical Networks using Latent Space Modeling

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Abstract

Lexical networks may vary as a function of individual differences in vocabulary knowledge and word-level features. Analyses often rely on descriptive network statistics, which do not support robust inferences. This study introduces the latent space model as a method for assessing the degree to which network structure is accounted for by word-level features. We analyze lexical networks from adults with below-average vs. above-average receptive vocabulary knowledge (n = 22 per group). We used latent space models to assess effects of semantic, taxonomic, and phonological similarity between words on network structure as well as effects of part-of-speech, concreteness, age-of-acquisition, and word frequency. For both groups, we found significant effects of semantic and taxonomic similarity, with additional effects of phonological similarity and concreteness for the low vocabulary group. These findings suggest increased reliance on fewer cues in lexical networks of adults with larger vocabularies. Implications for inferential modeling of lexical networks are discussed.

Keywords: lexical networks, network analysis, latent space modeling

Introduction

Everyday talk is populated by an immense number of words, most of which are recognized and produced effortlessly. One's ability to access words efficiently relies on the quality of representations in the mental lexicon, a storehouse of linguistic representations that encompasses one's vocabulary knowledge and other information about word usage (Libben & Jarema, 2002). It has long been suggested that the mental lexicon is structured as a network (Collins & Quillian, 1969; Harris, 1954), where lexical representations are connected via shared features (McCarthy & Miralpeix, 2019). Thus, research has aimed to identify specific features of words responsible for shaping the lexicon, such as shared distributional statistics (Landauer & Dumais, 1997; Blei et al., 2003), phonological features (Siew, 2013), and embodied features of word meanings (i.e., concrete vs. abstract; Ding et al., 2017).

How the structure of the mental lexicon changes as individuals accrue vocabulary knowledge is an understudied question (Borovsky, 2022). While the average American young adult knows approximately 42,000 words (Brysbaert et al., 2016), vocabulary knowledge varies markedly across individuals (lowest 5% = 27,100 words; highest 5% = 51,700 words). Individual differences in vocabulary knowledge influence lexical processing, starting as early as 18 months of age (Borovsky & Peters, 2019) and extending into adulthood (Mainz et al., 2017). Vocabulary size is associated with speed of word recognition (Walley, 1993), comprehension accuracy (Fernald et al., 2006), and facility in learning new words (Bion et al., 2013). Vocabulary growth increases learners' depth of knowledge about word meanings and patterns of usage across contexts (Schmitt, 2014), which, in turn, may influence lexical organization. That is, increased differentiation in word meanings may result in more well-defined clusters of lexical representations within the lexical network. Vocabulary size might also affect the types of word relations that are most prominent in shaping the lexicon, such that smaller lexicons may be structured to a greater extent by phonological relatedness and larger lexicons by semantic relatedness (Sheng & McGregor, 2010; Wolter, 2001).

Various experimental methodologies have aimed to investigate how different types of word relations and associations influence the organization of the mental lexicon. These include semantic priming and inference experiments (Schriefers et al., 1990; Meyer & Schvaneveldt, 1971; Stroop, 1935), and various eye-tracking paradigms, such as looking-while-listening (Fernald et al., 1998; 2006) the visual-world studies (Huettig et al., 2011; Tanenhaus et al., 1995). A less widely used methodology is the repeated word association task (Elbers & van Loon-Vervoorn, 1999; Sheng & McGregor, 2010). This involves presenting a series of words to participants with instructions to say the first word coming to mind, and then repeating the list one or more times to obtain multiple associations for each word. The pool of word associations can then be modeled using a network analysis to identify patterns of shared responses in different participant groups (e.g., Brooks et al., 2017, comparing word associations of children with and without language impairment).

Word association networks may comprise a set of nodes (e.g., words) and relations between nodes (e.g., semantic similarity), also known as edges. Zortea (2014) constructed semantic word association networks for children, adults, and elderly participants, and found increased clustering of words with age, suggestive of changes in lexical organization with vocabulary growth. Network representations are extremely powerful, in that most any kind of data can be represented as a network. Such models allow one to examine the complex relations that may exist in a given system, thus providing a more direct analysis of underlying structural properties (Baronchelli et al., 2013; Siew et al., 2019).

