Examining Search Processes in Low and High Creative Individuals with Random Walks

Yoed N. Kenett (yoed_kenett@brown.edu)
Joseph L. Austerweil (joseph_austerweil@brown.edu)
Department of Cognitive, Linguistic, and Psychological Sciences
Brown University, Providence, RI 02912 USA

Abstract

The creative process involves several cognitive processes, such as working memory, controlled attention and task switching. One other process is cognitive search over semantic memory. These search processes can be controlled (e.g., problem solving guided by a heuristic), or uncontrolled (e.g., mind wandering). However, the nature of this search in relation to creativity has rarely been examined from a formal perspective. To do this, we use a random walk model to simulate uncontrolled cognitive search over semantic networks of low and high creative individuals with an equal number of nodes and edges. We show that a random walk over the semantic network of high creative individuals "finds" more unique words and moves further through the network for a given number of steps. Our findings are consistent with the associative theory of creativity, which posits that the structure of semantic memory facilitates search processes to find creative solutions.

Keywords: Creativity; Semantic Networks; Random Walks; Cognitive Search

Introduction

How do people vary in their creative ability? While creativity is a multifaceted construct, here we focus on the role of representation and search processes in memory to creative ability. One relevant theory of what differentiates low and high creative individuals focuses on bottom-up factors: the structure of semantic memory (Kenett, Anaki, & Faust, 2014). An alternative theory focuses on the role of top-down, executive processes. This theory argues that top-down control is necessary to produce observed differences between low and high creative individuals (Benedek et al., 2014). In this paper, we demonstrate that a bottom-up, associative account is sufficient to produce some of these results.

Previous work on the relation between creativity and cognitive search has examined how different search processes over semantic memory (memory for knowledge and facts, Jones, Willits, & Dennis, 2015) are related to goal-directed creative tasks (Christoff, 2013; Sawyer, 2011). One major distinction between search processes is whether they are controlled (goal-directed) or uncontrolled (undirected; Christoff, 2013). Controlled search processes involve goal directed search for a specific creative solution (Mednick, 1962). Uncontrolled search processes wander across semantic memory, which can lead to novel combinations and insight (Baird et al., 2012). According to this account, differences in creative behavior are related to differences in memory structure that facilitates random mind wandering to connect distant associations, which are then evaluated for their appropriateness (Christoff, 2013; Sawyer, 2011).

Recent studies have used computational network science to analyze semantic memory structure as a semantic network (e.g., Baronchelli et al., 2013). A semantic network is a set of nodes and edges, where nodes correspond to words or concepts and edges connect pairs of nodes and signify some sense of association between them. Previous theoretical work has proposed that creative solutions and insight are the result of either sophisticated search processes and/or the creation of new edges in semantic networks (Schilling, 2005). However, previous work has not examined the nature of this search process in creativity, whether it be controlled or uncontrolled.

In this paper, we examine how well uncontrolled search on semantic networks can capture some of the differences in how low and high creative individuals conduct cognitive search. To this end, we simulate random walks over the semantic networks of low and high creative individuals. Based on the associative theory of creativity, we hypothesize that the structure of the semantic network of high creative individuals enables them to use simple search processes that reach further and to more weakly connected concepts, than low creative individuals. Specifically, we predict that random walks over the semantic network of high creative individuals will reach more nodes than the walks over the network of low creative individuals. Further, the similarity of the initial and final visited nodes in the walk will be weaker for the network of high creative individuals than for the network of low creative individuals.

The plan of the paper is as follows: First we describe previous work on uncontrolled search and differences in semantic memory structure between low and high creative individuals. Next, we investigate whether a purely uncontrolled random walk process on the two semantic networks captures differences in cognitive search performance between low and high creative individuals. We conclude with a discussion of the implications and limitations of our simulation results.

