Dynamic Effects of Conceptual Combination on Semantic Network Structure

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Abstract

The generative capacity of language entails an ability to flexibly combine concepts with each other. Conceptual combination can occur either by using an attribute of one concept to describe another (attributive combination) or by forming some relation between two concepts to create a new one (relational combination). Prior research has addressed whether common or distinct processes support these two putatively different types of combinations. We turn the question around and ask whether the *consequences* of these combination types on our conceptual system might differ, by comparing semantic memory networks before and after participants perform either attributive or relational conceptual combinations. We find a general effect on the semantic networks: the structure of network decreases after participants conceptually combine some of the concepts in the network. However, the relational combination manipulation has a greater effect. Furthermore, only the relational combination manipulation leads to an increase in the network's connectivity.

Keywords: Conceptual combinations; Semantic Networks

Introduction

Language generation involves the ability to combine concepts into novel combinations (Boylan, Trueswell, & Thompson-Schill, 2017). Investigating how individuals combine concepts can shed unique light on different aspects of conceptual knowledge, including the cognitive mechanisms that enable the generative and flexible use of language. For example, consider the noun-noun combination *robin hawk*: while some interpret this combination as "a red-breasted hawk", applying the attribute "red-breast" of the robin to the hawk; others interpret this combination as "a hawk that preys on robins", applying a thematic, relational role between robins and hawks (Wisniewski, 1996). While these two types of conceptual combination mechanisms—attributive and relational—are studied via behavioral and neurocognitive means (Boylan et al., 2017; Estes, 2003), whether these two mechanisms are similar or distinct remain an open question. Furthermore, the effect of these mechanisms on semantic memory structure has not yet been studied. In this paper, we apply a computational network science methodology to examine the effects of attributive and relational mechanisms on semantic memory structure. Specifically, we will focus on conceptual combinations in noun-noun compounds.

Noun-noun compounds contain a modifier noun followed by a head noun. The modifier noun can be either "attributive" (as in *zebra clam*, where *zebra* denotes the attribute "striped") or "relational" (as in *mountain lake*, where "mountain" is an object bearing a spatial relation with "lake"). An attributive based conceptual combination involves applying an attribute from the modifier noun to describe the head noun, such as *zebra clam* ("a clam that has stripes") A relational based conceptual combination, however, cannot be paraphrased this way - *tennis ball* is not "a ball that is tennis", but rather "a ball for playing tennis" (Downing, 1977; Gagné & Shoben, 1997).

An open theoretical issue is whether attributive and relational mechanisms are similar or distinct; and if distinct, how these mechanisms are applied (Estes, 2003; Gagné, 2000; Gagné & Shoben, 1997; Rogers & McClelland, 2004). We address this issue from a novel perspective: we apply a network science methodology to represent and compare semantic memory networks before and after participants conceptually combine some of the concepts in the network with other concepts in either an attributive or a relational manner. Such an approach allows us to examine, for the first time, in what way conceptual combinations affect semantic memory structure, and how it differs based on attributive or relational mechanisms. We posit that such a conceptual combination manipulation will have restructuring effects on the semantic network, by changing or creating new connections between concepts in the network.

Recent studies have used computational network science to represent the structure of semantic memory (memory for knowledge and facts, Jones, Willits, & Dennis, 2015), using network science tools, as a semantic network and analyze its properties (for a review, see Borge-Holthoefer & Arenas, 2010). A semantic network comprises a set of nodes and edges, where nodes correspond to words or concepts and edges connect pairs of nodes and signify some sense of relations between the connected nodes. Of the various network models developed in network science theory, the network model that has been widely used to examine complex systems is the Small World Network (SWN) model. A SWN is a network that is characterized by both high local connectivity and short global distances between nodes, allowing for efficient transfer of information. This network type is known as a small world network because every node is relatively close to other nodes. Analyses of different languages have consistently shown how different linguistic systems exhibit such SWN characteristics, characteristics which are now considered fundamental in facilitating efficient and quick retrieval of linguistic information (Borge-Holthoefer & Arenas, 2010). Common parameters of network structure include - the networks clustering coefficient (CC), the average shortest path length (ASPL), and the modularity index (Q).