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However, one complication involves the difficulty of knowing whether a given network characteristic is of a meaningful magnitude. A common solution is to construct a series of random graphs that have the same number of nodes and edges as the observed network, but with the connections between nodes randomized (Erdös & Rényi, 1960). The random graphs are then used to create a null distribution, against which the observed network statistic can be compared, much like a permutation analysis. As an example, Beckage et al. (2011) compared the structure of networks constructed from a corpus of child directed speech to a collection of random networks, and found that the networks based on the corpus had higher clustering than one would expect if words were learned at random.

Such methods, however, are limited in terms of explanatory value. Comparing a given network to a null distribution is akin to a one-sample *t*-test. By focusing on coarse-grain whole network characteristics, this approach offers little insight into why networks are structured as they are, nor does it allow for network comparison. What is missing is a robust method for inferential analysis of networks that is amenable to the aims of cognitive scientists, such as controlling for different types of covariates, group comparisons, and inclusion of statistical concepts typical for cognitive science, such as random effects and clustering.

The inferential analysis of networks is difficult due to the radically interdependent nature of network data. That is, the probability of two nodes having an edge may depend on either node sharing an edge with another node in the network. This interdependency makes even more advanced models, such as hierarchical models, insufficient (Crammer et al., 2021). Within the field of social network analysis, there have been efforts to develop robust statistical methods for identifying factors that influence network structure, while also accounting for the interdependent nature of the data. Such methods include exponential random graph models, block models, and latent space models. The exponential random graph model explicitly models network properties, such as clustering (Robins et al., 2007). Block models represent structure by assigning nodes partial membership in classes, similar to latent class models (Abbe, 2018). Latent space models, also known as latent position models, model structure by assuming that nodes exist in a latent space, and that their proximity in that space determines, partially, the probability of an edge existing between them. The present study adopts a latent space modeling approach, due to the intuitive interpretation of the latent space in the context of lexical networks.

The original formulation of the latent space model, adapted from Hoff et al. (2002), is:

$$\begin{aligned}\eta_{i,j} &= logodds(y_{i,j} = 1 | z_i, z_j, x_{i,j}, \alpha, \beta) \\ &= \alpha + \beta'_{i,j} - |z_i - z_j|\end{aligned}$$

Under this formulation, the probability (or strength for weighted networks) of an edge between two nodes, i and j, is a function of their distance from each other in a latent space ($|z_i – z_j|$), an intercept term α, as well as any optional covariates (β). Distances between nodes in the latent space are estimated by positing a latent variable for each dimension of the latent space, the values of which are estimated as part of the model-fitting process alongside the other model parameters. In this framework, a given word's position in the latent space may be interpreted as its position within the mental lexicon.

The original formulation of the latent space model has been extended in various ways. Newer models can handle random effects at the node level, with the aim of explaining variation in edge strength not captured by covariates and latent positions (Austin et al., 2013). Additionally, clustering models have been introduced to detect communities of nodes within the latent space (Handcock et al., 2007).

While latent space modeling has been adopted in studies of brain connectivity (Aliverti & Durante, 2019; Wang et al., 2025; Wilson et al., 2020), wider application of these models, and inferential network models in general, in cognitive science has been scarce. Given broad interest in the use of network models to study cognitive processes (Siew et al., 2019), we explore latent space models as a potentially important tool for drawing inferences about network properties, with a specific focus on the role of vocabulary knowledge in structuring the mental lexicon.

Research Aims

The present study applied latent space random effects models to repeated word association data in an effort to understand how individual differences in vocabulary knowledge might influence network structure. We focused our analysis on edge strength (weights), and included semantic, taxonomic, and phonological similarity, as well as part-of-speech, age-of-acquisition, and word frequency as covariates. This allowed us to examine the extent to which edge weights were associated with nodal and edge (relational) properties of words, while also obtaining estimates of network structure within the latent space. We hypothesized that words with similar nodal and edge attributes would have stronger connections than dissimilar words. We also predicted that the network derived from the word associations of adults with above-average vocabularies would show greater differentiation of cues (i.e., a lower clustering coefficient; more distinct communities of cues) than the corresponding network for adults with below-average vocabularies.