Previous work

Creative and Uncontrolled Search

Current neurocognitive research has progressed our understanding of the roles of specific cognitive processes (such as working memory and attention) and how they interact to produce creative behavior (Sawyer, 2011). One of these processes is the ability to search through memory and connect seemingly unrelated concepts into something novel (Mednick, 1962). Mednick (1962) theorized that novel combinations of unconnected concepts are more creative the farther apart they are in memory (but see Sawyer, 2011 for an alternative viewpoint). He proposed that this will be evident in the type of associations low and high creative individuals generate to cue words: When presented with the cue word *table*, low creative individuals will generate responses that are mainly restricted to the common response *chair*. Conversely, high creative individuals will generate less frequent responses such as *leg* and *food* (Mednick, 1962). To test his theory, Mednick et al. (1964) had low and high creative individuals generate responses to cue words in a fixed amount of time. He found that high creative individuals generate more responses than low creative individuals. However, what can researchers infer about the differences in representation and processes of low and high creative individuals based on these results? To do so requires a formal account of the representation and processes responsible for producing responses to cognitive search tasks.

A classic uncontrolled search process is spreading activation (Collins and Loftus, 1975). According to this search process, activation spreads over links through words and quickly dissipates with time and distance. Spreading activation over networks can also capture similarity relations: Two words are similar to the extent that they activate each other. Computationally, spreading activation can be implemented as a random walk over a network. Starting at a particular node, a random walk selects an outbound edge with a probability proportional to the edge's weight and moves across it. As this process progresses, it explores more nodes in the network. Analogous to how spreading activation decays over a network, the probability that a walk moves from one node to another decays in their distance. Thus, the probability of moving from one node to another in a small number of steps captures their similarity.

Recent research has explored how random walk models can capture memory retrieval (Abbott, Austerweil, & Griffiths, 2015; Capitán et al., 2012; Griffiths, Steyvers, & Firl, 2007) and performance in creative tasks which require cognitive search (Bourgin, Abbott, Griffiths, Smith, & Vul, 2014; Smith & Vul, 2015). These studies investigated how well a random walk on a representation captures *general* performance on cognitive search and creative tasks. However, they have not examined whether *differences* in creative ability can be understood in terms of the same random walk process on different representations.

In the present study, we conduct naïve random walk simulations on the semantic networks of low semantic creative (LSC) and high semantic creative (HSC) individuals estimated in a previous study (Kenett et al., 2014). This study found that the semantic networks of low and high creative individuals had different structural properties. This was the case despite both networks having an equal number of nodes, edges and average number of edges per node.

Using Kenett et al.'s semantic networks of LSC and HSC individuals, we can test Mednick's (1962) associative theory of creativity using random walks. We formalize the search process proposed by the associative theory as an uncontrolled random walk, and predict that (on average) a random walk over the semantic network of HSC individuals will visit more nodes that are weaker in similarity than an equivalent length random walk over the semantic network of LSC individuals. This would reproduce previously reported differences in human performance by LSC and HSC individuals in generating and judging the strength of associative responses to cue words (Mednick et al., 1964; Rossman & Fink, 2010). We test these predictions via random walk simulations to see whether differences in representation are sufficient to produce observed differences in creative performance.

Semantic Networks of LSC and HSC Individuals

Here we describe how Kenett et al., (2014) estimated different semantic networks for LSC and HSC individuals.

Creativity Assessment - Participants (N = 140) were recruited as part of a larger research study on individual differences in creative ability (Kenett et al., 2014). They completed the following creativity tasks: The Remote Association Test, which measures associative thinking related to creativity (Nevo & Levin, 1978), Tel-Aviv University Creativity Test (Milgram & Milgram, 1976), a battery of divergent thinking tests (e.g., *what are all the things you can do with a brick*), frequently used in creativity research (Runco & Acar, 2012), and the Comprehension of Metaphors task (Faust, 2012), which compares processing of word-pairs that have different semantic relations (either literal, conventional metaphoric, novel metaphoric, or are meaningless). Participants were classified as LSC or HSC individuals using these scores. To do so, Kenett et al. (2014) used the JMP classification and regression tree approach (Galimberti & Soffritti, 2011), to predict performance on the Remote Association Test based on their divergent thinking performance (scores on fluency and quality of responses). Using the decision tree, they defined participants in the lower third of performance as low creative and those in the upper third as high creative. This classification was verified based on the performance of the two groups on the Comprehension of Metaphors task (not used to construct the decision tree).

