Novel conceptual combination can dynamically reconfigure semantic memory networks

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Abstract

We do not simply *have* concepts; we *use* concepts. And, the way in which we use concepts can dynamically change the relations among them. One way to shed light on this dynamic nature is to examine how the novel processing of concepts—in our case, interpreting unfamiliar nominal compounds—might reconfigure semantic memory networks. We used network science tools to characterize properties of participants' semantic networks (e.g., connectivity), and we compared these networks before and after participants constructed novel conceptual combinations. Furthermore, we contrasted combinations in which one attribute of one concept is used to describe another (attributive) with those in which a relation is identified to link two concepts (relational). We found that relational, but not attributive, combinations increased connectivity and lowered structure in the network. We suggest that constructing relational interpretations of compounds requires the generation of novel contexts, thus leading to greater restructuring of the semantic network.

Keywords: Conceptual combinations; Semantic Networks

Introduction

Current theories of semantic memory posit that conceptual representations are not invariant 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)¹⁻⁴. Such a dynamic perspective describes a semantic memory system that allows for flexible, generative language^{4,5}. Our central question is whether the flexible use of concepts in turn leads to a flexible reconfiguration of semantic networks that describe the relations among concepts. To answer this question, we measured properties of semantic memory networks on two occasions, separated by a manipulation designed to influence the interpretation of some of the concepts in the network—namely, the interpretation of unfamiliar nominal compounds—in order to determine whether and how different types of conceptual combination reconfigure the semantic network.

Conceptual combination—the ability to construct complex concepts from simpler constituents—is fundamental to many aspects of cognition⁶⁻⁹. For example, consider the novel nominal compound *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 hawks¹⁰ (**Fig. 1**). These two putatively different types of conceptual combination processes—attributive and relational—have been studied via behavioral and neuroscientific means^{11,12}, but the extent to which these two cognitive processes are similar or distinct remains an open question⁹. If comprehension of nominal combinations in either an attributive or a relational manner has dissociable effects on the semantic memory network, this result would not only illustrate the dynamic nature of conceptual systems but also would lend support to the claim that the two combinatorial processes are distinct.

In the current study, 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 how conceptual combinations affect semantic memory, and how it differs based on attributive or relational processes. Such effects have only been indirectly and theoretically proposed in previous research¹³⁻¹⁷. Estes and Jones¹³ have argued, via indirect behavioral measures, that relations between concepts act as independent representations that can offer connections between concepts in semantic memory. Solomon and Thompson-Schill¹⁸ have shown how focusing on conceptual properties can “stretch” a concept’s meaning, thus changing memory structure¹⁹. Thus, we hypothesize that relational and attributive combination manipulations will both lead to restructuring effects on the semantic network, by either changing or creating new connections between concepts in the network.

What is a Robin Hawk?

Attributive

Relational

Fig. 1: Illustrative interpretations of the noun-noun compound combination *robin-hawk*. When asked what this compound means, participants either generate an attributive (e.g., *a red-breasted hawk*) or a relational (e.g., *a hawk that preys on robins*) interpretation.

Recent studies have used network science methods to represent semantic memory as a semantic network and analyze its properties. Network science is based on mathematical graph theory, providing quantitative methods to investigate complex systems as networks²⁰. A network is comprised of nodes, which represent the basic unit of the system (e.g., concepts in semantic memory), and links, or edges, which signify the relations between them (e.g. semantic similarity). A growing body of research uses network science tools at the cognitive level to investigate the structure of language and memory²⁰⁻²³. For example, the use of network science tools in cognitive science has enabled the direct examination of the theory that high creative individuals have a more flexible semantic memory²⁴, identified mechanisms of language development through preferential attachment^{25,26}, shed novel light on statistical learning²⁷, shown how specific semantic memory network parameters influence memory retrieval^{28,29}, and provided new insight on second language in bilinguals³⁰.