Method

Participants

College students were recruited from a psychology department subject pool (N = 44; 30 women and 14 men; M age = 21.1 years, SD = 2.8, *range* = 18–30). All participants were native speakers of English. They completed the Peabody Picture Vocabulary Test (PPVT; Dunn & Dunn, 2007) as a measure of receptive vocabulary knowledge. Participants were split into two age-matched groups to reflect differences in receptive vocabulary knowledge (below-average group: n = 22 [18 women, 4 men], PPVT standardized scores < 90, M = 81.2, SD = 6.5; above average group: n = 22 [12 women, 10 men], PPVT scores > 100, M = 117.0, SD = 9.3).

Materials

The repeated free association task followed procedures of Sheng and McGregor (2010). The cues comprised 24 nouns (e.g., *broom, dog*), and 24 verbs (e.g., *crawl, squeeze*), recorded by a female native speaker of midwestern American English and presented through headphones. Participants heard the series of cue words one and a time in a random order, and responded with the first word coming to mind. The series was repeated three times (48 cues, 144 trials). The experiment was run on an ACER laptop using E-Prime software (version 2.1; Schneider et al., 2012).

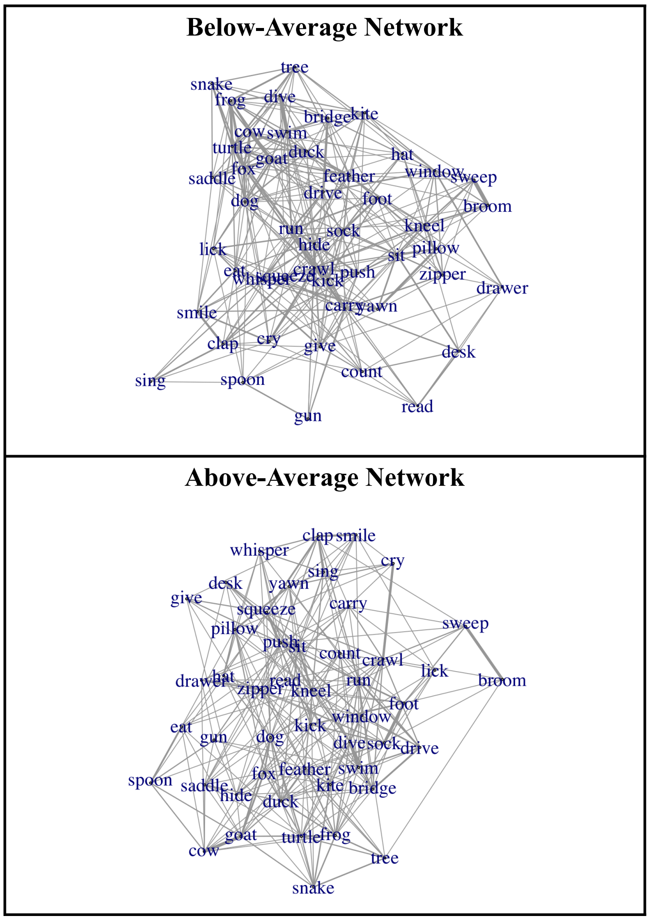

Figure 1. Networks for groups with below-average and above-average vocabulary knowledge (n = 22 per group). Edge width corresponds to weight.

Lexical Network Construction

We constructed lexical networks using igraph (Csárdi et al., 2024) in R, treating cue words as nodes in the network. Edges between cues indicated that participants gave the same response to both cues (e.g., *across* in response to the cues *bridge* and *crawl*). This resulted in a weighted, undirected network for each participant. The network weights for each individual network were then summed to create networks for participant groups with below-average vs. above-average vocabulary knowledge; see Figure 1.