The CC measures the network's connectivity. It refers to the probability that two neighbors of a node will themselves be neighbors (i.e., a neighbor is a node *i* that is connected through an edge to node *j*). The ASPL and Q index measure the global structure of the network. The ASPL measure refers to the average shortest number of steps needed to be taken between any two pair of nodes. The Q measure examines how a network breaks apart (or partitions) into smaller sub-networks. The larger the modularity measure, the more the network comprised of sub-networks (Newman, 2006). A SWN is characterized by having a high CC and a short ASPL. To examine whether a specific network is a SWN, the statistical properties of empirical data are compared to those of a random null network with the same number of nodes and edges.

Previous work has conducted such analysis to examine cognitive phenomena such as language development, bilingualism, memory search and retrieval, and creative ability (Borge-Holthoefer & Arenas, 2010). For example, Kenett et al. (2014) found that low and high creative individuals show different semantic network structure. The semantic network of high creative individuals exhibited lower ASPL and Q values, and higher CC values compared to that of the low creative individuals. This was the case despite both networks having an equal number of nodes, edges and average number of edges per node. Thus, semantic networks analysis can be applied to examine differences in semantic memory structure related to different conditions such as attributive or relational combinations.

Some current theories of semantic memory posit that conceptual representations are not invariable across people or across time, but rather dynamically change contingent on context (e.g., task demand, stimulus modality) and individual differences (e.g., processing preferences), with short- and long-term effects on the structure of semantic memory (Yee & Thompson-Schill, 2016). Such a dynamic perspective describes an experienced-based, distributed, semantic memory system that allows for flexible, generative language. We apply semantic network analysis to examine how the process of combining concepts changes the semantic network and whether such effects depend on the different mechanisms (attributive or relational) applied in such combinations (see also Schilling, 2005).

Here, we present preliminary results of an on-going study where we examine and compare the structure of semantic memory networks before and after an attributive or relational conceptual combinations task. We operationalize the effects of the different conceptual combination mechanisms on semantic memory structure as differences in quantitative measures of the semantic network before and after the conceptual combination task. Specifically, we focus on global measures of the network's structure (ASPL and Q) and connectivity (CC). We predict that any possible differences between these two mechanisms will be manifested in the post-manipulation networks.

Materials & Methods

Participants

Participants (N = 26) were recruited from the University of Pennsylvania as part of a larger on-going research study on conceptual combinations and semantic memory structure. Participants were 55% female, average age of 22.6 years (SD = 3.9) and with an average 16.4 years of education (SD = 3). Participants were randomly assigned to the attributive combinations (AC) or relational combinations (RC) conditions (N = 13 in each group). This study was approved by the University of Pennsylvania Institutional Review Board.

Design Overview

We characterized the semantic network of participants using their free association responses obtained twice, before and after completing a conceptual combination task that was biased (using both detailed instructions and a priming manipulation) to elicit either attributive or relational interpretations. With this procedure, we were able to assess the main effect, within subjects, of conceptual combination (by comparing the structure of the semantic networks at both time points) as well as the interaction, between subjects, of the *type* of conceptual combination on network change. We also collected a number of measures of cognitive ability that will be used in planned analyses of individual differences in these effects. We will first describe the conceptual combination task we used to manipulate the type of combination process (attributive or relational). We will then describe the method we applied to represent the semantic networks (before and after the conceptual combination task).

Conceptual Combination Task

Participants were presented with 25 noun-noun combinations and were required to come up with an interpretation for each combination (Wisniewski & Love, 1998). They were also asked to indicate how familiar they were with each combination and how hard it was for them to retrieve the interpretation they gave. In order to examine the effect of attributional and relational combination mechanisms on semantic memory, we used ambiguous noun-noun combinations—combinations that can either have an attributive or relational interpretation—and we primed the participants to generate either attributional or relational interpretations. This was achieved both by an instruction manipulation and by an initial noun-noun combination priming phase (Wisniewski, 1996). Our task comprised the following parts: instruction manipulation, priming phase, and ambiguous conceptual combination task. Participants performed this task between two sessions of semantic network estimation (a week apart; see *Semantic Network Estimation*). This allowed us to examine the effect of the different conceptual combination mechanisms on semantic memory structure.