Common parameters of network structure include the network's 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). In semantic networks, CC denotes the similarity between concepts, where a higher CC relates to higher overall connectivity in the network. The ASPL and Q index measure the global structure of the network. The ASPL measure refers to the average shortest number of steps that need to be taken between any two pair of nodes. The higher the ASPL, the more spread out a network is. Previous research has shown that ASPL in semantic networks corresponds to participants' judgments regarding whether two concepts are related to each other³¹. The Q measure

examines how a network breaks apart (or partitions) into smaller sub-networks. The larger the modularity measure, the more the network comprises sub-networks^{32,33}. Such subcommunities can be subcategories in a semantic network. In creativity research, for example, higher creative individuals exhibit a more connected (higher CC), less structured (lower ASPL and Q) semantic network than lower creative individuals²⁴, differences that were related to their flexibility of thought³⁴.

In the current study, we applied semantic network analysis to examine how the process of combining concepts affects semantic memory, and whether such effects depend on the different processes (attributive or relational) applied during such combinations (see also³). We operationalized the effects of conceptual combination on semantic memory as differences in quantitative properties of connectivity (CC) and structure (ASPL and Q) of the semantic network estimated to 50 cue words based on a free association task. Participants completed the free association task, and then returned one week later to complete the free association task a second time, following the experimental intervention: participants performed a conceptual combination task that was biased (using both detailed instructions and a priming manipulation) to elicit either attributive (AC group) or relational (RC group) interpretations to the same ambiguous nominal compounds (i.e., compounds that can elicit either an attributive or relational interpretation). A third group of participants completed the free association task at two time points (one week apart) without the intervening conceptual combination task (baseline condition; BC). With this procedure, we were able to assess how conceptual combination affected the semantic networks, and identify differential effects of the *type* of conceptual combination on network change.

Results

Effects of conceptual combination on properties of semantic networks

We estimated the semantic network of each group of participants using their responses on a continuous free association task obtained both before and after completing a conceptual combination manipulation task. In the conceptual combination task, participants gave either attributive or relational interpretations to a list of 25 ambiguous nominal compounds (e.g., *robin hawk*). In the free association task, participants had one minute to generate as many responses they could think of to each of 50 cue words. These 50 cue words were drawn from five categories (*animals, fruits and vegetables, nature, food, and home*); for each category, half of the cue words (“manipulated cues”) appeared in the conceptual combination task as a modifier noun (the first noun in the noun-noun pair; e.g., *robin*) and half of the cue words (“unmanipulated cues”) did not (e.g., *octopus*; see Appendix). Thus, the semantic network comprised both manipulated and unmanipulated cues, allowing us to examine specific and general effects of the conceptual combination manipulation on the post-manipulation semantic network.

To visualize the networks, we used the force-directed layout of the Cytoscape software (**Fig. 2**)³⁵. In these 2D visualizations, nodes are represented as circles and links between them are represented by lines. Since these networks are unweighted and undirected, the links convey symmetrical relations between two nodes. Visual inspection of the networks revealed that the cue words overall cluster according to their a priori categories, and that there is a more profound change in the overall structure of the networks for the pre- and post- RC conditions (**Fig. 2**).

Fig. 2: 2D visualization of the pre- and post- BC, AC, and RC of the semantic networks of the 50 cue words (nodes). Edges denote symmetrical, binary relations between nodes. Colors represent category membership.

The group-based network analysis computes a single value for each network measure for the different networks (CC, ASPL, Q). In order to test the statistical significance of differences between the networks, we applied a bootstrapped partial networks analysis^{36,37} to generate a distribution of values for each of the network measures from the empirical data (see *Methods*). Partial networks were constructed for a randomly chosen set of 25 nodes from the full network. Network measures were computed for each partial network and this procedure was reiterated 1,000 times. This resulted in a sample distribution of

1,000 samples for the properties of connectivity (CC) and structure (ASPL and Q) for all six networks (Fig. 3).

CC: A Session (pre, post) $\times$ Group (BC, AC, RC) mixed model ANOVA revealed a significant interaction between Group and Session, $F(2, 2997) = 5.18, p < .01, \eta^2 = .002$. Post-hoc paired-samples t -test analyses revealed that only the RC group had a significant increase in CC after the manipulation task, $t(999) = -3.42, p < .001$. No significant change was found for the BC group or the AC group (both $ps > .4$) and there were no significant differences in the pre- session CC values between the three groups (all $ps > .4$).