Network covariates were of two types: edge and node covariates. Edge covariates are relations between words (i.e., the cues in the word association task). They are represented in the same way that a network is represented, i.e., as a $N \times N$ matrix, with each entry corresponding to a relation between two words. For the edge covariates, we calculated semantic, taxonomic, and phonological similarities between each pair of cues. To compute semantic similarity between cues, we used the cosine similarity metric from Word2Vec (Mikolov et al., 2013). Likewise, taxonomic similarity was computed using WordNet (Fellbaum, 1998). Following Beckage et al. (2015), phonological similarity was computed using cue pronunciations represented in IPA format.

Networks were embedded with node attributes, which provide additional information about the cue words to be used as covariates. The node covariates correspond to the features of the individual cue words, such as their predominant part-of-speech (PoS), concreteness ratings, age-of-acquisition (AoA), and word frequency. Node covariates were used to model the probability of edges based on node attributes. Covariates were selected based on prior work on lexical network structure (e.g., Stella et al., 2017). AoA and word frequencies were taken from the English Lexicon Project (Balota et al., 2007), and concreteness ratings from Brysbaert et al. (2014).

Results

First, we computed descriptive statistics for each network, including degree (number of edges connected to each node) and clustering coefficients (number of closed triangles in the network); see Table 1. Clustering was computed using agglomerative hierarchical clustering, which attempts to cluster nodes based on minimizing modularity (exclusivity) of clusters (Clauset et al., 2004). We used the Quadratic Assignment Procedure (QAP; Hubert & Schultz, 1976) to compute correlations between each network (below-average, above-average) and the networks representing semantic, taxonomic, and phonological similarities between cues. QAP correlations measure the similarity between two matrices and can be interpreted as Pearson correlations. We also calculated the assortativity based on PoS concreteness, AoA, and frequency. Assortativity is a measure of preferential clustering of nodes based on node attributes (Newman, 2002).

The descriptive analysis showed higher mean degree strength, as well as a higher clustering coefficient, in the below-average network compared to the above-average network. The below-average network also had a fewer number of communities than the above-average network, though the modularity of these communities were the same. Both networks exhibited small correlations with semantic and taxonomic similarity, and no correlation with phonological similarity. Across both networks, there was a small degree of assortativity with PoS and concreteness, and no assortativity with AoA and word frequency.

Table 1. Descriptive analysis of networks for below-average and above-average vocabulary groups

Variable	Below-Average Network	Above-Average Network
Mean Degree	12.9 (4.3)	11.4 (4.0)
Clustering Coefficient	0.39	0.34
# of Communities	5	7
Modularity	0.41	0.41
QAP Correlations		
Semantic	0.39	0.35
Taxonomic	0.25	0.22
Phonological	0.01	–0.01
Assortativity		
Part-of-Speech	0.28	0.30
Concreteness	0.26	0.22
AoA	0.04	–0.05
Word Frequency	0.06	0.01

Two-dimensional latent space models were fit separately for each network using the latentnet package (Krivitsky & Handcock, 2024). We opted for a two-dimensional model for the ease of visualization. Each model had the same predictors: semantic similarity, taxonomic similarity, phonological similarity, PoS, concreteness rating, AoA, and word frequency. For semantic, taxonomic, and phonological similarities, the model examined whether similarity strength was associated with the edge weights. For PoS, the model examined if the cues with the same PoS (i.e., nouns vs. verbs) were more likely to form strong edges. For concreteness, AoA, and frequency, the model examined whether the cue's degree (i.e., number of incident edges) could be predicted as a function of each covariate. Both models included a random effect for cue to capture variation that was not explained by either the covariates or latent distances. Latentnet estimates models within a Bayesian framework via Markov chain Monte Carlo (MCMC) sampling. For compatibility, both models had the same hyper-parameters (e.g., burn-in size, sampling size). Due to the difficulty in obtaining convergence in larger networks of sufficient complexity, the burn-in size was increased to 5,000,000 samples for both models (Cranmer et al., 2020).

Full reporting for both networks is presented in Table 2. For the below-average vocabulary group, semantic similarity, taxonomic similarity, and phonological similarity predicted edge weights, indicating that words (i.e., cues) similar in meaning, category, and phonology tended to have stronger connections between them. Additionally, more abstract words seemed to have more connections to other words in general than concrete words. For the above-average network, both semantic and taxonomic similarity were positively associated with edge weights, whereas no other variables reached statistical significance.