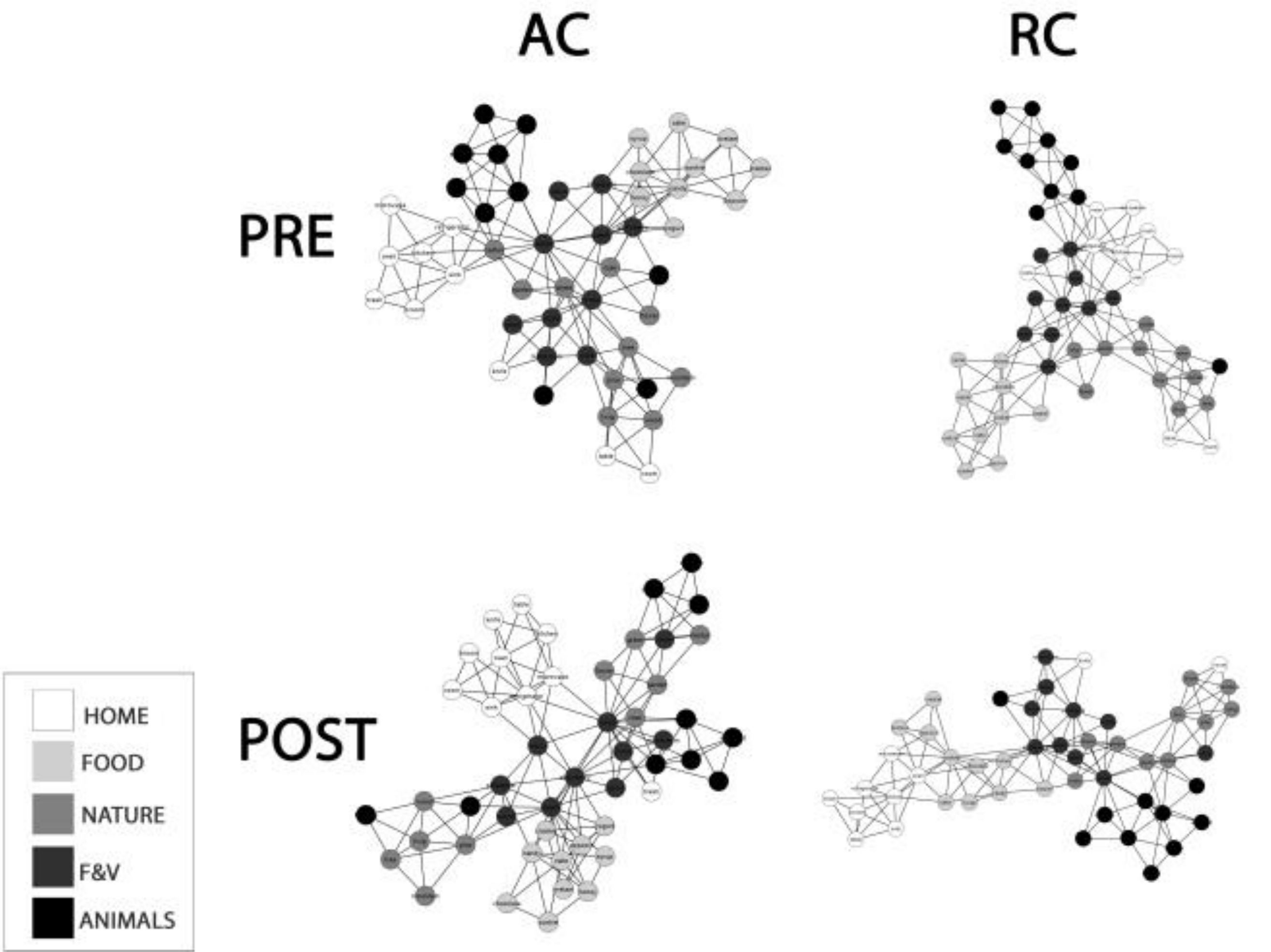

Figure 1: 2D visualization of the pre- and post- AC and RC semantic networks

During the instructions stage, both participant groups received the same general description of the task. They were then told that there are different strategies that people use to combine concepts together and were given either attributional or relational instructions. In the attributional instructions, participants were told that one such strategy entails applying one dominant attribute of one word to explain the other. In the relational instructions, participants were told that one such strategy entails relating both words in some way. Participants read three ambiguous noun-noun combinations in which the specific required interpretation was emphasized. For example, participants read *ant apple*. In the attributive instructions participants were told that this could mean 'a small apple' but not 'apple with ants on it'. In the relational instructions participants were told that this could mean 'apple with ants on it' but not 'a small apple'.

In order to increase the difference between the two experimental conditions, we followed these instructions with an attributive or relational priming phase in the conceptual combination task, following from Wisniewski (1996), which showed that noun-noun combinations can be primed to generate either attributive or relational interpretations. We presented participants with ten modifier-head noun-noun combinations, where the head noun remained constant but the modifier noun either primed an attributive combination or a relational combination (e.g. *razor insult* for the attributive combination condition vs. *girlfriend insult* for the relational combination condition).

Finally, participants completed the ambiguous noun-noun conceptual combination task for 25 word-pairs. In order to select stimuli not only that were ambiguous (in that they elicited attributive and relational interpretations across subjects) but also that were flexible (in that the percentage of attributive and relational interpretations could be affected by an instructional manipulation), we conducted a norming study via Amazon's Mechanical Turk (AMT). The AMT surveys were conducted on a larger pool of 50 noun-noun pairs, divided into two surveys of 25 noun-noun pairs each. We conducted three different variations of these surveys with 20 AMT participants in each survey. In the first variation (baseline condition), participants were presented with the