ASPL: A Session (pre, post) $\times$ Group (BC, AC, RC) mixed model ANOVA revealed a significant interaction between Group and Session, $F(2, 2997) = 3.6, p < .03, \eta^2 = .002$. Post-hoc paired-samples t -test analyses revealed that only the RC group had a significant decrease in ASPL, $t(999) = 2.93, p < .001$. No significant change was found for the other two groups (both $ps > .3$), and there were no significant differences in the pre- session ASPL values between the three groups (all $ps > .4$).

Q: A Session (pre, post) $\times$ Group (BC, AC, RC) mixed model ANOVA revealed a significant interaction between Group and Session, $F(2, 2997) = 4.45, p < .01, \eta^2 = .002$. Again, only the RC group exhibited a significant decrease in Q, $t(999) = 3.42, p < .001$. No significant change was found for either the BC group or the AC group (both $ps > .3$), and there were no significant differences in the pre- session Q values between the three groups (all $ps > .12$).

Finally, we examined whether the manipulated and unmanipulated cues were affected differently in the post-manipulation AC and RC networks. We computed for each node—in the pre- and post- AC and RC networks—its local CC and local ASPL³⁸. The local CC measures the average of each node's CC vector. The local ASPL measures the average distance for each node to all other nodes. We then conducted, for each group (AC and RC) and each measure (local CC and local ASPL), a Type (manipulated, unmanipulated) $\times$ Session (pre, post) mixed model ANOVA. These analyses did not reveal any significant differences in the effect of session on the type of nodes (all ps ns). Thus, the manipulation had a general, global effect on the properties of the network post-manipulation¹⁹.

Fig. 3: Partial network analysis for CC (left), ASPL (center), and Q (right) for the pre- and post- BC, AC, and RC groups. X-axis – BC, AC, and RC groups. Y-axis – dependent variables (CC, ASPL, and Q; Error bars denote standard error).

Effects of conceptual combination on the content of free associations

The analyses of semantic networks based on free association data reported above indicate that relational conceptual combination changes patterns of responses to the free association task but do not, on their own, reveal what about those responses has changed. To examine the types of associations that are retrieved post-manipulation, we recruited a group of Amazon Mechanical Turk raters³⁹ to rate each of the associative responses generated in the pre- and post- sessions for all three groups. These raters rated each of the associative responses as either a property of the cue word (e.g., generating *strong* for *wood*), in relation to the cue word (e.g., generating *tree* for *wood*), or neither (see *Methods*). From these ratings, we computed the average percentage of responses rated as property-based and examined the effect of group and session on this percentage (**Fig. 4**). A Group (BC, AC, RC) $\times$ Session (pre, post) mixed model ANOVA revealed a significant interaction between Group and Session, $F(2, 147) = 7.44, p < .001, \eta^2 = .09$. Post-hoc paired-samples *t*-test analyses revealed a significant increase in the percentage of attributive responses in the AC group and a significant decrease of attributive responses (and an increase in relational responses) in the RC group (all $ps < .01$) post manipulation. No significant changes were found in the BC group, and there were no significant differences in the pre- session responses between the three groups (all $ps < .6$). Thus, the conceptual combination task affected the content of the free associations generated to the cue words post-manipulation, by increasing attributive responses in the AC condition and increasing relational responses in the RC condition.

Fig. 4: Percentage of associative responses rated as property-related for each of the conditions.

Our method of network estimation relies on the overlap of associative responses between cue nodes: The more similar the associative responses generated by participants in the group to two cue words, the stronger these two words will be related to each other at the semantic network (see *Methods*). As a result, it is possible that a change in the *number* of responses generated may influence the changes in our network measures. We examined the effect of the conceptual combination task on the number of free associations generated, on average, to the cue words by participants in the three groups (**Fig. 5A**). A Group (BC, AC, RC) $\times$ Session (pre, post) mixed model ANOVA revealed a significant effect only for Session, $F(1, 147) = 10.99, p < .001, \eta^2 = .07$. Post-hoc *t*-test comparisons revealed a significant reduction in the number of associations generated by participants during the post session for the AC ($p < .02$) and RC ($p < .02$) groups, but not for the BC group ($p = .43$). Therefore, this factor cannot explain the effects found only for the post-manipulated RC semantic network.