Semantic Network Estimation - The semantic networks of the LSC and HSC groups were computed using the computational approach developed by Kenett et al. (2011). This approach consists of two parts. First, participants generated continuous free association responses to cue words. The LSC and HSC groups generated free associations to a list of 96 cue words. The cue words were based on fluency norms collected to a list of 36 categorical norms gathered by Henik and Kaplan (2005; e.g. fruits, trees, countries). The top four high frequency words from each category were selected. These words were then tested for their degree of concreteness, on a seven point Likert scale, and only concrete words were selected (words scoring more than three points on the scale). The final pool of cue words consisted of 96 words from 24 categories.

Kenett et al. (2014) used the associative responses for these 96 cue words to estimate semantic networks for LSC and HSC individuals. This was achieved in the following steps: First, the data was preprocessed to standardize responses and fix any spelling mistakes. This resulted in a matrix where each row was a unique associative response, each column was a cue word and each cell contained the amount of participants generating response *i* to cue word *j*. Second, a *N* x *N* association matrix *A* was constructed, where element (*i, j*) was the Pearson's correlation of the response similarity between cue words *i* and *j*. Spurious correlations from the connectivity matrix were removed using a filter (planar maximal filtered graphs) and any non-zero cells were binarized to equal one. Thus, the resulting semantic network is unweighted (the weight of any existing edge is one) and undirected (symmetric relations). Although we plan to explore weighted networks in the future, some previous work has found qualitatively similar behavior for unweighted and weighted semantic networks (Abbott et al., 2015) and so, we used an unweighted network for simplicity and brevity. Importantly, the semantic networks for different groups (LSC and HSC) were comprised of the same nodes (96 cue words) and had an equal number of edges (282 edges). Further, the average degree, the average amount of edges per node in both networks was equal (average of 5.88 edges per node). Thus, differences in behavior between the random walks on the two networks cannot be explained as simply there being more connections in one of the networks.

Current Work

A naïve random walk approach was used to examine the theory that HSC individuals can search further in their semantic networks and reach weaker related nodes. Accordingly, we examine two properties of each walk: the amount of unique visited nodes (indicating the breadth of the search) and the distance between initial and final visited nodes (indicating the strength between initial and final nodes). The random walk analysis over the semantic networks of the two groups was conducted in the following steps: First, we computed the transition probability matrix for each group. As the networks are unweighted, and undirected, the transition probability T_{ij} of moving from node *i* to node *j* is

$$T_{ij} = \frac{A_{ij}}{\sum_{k=1}^{n} A_{kj}} \qquad (1)$$

where A_{ij} is the fully processed association matrix (1 if *i* is connected to *j*, and 0 otherwise) and the denominator is the number of nodes that node *j* is connected to.

Second, we choose an initial starting node (cue word) for both networks from which the walk initiates. For each walk simulation, the initial node (X_{IN}) is randomly chosen from a uniform distribution over the 96 nodes in the network. The random walk starts at $X_0 = X_{IN}$, and then at step n randomly generates the next state X_{n+1} according to the transition matrix *T*. In this model, the transition matrix is unweighted, meaning that the next state is uniformly chosen at random from all nodes connected to node X_n. Further, our model is a *non-jumping* model, which means that the cue word simply initiates the walk. We did not include jumps because previous work found that they did not substantially affect the pattern of first visits to each node by random walks (Abbott et al., 2015).

After running the random walk simulations on the LSC and HSC semantic networks, we examined differences in "search" behavior (the behavior of the random walks) due to the structure of the semantic networks. We computed two different measures of how "creative" a walk was to examine whether the random walks on the LSC and HSC networks capture differences in creativity.