Figure 2 displays the latent positions in the estimated two-dimensional space (Z1 and Z2) for the below-average and above-average vocabulary groups respectively. Unlike standard network visualization methods, which prioritize visual clarity (e.g., avoiding overlapping nodes), the benefit of the latent space representation is that the locations of the nodes are estimated as part of the model-fitting process, and adjusted for the effects of covariates. Visual assessment suggests that the latent space for the below-average vocabulary group was more spread out and uniform in its distribution. In contrast, the latent space for the above-average vocabulary group had a very dense middle cluster and outer islands. Notably, the very dense cluster of words in the middle of the above-average network contained the majority of animate words. These characteristics may indicate greater differentiation in the word associations and lexical representations of adults with larger vocabularies.

Table 2. Results of latent space network models predicting edge weights

Variable	*β*	*CrI*	*p*
Below-Average Network			
Intercept	0.73	[–0.26; 1.76]	.138
Semantic Similarity	5.14	[4.31; 5.85]	< .001
Taxonomic Similarity	1.19	[0.26; 2.08]	.025
Phonological Sim.	0.25	[0.21; 2.08]	< .001
Part-of-Speech	0.05	[–0.08 0.23]	.684
Concreteness	–0.13	[–0.22; –0.06]	< .001
AoA	0.09	[–0.05; 0.23]	.234
Frequency	–0.02	[–0.11; 0.04]	.531
Above-Average Network			
Intercept	1.07	[–0.41; 3.03]	.199
Semantic Similarity	5.53	[4.41; 6.66]	< .001
Taxonomic Similarity	1.31	[0.09; 2.47]	.040
Phonological Sim.	–0.13	[–0.55; 0.35]	.590
Part-of-Speech	0.08	[–0.19; 0.33]	.521
Concreteness	–0.00	[–0.09; 0.14]	.856
AoA	–0.08	[–0.24; 0.08]	.380
Frequency	–0.05	[–0.12; 0.03]	.235

Model Goodness-of-Fit

Assessing the goodness-of-fit of latent space models is not straightforward. One suggestion is to generate simulated networks from the posterior distribution of the model and compare the network characteristics of the simulated networks with the observed network characteristics (Kolaczyk & Csárdi, 2020). If the model fits the network, then the observed network characteristics should fall between the first and third quantiles of the distribution of simulated network characteristics. Accordingly, we simulated 1000 networks for each model, and compared the observed networks to the distribution of simulated networks.