For similar reasons, we examined the effect of the conceptual combination task on the number of *unique* associative responses generated to the cue words (**Fig. 5B**). An change in the unique number of free associations generated at the group level to a cue word may change the estimated relations between cues in the semantic network. A Group (BC, AC, RC) $\times$ Session (pre, post) mixed model ANOVA revealed a significant main effect of Group, $F(2, 147) = 13.9, p < .001, \eta^2 = .16$. Post-hoc *t*-test comparisons revealed that this effect is driven by the AC group having significantly lower number of unique responses compared to the BC and RC groups (both $ps < .001$). This analysis also revealed a significant main effect of Session, $F(1, 147) = 354.13, p < .001, \eta^2 = .71$. This effect was driven by a

significant decrease in the amount of unique associative responses generated in the post session in all groups (all p 's < .001). Finally, this analysis revealed a significant interaction between Group and Session, $F(2, 147) = 8.23, p < .001, \eta^2 = .10$. To examine what drives this interaction effect, we computed change scores (post minus pre) for all three groups and conducted a one-way ANOVA on these change scores^{40,41}. This analysis revealed a significant main effect of Group, $F(2, 147) = 8.3, p < .001, \eta^2 = .1$. This effect was driven by a significant difference between the AC group (change score = -29.7, SD = 13.6) and both RC (change score = -19.6, SD = 16) and BC (change score = -19, SD = 14.8) groups (all $ps < .001$). No significant difference was found between the BC and RC groups ($p = .9$). Thus, although a significant decrease of number of unique associations at the post-session occurred for all three groups, it had the strongest effect for the AC group.

Finally, we conducted these two types of analyses—the effect of the conceptual combination task on the average number of associations and number of unique associations—for the manipulated and unmanipulated cues separately in the AC and RC groups. These analyses for each of these subsets led to similar results as those reported above (all $ps < .001$). Thus, similar to the network analysis, the conceptual combination manipulation task had a general, global effect on the generated free associations post manipulation.

Fig. 5: The effect of the conceptual combination task on the free association task. (A) Average amount of associative responses generated per participant per cue word for each of the conditions. (B) Average amount of unique associative responses generated to the cue words for each of the conditions.

Discussion

In the current study, we used a network science approach to examine the dynamic nature of semantic memory. We did so by examining how different processes of combining concepts may affect the properties of semantic networks. Participants' semantic networks were estimated based on a free

association task, before and after completing a conceptual combination task that biased them to produce either relational or attributive interpretations of ambiguous noun-noun compounds. These semantic networks were compared to a baseline condition, in which participants' pre- and post- semantic networks were estimated without the intervening conceptual combination manipulation task. Our findings are in line with current theories of semantic memory, which view it as a dynamic system¹⁻³. Such theories argue that both context (task demands) and individual differences (processing style) lead to short- and long-term changes in semantic memory structure.

At the network level, using a bootstrapping approach we found that the conceptual combination manipulation task influenced CC, ASPL, and Q. Specifically, the RC post-manipulation network exhibited significantly higher global connectivity (CC), lower global distances (ASPL) and lower modularity (Q) compared to the pre-manipulation network. No differences were found for these properties between the pre- and post-networks for either the AC or BC groups. Finally, we did not find any differences between the local measures of connectivity and distances between the manipulated and unmanipulated cue words (nodes) across the pre- and post- AC and RC networks. As such, we argue that the differences we observed at the semantic network level are attributable to the effect of the manipulation task on the global semantic network, rather than reflecting item-specific changes in retrieval processes. Thus, despite a similar effect of the manipulation task on performance in generating free associations, we found significant changes of the network properties only for the RC group.