noun-noun pairs and asked to generate an interpretation to it. These interpretations were then classified as either attributive or relational by two independent judges (inter-rater agreement > .8). This variation allowed identifying ambiguous noun-noun pairs, classified as pairs that ranged from 30%/70% to 50%/50% interpretations. The second and third AMT variations (biased conditions) manipulated task instruction, as described above, to examine how much these noun-noun pairs could be "pushed" into one type of interpretation. These interpretations were similarly rated as attributive or relational by two independent judges (inter rater agreement > .8). Finally, we examined the effect of the instruction manipulation on biasing the interpretations. We calculated a percent signal change, which quantified the percentage change in interpretations of an ambiguous word-pair from the baseline condition to the biased interpretation condition. This was calculated for both types of interpretations for all noun-noun combinations.

Based on the AMT surveys, 25 noun-noun combinations were chosen. These combinations were chosen so that the modifier-nouns were comprised from five different semantic categories (animals, fruits and vegetables, nature, food, and home). All of the modifier nouns, and none of the head nouns, were included in the semantic network analysis as described below. The average ambiguity of these word pairs was 54%/46% attributive/relational interpretations. Percent signal change from baseline to biased attributive interpretations was 28% and biased relational interpretations was 42%. No significant differences were found between the percent signal change for attributive vs. relational interpretations ($p < .4$).

Semantic Network Estimation

The semantic networks of the AC and RC groups were computed using the computational approach developed by Kenett et al. (2011). Participants in both groups performed a continuous free association task twice, once before and once after the conceptual combination task. Participants were presented with a cue word and had one minute to generate as many associative responses they could for that cue word. Participants generated free associations to a list of 50 cue words. These 50 cue words consisted of five categories used in the conceptual combination task, including the five modifier nouns for each category and five other category members. Thus, the *a priori* structure of the semantic network consists of five (category) communities.