The first measure of walk creativity was the number of unique nodes visited by the search. This measure indicates the breadth of the search achieved by the walk. The second measure of walk creativity was the similarity between the initial and final node visited by the walk. This was defined as

$$s = \exp\left(-D_{ij}\right) \qquad (3)$$

where D_{ij} is the length of the shortest path between initial (*i*) and final (*j*) nodes through the network. The shortest path between two nodes is the smallest number of edges a walk could traverse to get from one node to the other node. Both measures were averaged over simulations per different numbers of steps and compared via Wilcoxon signed rank tests.

Results

We ran 10,000 random walks over both networks for a varying number of steps (10-200 steps in increments of 10 steps). Similar results held for 100,000 simulations. At the start of each simulation, the initial node was randomly chosen and identical for both networks. For each simulation, we computed the mean number of unique nodes visited during the walk and the similarity score between initial and final nodes per amount of steps for the two groups (as described in the subsequent subsections).

Unique Visited Nodes

For both walks, the average amount of unique visited nodes in the network increased with the number of steps of the walk. For the walks on the LSC network, the average number of unique visited nodes ranged from 7.21 (1.42)[1] for

[1] We report standard deviation in parentheses.

simulations taking 10 steps to 52.52 (10.35) for simulations taking 200 steps. For the walks on the HSC network, the average amount of unique visited nodes ranged from 7.24 (1.43) for simulations taking 10 steps to 54.94 (9.34) for simulations taking 200 steps. Overall, walks over the HSC network visited more unique nodes for a given number of steps than over the LSC network (Wilcoxon rank test significant at $p < 0.001$ for all walks longer than 20-steps).

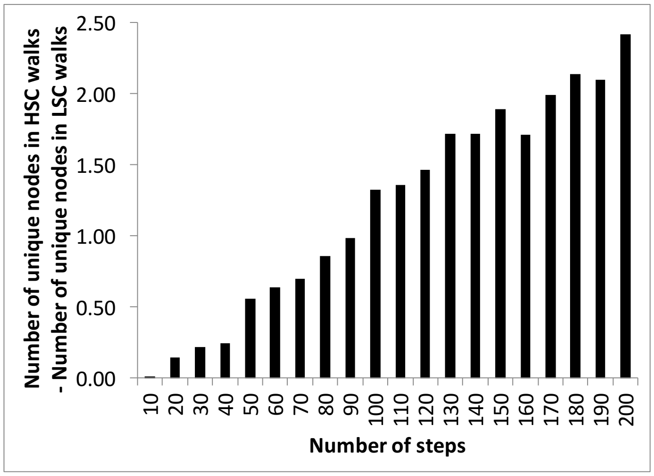

Figure 1: Difference score of the number of unique nodes visited by walks over the LSC and HSC networks varying the number of steps.

As shown in Figure 1, the difference between the number of unique visited nodes by the HSC and LSC walks increases with the number of steps. Generally, the increase is monotonic, but it is not always. In these cases, it is likely that increasing the number of steps allowed the LSC walk (on average) to reach nodes it had not reached with fewer steps, but were already reached by the HSC walk. It is not simply noisy – running more simulations led to similar results. These results are consistent with previous work showing that high creative individuals generate more associative responses than low creative individuals (Mednick et al., 1964).