Despite the success of the attributive manipulation in biasing participants' interpretations of the ambiguous noun-noun combinations and increasing the percentage of property-based associative responses post-manipulation, the semantic network properties of the AC group did not change. The lack of change across the pre- and post- AC networks may be related to participants focusing on retrieving prototypical properties of the cue words, which may lead to lower overlap of associative responses across the cue words. This finding lends further support to independent attributive and relational conceptual combination processes, given their differential effect on semantic networks. Previous studies using semantic networks have shown how higher CC and lower ASPL and Q have been related to higher creative ability²⁴. As such, the effect of the relational combination on the semantic network—increasing connectivity and lowering structure—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 (see also³). Finally, relational combinations entail various types of relations^{9,42,43}. In our task participants were only required to make relational interpretations, and not a specific type of relation. Future research is needed to examine the effect of specific types of relations on the structure of semantic networks.

Our findings raise an important general question: Has the conceptual combination manipulation task affected the structure of semantic representations, possibly via transient changes in weights connecting across cue words in the semantic network^{5,44,45}, or has it enhanced sensitivity to specific features of these concepts? Previous studies have shown how participants can use various retrieval cues to create “wormholes” in memory while retrieving category members in a verbal fluency task⁴⁶. Furthermore, some have argued that free associations entail retrieval strategies that confound the ability to estimate semantic spaces⁴⁷. Thus, our manipulation task may have either emphasized various retrieval strategies, that led to the changes found in the post-session RC semantic network, or induced an effect at the representational level. However, the conceptual manipulation task did lead to a higher/lower percentage of attributive/relational responses in the attributive/relational group, demonstrating the effect of the conceptual combination task on the content of the associations retrieved and not on the retrieval process itself. Finally, the post-session led to a reduction in the number of free associations and to a lower amount of idiosyncratic associative responses generated to the cue words across all three groups, a reduction that was most pronounced for the AC group. Such effects on the post-session performance in generating free associations were found for both manipulated and unmanipulated cue words. Indeed, disentangling retrieval strategies from representations is a main open issue in the application of network science to cognitive science²⁰. A potential method to further elucidate these two alternative interpretations is to reproduce the findings of our study via other methods of estimating semantic spaces that minimizes retrieval strategies⁴⁷. Another potential method is to conduct a multiplex network analysis that allows examining memory structure as a multidimensional structure with different network layers^{48,49}.

Overall, our approach offers a quantitative method to examine the dynamic nature of semantic memory. Here, we achieve this by examining the effect of conceptual combination processes on semantic networks, effects that previously have only been proposed indirectly and theoretically¹³⁻¹⁷. Such proposals either argue that interpreting a conceptual combination involves the activation of a relational link between concepts in a semantic memory network^{13,14}, or is based on semantic composition—the construction of a meaning for a compound by integrating the semantic representation of its constituents^{15,17}. Our findings support the latter, indicating that relational processing of concepts requires the generation of novel context between them that may increase such an integration process. Our findings are also related to recent studies investigating how relational and attributive based categories differentially affect cognitive processing, such as typicality effects and learning⁵⁰⁻⁵². For example, Asmuth and Gentner examine the distinction between relational and entity nouns⁵⁰. Relational nouns require a relational structure between concepts (e.g., a bridge connects places), while entity nouns have many intrinsic properties (e.g., cats share many similar properties). The authors show how relational nouns are more

“mutable”—harder to recognize by participants and more affected by the context in which they were presented in memory—than entity nouns⁵⁰. While our study focuses on the relational processes people use to combine concepts, and not their linguistic category membership, the findings of Asmuth and Gentner⁵⁰ are in line with our results. We find that while it was more difficult (i.e., lower interpretation accuracy) for participants to generate relational interpretations to the ambiguous conceptual combinations, only the relational manipulation affected the structure of the semantic network, potentially via creating new links in it^{3,19}.

Finally, there are a few limitations to this study. First, we found that it was harder for participants to generate relational interpretations for the ambiguous noun-noun combinations (83%), compared to generating attributive interpretations (93%). Nevertheless, we show an effect of the conceptual combination manipulation on the semantic network only under the relational combination manipulation. Second, the overall agreement (ICC) in our AMT survey to assess the percentage of free association responses judged as attributive across conditions was low (ICC = .45). However, this is adequate agreement in a task that has high ambiguity embedded in it: AMT raters were asked to rate how single word associative responses were related to a cue word. This increased ambiguity most likely decreased inter-rater agreement. Third, our research estimated 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^{53,54}. Finally, While our design does not allow us to examine whether such changes are short or long term, it demonstrates the strength of network science in empirically and quantitatively investigating the dynamics of semantic memory²⁰.