The semantic network of these 50 cue words was computed and compared between the pre- and post- AC and RC conditions: First, the data were preprocessed to standardize responses and fix any spelling mistakes. Second, the associative correlation between any pair of cue words was calculated using Pearson's correlation. This resulted in a 50 x 50 matrix where each cell denotes the association correlation between node *i* and node *j*. Finally, the planar maximally filtered graph filter was used to remove spurious correlations (Kenett et al., 2014). This produced an adjacency (connectivity) matrix that represents the associative correlations between any pair of nodes. As our focus is on the structure of the networks, the association correlations were binarized to equal one. Thus, the resulting semantic networks are unweighted (all weights equal one) and undirected (symmetrical relations). Constructing semantic networks for different groups (pre- and post- AC and RC) that are comprised from the same nodes (50 cue words) and with an equal number of edges (288 edges) allows comparing between them. Furthermore, the average degree, the average amount of edges per node in all networks was equal (average of 5.76 edges per node).

Analyses were performed with the Brain Connectivity Toolbox for Matlab (Rubinov & Sporns, 2010). The clustering coefficient (CC; measuring network connectivity) and the average shortest path length (ASPL; measuring global distances) were calculated (Boccaletti, Latora, Moreno, Chavez, & Hwang, 2006). The network's CC and ASPL were evaluated qualitatively against the equivalent parameters in a random network with the same number of nodes and edges (CC_{rand} and $ASPL_{rand}$, respectively). Lastly, the modularity (Q) index was calculated (Newman, 2006). In order to assess the reliability (i.e., statistical significance) of observed differences across time points and across subject groups, we used a bootstrap method (Efron, 1979) to simulate and then compare partial networks for each of the conditions. We reasoned that if the networks differed from each other, then any partial network consisting of the same nodes in the networks should also be different. Furthermore, the bootstrap method makes it possible to generate many simulated partial semantic networks, allowing for statistical examination of the difference between them. The bootstrapping procedure involves random selection of half of the nodes comprising the networks. Partial networks were constructed for each condition (pre- and post- AC and RC) separately for these selected nodes. This method is known as the without-replacement bootstrap method (Bertail, 1997). Finally, for each partial network, the CC, ASPL, and the Q index were computed. This procedure was simulated with 10,000 realizations. The difference between the bootstrapped partial networks on each network parameter was then tested using a mixed model analysis of variance (group [AC, RC] x time [pre, post]).

Procedure

Participants completed all tasks using the Qualtrics software on two different sessions a week apart. In the first session, participants completed the free-association task. In the second session, participants first completed the conceptual combination task and then the free association task. In the free association task, participants were instructed to generate, in one minute, as many different responses they could think of to a cue word. In each trial, the cue word was presented in the center of the screen with a response box below it, where participants typed their responses. Below the response box appeared a timer, counting down from 60 seconds. After 60 seconds elapsed, a new trial immediately began. Cue words were presented randomly and after 25 cue words participants had a short break. In the conceptual combination task, participants were first instructed on the task with the task manipulation instruction (attributive or relational). Next, a short practice was conducted with the experimenter, who gave feedback on the participant's interpretations. Stimuli used in the practice were not used in the task itself. In each trial the noun-noun combination appeared in the center of the screen with a response box below it. Participants were instructed to write their interpretations in the response box. Underneath the response box the participant had to choose how familiar s/he was with the noun-noun compound on a five point Likert scale (ranging from *extremely familiar* to *not familiar at all*) and how easy it was for them to generate the interpretation on a seven point Likert scale (ranging from *extremely easy* to *extremely difficult*). Participants were randomly assigned to the attributive and relational conditions. The stimuli were randomly presented.

Results

We computed the semantic networks for the pre- and post- AC and RC conditions based on the procedure outlined above. Next, we computed and compared the different network measures for all four networks (Table 1). To visualize the networks, we used the force-directed layout of the Cytoscape software (Shannon et al., 2003) to plot the graphs (Figure 1). In these 2D visualizations, nodes (cue words) are represented as circles and links between them are represented by lines. Since these networks are unweighted and undirected, the links merely convey symmetrical relations between two nodes. The grayscale of the nodes relate to the five semantic categories used in our study.

The network analysis revealed both general and specific differences between the pre- and post- AC and RC networks. In regard to structural properties of the networks, ASPL and Q, the post session led to lower ASPL and Q values, which was stronger for the RC network. In regard to connectivity property of the network, CC, the post session led to different effects in the AC and RC networks: while the AC network had a lower CC value, the RC network had a higher CC value, compared to the first session (**Table 1**).