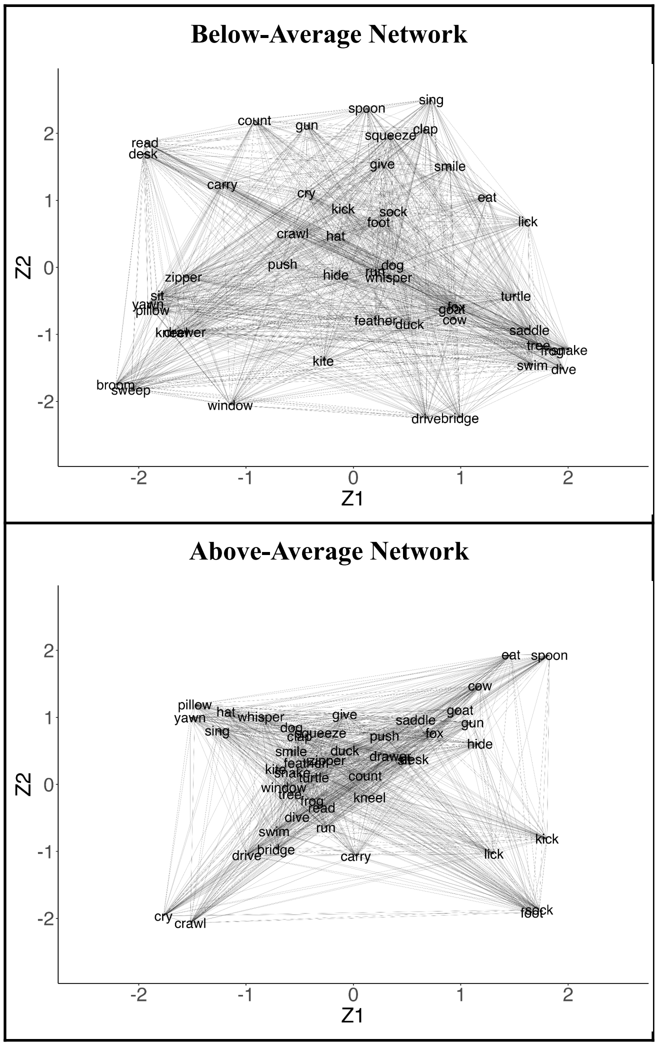

Figure 2. Latent positions for the below-average and above-average vocabulary networks. Edges represent predicted connections between words.

Both simulated networks demonstrated a poor fit to the data. The simulated networks overestimated the degree (below-average network: observed *M* degree = 12.9, estimated interval [18.7; 20.8]; above-average network: observed *M* degree = 11.4, estimated interval = [16.0; 18.1]) and the clustering coefficient of the observed networks (below-average network: observed clustering = 0.39, estimated interval = [0.50; 0.54]; above-average network: observed clustering = 0.34, estimated interval = [0.42; 0.47]). Additionally, inspection of the trace plots revealed poor convergence despite a large number of burn-in samples and interactions.

Discussion

This study sought to examine possible links between vocabulary size and lexical network structure. We constructed lexical networks using the repeated word associations of adult English speakers with below-average vs. above-average receptive vocabulary knowledge. After pooling responses by group, we examined the structural characteristics of the two networks, and employed latent space models to evaluate which features of cues (nodes) and similarities between cues accounted for observed edge weights within the networks.

Descriptive analyses of network characteristics revealed that both networks had a moderate level of clustering, with a slightly higher clustering coefficient in the below-average network. Additionally, the below-average network had fewer communities, suggesting a lesser degree of word differentiation in that network. This is in line with the hypothesis linking increased vocabulary size with increased differentiation in the lexical network, which may be attributed to greater depth of semantic and contextual knowledge about word usage (Schmitt, 2014). Other descriptive measures of network structure were roughly equivalent across the two groups.

Turning to the latent space models, we found differences between the two networks in the number of factors associated with cue connectivity. For the below-average network, semantic, taxonomic, and phonological similarities between cue words, as well as concreteness, predicted the strength of connections between cues. In contrast, for the above-average network, only semantic and taxonomic similarity were significant predictors of edge weights. Overall, network structure was dependent on a wider range of lexical features for the group with less vocabulary knowledge. This parallels work on children's lexical networks identifying contributions of lexical co-occurrence, semantic features (Peters & Borovsky, 2019), and phonological features (Hoff et al., 2008) in vocabulary development. The lack of a significant effect of phonology in the above-average network suggests that, as the lexicon grows, semantic relations supersede phonological relations in shaping lexical organization, in line with previous findings (Sheng & McGregor, 2010; Wolter, 2001).

A second aim of this study was to demonstrate the feasibility of the latent space model as an analytical technique for cognitive science. The latent space model has several advantages over descriptive network analysis. The ability to put multiple predictors into the model allows us to see how different features of a network interact. This may reveal hidden patterns that are not detectable from statistics derived in isolation. For example, in both networks, the assortativity of part-of-speech suggests that words may cluster based on grammatical information. However, this apparent effect disappeared in both models when other variables were examined in tandem, suggesting that other features, such as semantics, better explain network structure. The opposite was demonstrated by phonological similarity, which had a negligibly low correlation with edge strength in both networks, though it reached statistical significance in the below-average network in predicting edge weights. The ability to include multiple predictors and reveal hidden patterns is a core strength of the latent space approach and is missing in standard network analyses.