In conclusion, the work reported here is a first step at harnessing computational network science to investigate the effects of comprehension of novel conceptual combinations on the reconfiguration of semantic memory networks. Our findings are in line with current theories of semantic memory that view it as a dynamic system, contingent on context and individual differences. Overall, our results demonstrate that semantic networks can be used as a quantitative method to study effects of different conceptual combination processes and more generally the dynamic nature of semantic memory. Thus, our study contributes to the growing body of literature demonstrating the efficacy of applying network science methods to study the structure and dynamics of cognitive systems.

Methods

Participants. 165 participants were recruited from the University of Pennsylvania and were randomly assigned to the attributive combinations (AC), relational combinations (RC), or baseline (BC) conditions.

Eight participants were excluded due to low performance on the free association task. Four participants were excluded as they did not return to the second session of the study. Data from three participants were lost due to technical issues. As such, the final groups included 50 participants in the BC group (70% female, mean age = 21.7 years [SD = 2.8 years]; mean education = 15.6 years [SD = 2.3 years]), 50 in the AC group (70% female, mean age = 21.8 years [SD = 3 years]; mean education = 16.5 years [SD = 2.8 years]), and 50 in the RC group (70% female, mean age = 21.3 years [SD = 2.6 years]; mean education = 15.8 years [SD = 2.5 years]). This study was approved by the University of Pennsylvania Institutional Review Board.

Conceptual combination task.

Stimuli. We created 25 unique nominal compounds for use in the conceptual combination task. These stimuli included some compounds that were used in previous studies conducted in our lab¹², and also some that were created for the purpose of this study. In order to select stimuli that not only were ambiguous (in that they elicited attributive and relational interpretations across participants) but also 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;³⁹). 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 raters in each survey. In the first variation (baseline condition), AMT raters were presented with the compounds and asked to generate an interpretation. These interpretations were then classified as either attributive, relational or neither by two independent judges (assessed with interclass coefficients ICC > .8). The compounds we chose to use were those that elicited interpretations that ranged from 30%-70% to attributive interpretations. The second and third AMT variations (biased conditions) manipulated task instruction to examine how much these compounds could be "pushed" into one type of interpretation. These interpretations were similarly rated as attributive or relational by two independent judges (ICC > .8). Finally, we examined the effect of the instruction manipulation on biasing the interpretations. We calculated a percent 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 compounds were chosen. These compounds were chosen such that the first noun of each pair—the modifier noun—was a member of one of five different semantic categories (*animals, fruits and vegetables, nature, food, and home*; see Appendix Table 1). All of these modifier nouns, and none of the second nouns of these pairs, were included in the free association task as described below (see Appendix Table 2). The average ambiguity of these word pairs was 54%/46%

attributive/relational interpretations. Percent change from baseline to biased attributive interpretations was 28% and biased relational interpretations was 42%. No significant differences were found between the percent change for attributive vs. relational interpretations ($p = .4$).

Procedure. Participants were presented with these 25 noun-noun pairs and were required to come up with an interpretation for each pair^{8,55}. 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 processes on semantic memory, we used ambiguous noun-noun combinations—combinations that can either have an attributive or relational interpretation—and primed the participants to generate either attributive or relational interpretations. This was achieved both by an instruction manipulation, a practice with feedback phase, and by an initial noun-noun combination priming phase¹⁰. Participants performed this task between two sessions of generating free associations (a week apart; see below). This allowed us to examine the effect of the different conceptual combination mechanisms on semantic memory structure.

During the instructions stage, both 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 attributive or relational instructions. In the attributive instructions, participants were told that one such strategy entails applying a 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 thematic way. Participants read three ambiguous noun-noun combinations in which the specific required interpretation was emphasized. For example, participants read the noun-noun combination *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’.

Next, participants completed a practice phase with feedback. During the practice phase, participants were presented with five ambiguous noun-noun combinations, not used in the main task, and were required to give an interpretation of these noun-noun pairs to an experimenter sitting next to them. The experimenter provided feedback to emphasize to the participants the type of interpretation required based on their condition (either attributive or relational).