Similarity Between Initial and Final Nodes

For walks on both networks, the average similarity score between the initial and final node in the walk decreased with the number of steps taken by the walk. For the simulations on the LSC network, the average similarity score ranged from 0.22 (0.22) for simulations taking 10 steps to 0.07 (0.14) for simulations taking 200 steps. For the simulations on the HSC network, the average similarity score ranged from 0.21 (0.22) for simulations taking 10 steps to 0.07 (0.13) for simulations taking 200 steps. Up to 110 steps, HSC walks resulted in lower similarity scores between the initial and final nodes (Wilcoxon rank test significance at $p < 0.1$ for 20-steps and $p < 0.01$ for all other number of steps). This reflects that until 110 steps, walks on the LSC network tended to remain closer to the initial node than walks on the HSC network. Related to this, Beaty & Silvia (2012) found that as more responses are generated in fluency tasks, the responses become more "creative" (as judged by subjective measures of the novelty and uniqueness). From 120 steps onwards, the results are less consistent and even reverse. For example, at 150-160 steps, the walk over the LSC network had a smaller average similarity score than the walk over the HSC network (Figure 2).

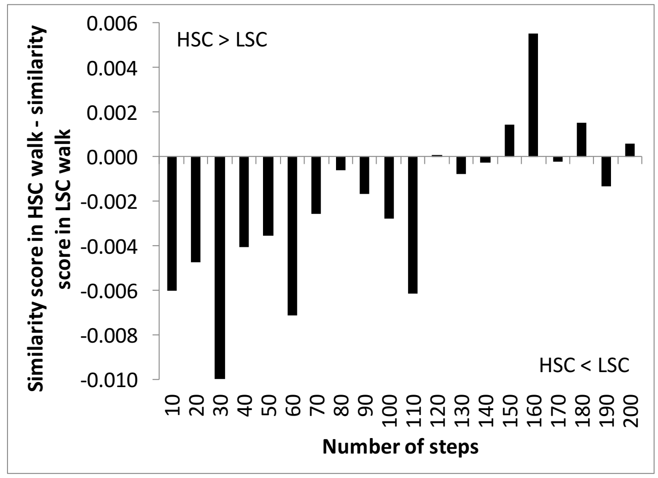

Figure 2: Difference score of the average similarity (shortest path) between initial and final visited nodes by walks over the LSC and HSC networks varying the number of steps.

This reversal in the difference score of the average similarity between initial and final visited walks by the two groups may be due to the large number of steps in the walk relative to the number of nodes (96), which enables the walk to traverse most of the network. Thus, the walk over the LSC network may reach farther in the network which will lower its average similarity score.

One question we had was whether the differences in similarity are simply due to the HSC network visiting more unique nodes. To control for this possible confound, we examined the similarity between the starting and ending node holding the number of visited nodes constant between walks on the two networks (rather than the number of steps). Due to the small amount of unique visited nodes for the 10 and 20 step walks, the truncated final node (the *k*th unique visited node after the initial starting node) was set to three for the 10-step walk, four for the 20-step walk and five for 30-step and onwards. Overall, walks over the HSC network resulted in a smaller similarity score between the initial and final truncated node compared to walks on the LSC network (Wilcoxon rank test significance at $p < 0.01$ for all steps; Figure 3). The reason that the relation between step size and similarity of initial and final node became unreliable in Figure 2 after 110 steps may be due to the HSC random walk traversing most of the network. We plan to investigate this in future work by examining whether the HSC random walk reaches stationarity before the LSC random walk.

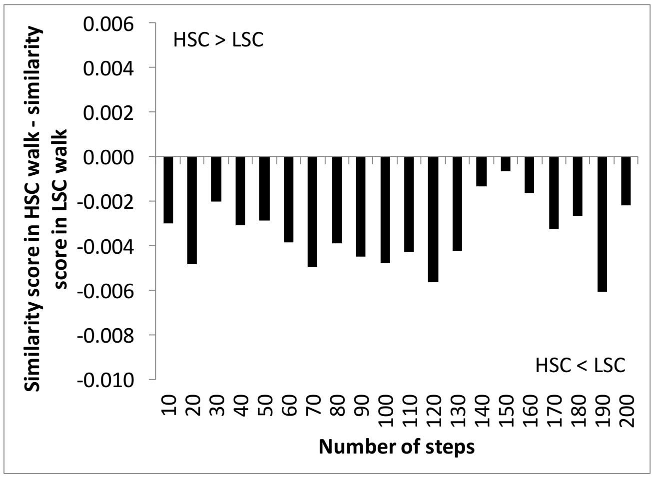

Figure 3: Difference score of the average similarity (shortest path) between initial and final truncated visited nodes by walks over the LSC and HSC networks varying the number of steps.