Latent space network modeling aligns with other more sophisticated attempts to analyze multi-layered lexical networks. Recent work has focused on multiplex analysis of lexical networks (Stella et al., 2017). These models conceive of the mental lexicon as a multi-layer network, with each layer representing different relations between words. The multiplex approach focuses on how the topographies of the different layers interact with each other. Another recent advance combines multiplex analysis with vector space analysis to identify word clusters, called language kernels, that may have a central place in the emerging mental lexicon (Citraro et al., 2023). While these approaches may provide information about the structure of the lexicon, they are non-parametric, which makes interpretation and inference difficult. That is, while a multiplex analysis may be able to construct rich representations of the lexicon, it may fail to provide insight into how such a lexicon came about, or why the lexicon has such-and-such structural properties.

One benefit of latent space models over multiplex analysis is that latent space models can take into account multiple layers of a network while providing an interpretable set of parameters. This makes it much more suitable for inference than multiplex analysis. However, this is also a drawback, as latent space models require a layer of the network to be designated as the network of interest. In our case, we used the word-association network as the layer of interest, and used the other layers as predictors, whereas in multiplex analysis, there is no need to specify any outcome layer. As such, latent space models may find their ultimate usefulness within experimental work where the researcher wishes to draw inferences about a network of interest, as opposed to observational or exploratory data commonly used in multiplex analysis.

Limitation of Current Latent Space Models

This study explored possible benefits of adopting inferential network models in cognitive science, using latent space models as an example. While the models presented here provide a useful first step, model fit was deemed unsatisfactory. The poor fit may stem from the fact that we collapsed data from multiple participants to create a single network for each participant group. This was necessary because the latent space model performs prediction over only a single network. However, collapsing data across participants ultimately compromises our ability to draw inferences about individual differences.

Being that the inferential model predicts edge weights, collapsing the participant networks into a single network introduced extreme outliers into the models. For example, for the below-average group, the vast majority of entries in the network adjacency matrix were 0s (72.6%), with only 15.9% of the edges having a weight of 1, and even fewer having a higher weight. Among the latter were outlier edges with weights of 19, 22, and 24. These outliers were difficult for the model to predict and may have biased the model towards overestimating the degree (i.e., edges per node). This was also apparent in the above-average network, though the outliers were less extreme. Additionally, poor fit may be due to the lack of convergence in the MCMC sampling, which might be solved by using a variational inference approach (Salter-Townshend & Murphy, 2012).

Our inability to analyze network characteristics at the participant level also impairs our ability to investigate standard questions within cognitive science, such as the role of macro-level covariates (e.g., participant characteristics) in predicting variation in network structure. Our results are further limited by the fact that we could not directly compare the networks for the two groups within a single model, and evaluate whether the effects of covariates were significantly different across networks. Recent extensions of latent space modeling implemented a hierarchical structure within a Bayesian framework to accommodate multiple networks within the same model (D'Angelo et al., 2019; Gollini & Murphy, 2016; Salter-Townshend & McCormick, 2017; Sos & Betancourt, 2021). These approaches allow information to be shared across networks, a common "shared" latent space to be estimated, and, in some cases, similarity to be estimated between networks. Other hierarchical approaches have been put forward to study brain connectivity with fMRI (Wilson et al., 2020), though these models tend to focus on network similarity rather than group comparison. Other similar models have been developed in educational research to facilitate group-level comparisons (Sweet et al., 2013), but their implementation may not be straightforward for cognitive tasks like word associations. Suffice it to say, a simpler approach, in line with standard statistical analysis within cognitive science, would be to implement a model with a random effect to account for network-level variance in edge strength, much like a multilevel linear model (Hofmann, 1997).

Conclusions

There is increasing interest in applying network models in cognitive science (Siew et al., 2017). This interest is especially pronounced in the language sciences, where it has long been recognized that words, and their representations, are radically relational. However, current network approaches are limited to qualitative descriptions of network properties, or simple comparisons against null distributions. The field lacks a tool set for making inferences over networks. This study applied a model from social network analysis, the latent space model, on word association data. While model fit was suboptimal, the model allowed for the estimation of covariate contribution to network structure, while estimating and controlling for the position of words in a latent space. This is a first step, and future work should be done to extend the model to accommodate individual level networks, which should allow for direct group comparisons, as well as the ability to test for individual differences.

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