In order to increase the difference between the two manipulation conditions, participants then underwent an attributive or relational priming phase. This priming phase is based on the findings of Wisniewski¹⁰, which showed that noun-noun combinations can be primed to generate either attributive or relational interpretations. We presented participants with ten noun-noun combinations from Wisniewski and Love⁵⁵, where the second noun of the pair remained constant but the first 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). These stimuli have been previously shown to prime participants into an attributive or relational interpretation⁵⁵.

Finally, participants completed the ambiguous noun-noun conceptual combination task for 25 pairs. In order to confirm that our manipulation elicited attributive and relational combination interpretations as expected, we computed the percentage of correct attributive and relational interpretations in the priming phase and the main phase of the task. Participants in the attributive condition generated attributive interpretations for 93% of the ambiguous trials (SD = 7%); participants in the relational condition generated relational interpretations for 83% of the ambiguous trials (SD = 14%). As expected, participants were at ceiling in making the correct interpretations for unambiguous stimuli presented in the priming phase, 95% in the attributive condition and 99% in the relational condition. These results indicate that while the manipulation task was successful in biasing participants' interpretation of the ambiguous stimuli, it was harder for participants to generate relational interpretations.

Continuous free associations task. Participants performed a continuous free association task twice, before and after the conceptual combination task. A third group of participants acted as a baseline condition, by completing both free association generation phases, without a conceptual combination manipulation task in between. For all groups, the free association generation sessions occurred a week apart. 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 first nouns of each pair for each category (manipulated cues) and five other category members (unmanipulated cues).

Semantic network estimation. The semantic networks of the pre- and post- BC, AC, and RC conditions were computed and compared using the computational approach developed by Kenett et al.⁵⁶. The core idea of this method is the definition of connections between concepts in the semantic network as the overlap of associative responses generated to these concepts. This notion is in accordance with Collins and Loftus⁵⁷ definition of semantic similarity, and is thus a cognitive inspired approach to examine semantic memory structure⁵⁶. Currently, growing evidence points to the strong coupling between associative and semantic relations⁵⁸. As such, it is plausible to use analysis based on free association responses to investigate semantic distance. The estimated semantic networks consisted of 50 nodes (cue words from the free association task), and their *a priori* structure consists of five (category) communities.

First, the data were preprocessed to standardize responses and fix any spelling mistakes. Furthermore, any of the cue words generated as associative responses were also removed. Next, similar associative response were merged, leading to unique associative response matrices. In these matrices, each column is a cue word, each row is a unique associative response given across the sample to any of the cue words, and a cell denotes the number of participants generating unique associative response y to cue word x . Second, the associative correlation between overlapping associative responses to 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^{37,59}. 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 (edge weights) were binarized to equal one. Thus, the resulting semantic networks are unweighted (all weights equal one) and undirected (symmetrical relations). Estimating semantic networks for different groups (pre- and post- BC, 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).

Conceptual combination analysis. To examine the effect of the conceptual combination manipulation task, two independent judges rated all of participants' interpretations of the conceptual combination stimuli, for both the priming phase and the main task ($ICC = .83$). In both conditions (attributive and relational) each of the stimuli interpretations were judged as being either an attributive interpretation, a relational interpretation, or neither. Finally, the averaged percentage of making correct interpretations (attributive/relational interpretations in the attributive/relational condition) was computed for both the priming phase and main task, after removal of interpretations that were judged as neither. To examine the effect of the conceptual combination task on the content of the free associations generated post-manipulation, we analyzed the percentage of free association responses judged as attributive across conditions (after removing responses that were judged as neither). The percentage of free association responses judged as attributive across all conditions was determined by AMT raters. To obtain independent ratings, we split the 300 cue words (50 cue words x 6 conditions) into lists of either 4 or 5 cue words. For each of the cue words in a list, identical associative responses generated by the entire sample were merged so that each list contained only unique responses. Each one of these lists were submitted, via Qualtrics (www.qualtrics.com), to an AMT rating survey. Each survey was sent to 5 AMT raters who rated all responses in their list. AMT raters were presented with all unique responses generated by all participants in one condition to a subset of four or five of the cue words. AMT raters were asked to

rate each of the associative responses as either describing a property of the cue word (attributive), as a response describing a relation to the cue word (relational), or as neither (see ⁵⁰ for a similar approach). Each list took about 45 minutes to rate. In total, this rating survey had a moderate rater agreement (ICC = .45) ^{60,61}.