Table 1: Network measures for the pre- and post- AC and RC networks

	AC-Pre	AC-Post	RC-Pre	RC-Post
CC	.702	.699	.697	.701
ASPL	2.930	2.814	3.223	3.034
Q	.578	.565	.583	.560
CC_{rand}	.103	.125	.131	.176
$ASPL_{rand}$	2.331	2.341	2.339	2.338

The bootstrapping analysis revealed a significant main effect of time (pre, post) for ASPL and Q, due to decreased values for the post-session (all p's < .001). This analysis also revealed for all measures a significant interaction between group and time (all p's < .001). For ASPL and Q, this effect resulted from a stronger effect for the RC group (all p's < .001) and for the CC resulted from an increase in CC for the RC group and a decrease in CC for the AC group in the post-session (all p's < .001).

Discussion

In this work, we applied a computational network science approach to examine the dynamic effects of conceptual combination mechanisms on the structure of semantic memory. We found general and specific effects on the network: In both groups, the post manipulation network exhibited lower structural properties of global distances and modularity, which was more pronounced in the RC group. Furthermore, while the AC post-manipulation network exhibited lower connectivity, the RC post-manipulation network exhibited higher connectivity. Thus, our results indicate that the relational combination manipulation has a greater effect on semantic memory structure than an attributive combination manipulation.

Notably, both networks have the same nodes, amount of edges, and average degree (number of edges per node). Thus, these differences reflect both a global task-induced effect on semantic networks and a local effect of relational combination manipulation on semantic memory structure. Both lower ASPL and Q have been related to higher creative ability (Kenett et al., 2014), thus indicating the creative effect of conceptual combinations on semantic memory. This stronger effect, combined with higher CC, in the RC group, suggests that relational combinations may demand the generation of novel contexts in which both nouns relate to each other, thus leading to higher re-structuring of the network. More fine grained examination is needed in order to test specific effects on these networks.

Our findings are in line with current theories of semantic memory, which view it as a dynamic system (Schilling, 2005; Yee & Thompson-Schill, 2016). Such theories argue that both context (task demands) and individual differences (processing style) lead to short- and long-term changes in semantic memory structure. Our current study applies semantic network analysis to examine how a conceptual combination task affects the structure of semantic memory and whether it is affected differently based on a specific conceptual combination mechanism. We show how manipulating concepts in the semantic network (through a conceptual combination manipulation) changes the structure of the network. We will also examine how individual differences affect the structure of semantic memory, based on the behavioral measures we are collecting in our on-going study. Our findings are also related to recent studies investigating how relational versus attributive based categories differentially effect cognitive processing, such as typicality effects and learning (Asmuth & Gentner, 2017; Gentner & Kurtz, 2005; Rein, Goldwater, & Markman, 2010). For example, Asmuth and Gentner (2017) show how relational nouns are more "mutable" (affected by context) in memory than entity nouns. Thus, our approach offers a quantitative method to examine such behavioral findings.

Finally, there are a few limitations to this study. First, our study currently has a small sample size, which can affect the reliability of our results. We are currently continuing to collect data to conduct these analyses with a larger sample size in each group to strengthen our results. Furthermore, our research computed semantic networks aggregated at the group-level. It is possible that within these aggregated group-based networks there are further individual differences that relate to semantic memory structure and conceptual combinations. Future research needs to examine the effects of conceptual combinations on semantic memory structure at the individual-level (Benedek et al., 2017).

In conclusion, the work reported here is a first step at harnessing computational network science to investigate the effects of different conceptual combination mechanisms on semantic memory structure. We plan to continue and increase sample size and examine how our findings relate to various behavioral measures we are also collecting, such as creative ability, intelligence and personality traits. Overall, our results demonstrate that semantic networks can be applied to study group-level effects of different conceptual combination mechanisms and contribute to the growing body of literature demonstrating their efficacy in understanding high-level cognition.

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