The effect of conceptual combination task on retrieval of free associations. To examine the effect of the conceptual combination task on the retrieval process of free associations post manipulation, we analyzed the average number of generated free associations and the number of unique free association responses generated across conditions per cue word, across all participants. The number of free associations generated per cue word across conditions was computed by averaging the number of association responses generated over all cue words across all six conditions. This was done to control for any possible confounds the number of responses generated across conditions could have on the construction of the semantic networks. The number of unique association responses generated on average across conditions was computed by averaging the number of unique association responses generated over all cue words across all conditions. This was done to examine the effect of the conceptual combination manipulation task on the breadth of free associations generated to the cue words.

Semantic network analysis. Analyses were performed with the Brain Connectivity Toolbox for Matlab ⁶². The global and local clustering coefficient (CC; measuring network connectivity) and the global and local average shortest path length (ASPL; measuring shortest path distances) were calculated ²⁰. Lastly, the modularity (Q) measure was calculated ³². The group-based network analysis computes a single value for each network measure for the different networks. In order to statistically compare the semantic networks across time points and across groups, we applied a bootstrap method ⁶³ to simulate a large distribution of the network measures from the empirical data and compare partial networks for each of the conditions. The bootstrapping procedure involves a random selection of half of the nodes comprising the networks. Partial networks were constructed for each condition (pre- and post- BC, AC, and RC) separately for these selected nodes. This method is known as the without-replacement bootstrap method ³⁶. Finally, for each partial network, the CC, ASPL, and Q measures were computed. This procedure was simulated with 1,000 realizations. The difference between the bootstrapped partial networks on each network measure was then tested using a Group (BC, AC, RC) $\times$ Session (pre, post) mixed model ANOVA.

Procedure. Participants initially signed a consent form and then completed all tasks using Qualtrics (www.qualtrics.com) 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. Participants in the baseline condition only completed the free association task in the second session. In the free association task, participants were instructed to generate, in one minute, as many different responses as 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 participants' interpretations. Stimuli used in the practice were not used in the task itself. During the main phase of the task, the 25 noun-noun combinations were presented to participants in a random order. 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 they were with the noun-noun combination 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 BC, AC, and RC conditions.

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Appendices:

Appendix Table 1

Stimulus used in the ambiguous noun-noun combination task.

Category	Stimuli
Animal	Robin Hawk; Shrimp Shark; Cheetah Baby; Alligator Mouth; Whale Boat
Fruits and Vegetables	Tomato Dye; Carrot Envelope; Melon Planet; Strawberry Sugar; Onion Bus
Nature	Pine Mushroom; Cactus Carpet; Tree Chest; Grass Necklace; Rose Hammer
Food	Cracker Wall; Cake Confetti; Honey Soup; Pretzel Rag; Chocolate Clay
Home	Oven Van; Refrigerator Parents; Sink Tub; Microwave Sandwich; Trash House

Appendix Table 2

Stimulus cue words used in the continuous free association task.

Category	Cue Words
Animal	Robin; Shrimp; Cheetah; Alligator; Whale; Octopus; Snake; Snail; Elephant; Bulldog
Fruits and Vegetables	Tomato; Carrot; Melon; Strawberry; Onion; Olive; Pineapple; Lemon; Peach; Mushroom
Nature	Pine; Cactus; Tree; Grass; Rose; Mountain; Wood; Garden; Twig; Flower
Food	Cracker; Cake; Honey; Pretzel; Chocolate; Cookie; Popcorn; Candy; Yogurt; Syrup
Home	Oven; Refrigerator; Sink; Microwave; Trash; Knife; Kitchen; Broom; Table; Room

Note - The first five cue words in each category are the first word (modifier noun) of each noun-noun pairs used in the noun-noun combination task.