Discussion

In this paper, we examined how differences in semantic memory structure and search processes interact and relate to individual differences in creative ability. According to the associative theory of creativity, individual differences in creativity should be related to differences in semantic memory structure, which in turn facilitate cognitive search (Kenett et al., 2014; Mednick, 1962). To test this theory, we conducted random walk simulations and examined differences in how uncontrolled search behaves over semantic memory for HSC and LSC individuals.

Our work is situated with a growing amount of research studying uncontrolled thought processes (Christoff, 2013), and complements existing research by examining the search processes of LSC and HSC individuals using computational methods. We found that a random walk process visits more unique nodes and that the similarity strength between initial and final nodes visited by the walk is weaker for walks over the HSC network than the LSC network. These results were robust to the starting node and the number of steps taken by the walk. Thus, individual differences in thought processes between LSC and HSC individuals can be produced by an uncontrolled search process on differing semantic networks, providing support for Mednick's theory.

Notably, both networks have the same nodes, amount of edges, and average degree (number of edges per node). Thus, the differences between the random walks cannot be due to the HSC individuals merely having more connections in their semantic network. Rather, this reflects that HSC individuals have connections that enable a random walk to move quickly through the network. It is important to note that this demonstrates *sufficiency,* but not *necessity*: It does not rule out that different processes are being used by LSC and HSC individuals. Regardless, by showing how differences in representation can produce differences in search behavior, these findings support the associative theory of creativity, which posits that HSC individuals have a semantic memory structure that facilitates novel combinations (Kenett et al., 2014; Mednick, 1962).

There are limitations to this study. First, we treated creativity as a binary construct due to technical constraints (existing semantic network estimation techniques require large data sets). However, creativity is a continuous construct and not a categorical one. Future research should examine the search processes over semantic networks in individuals (see Zemla, Kenett, Jun, & Austerweil, 2016) to provide a better understanding of how search processes relate to creative ability. Second, we only explored undirected, unweighted random walks. Future research should also examine the effect of using directed and weighted random walks on the different semantic networks. Finally, the semantic networks of LSC and HSC individuals were constructed based on free associations. Some researchers have argued that explaining cognitive search behavior as a random walk over a semantic network estimated from free association data is potentially circular (Hills, Todd, & Jones, 2015). However, in our research, creative ability was measured independently with different tasks (divergent thinking) than those used for representing their semantic networks (free associations). Thus, our results are limited to the measures we used to classify participants into LSC and HSC individuals, as well as the way we constructed the semantic networks and measured the random walks. Future research should use different measures for estimating creativity, and the semantic networks of low and high creative individuals.

More generally, this work demonstrates how random walk models can be used to examine thought processes in different populations, such as LSC and HSC individuals. Random walks are a computational implementation of the theoretical concept of spreading activation. This enables researchers to use these models to investigate how well uncontrolled search processes can capture different cognitive processes operating on semantic memory, such as mind wandering or creative thought (Christoff, 2013). Specifically, such models can be used to understand the contribution of both bottom-up and top-down processes in creativity. We do not expect a completely uncontrolled search process (such as the naïve random walk) to explain creativity in all of its complexity. Rather, we intend to use it as a yardstick for determining whether controlled search processes are necessary or if randomness is sufficient to produce the observed variations in behavior (similar to studies of drift in computational models of evolutionary genetics; Reali & Griffiths, 2009). In future work, we also plan to incorporate controlled search processes into the model and see what sort of behavior it can produce that cannot be replicated by an uncontrolled search process (keeping the semantic networks constant). This will guide the development of experiments that provide stronger results capable of dissociating bottom-up and top-down processes contributing to creativity.

Acknowledgments

Data was collected as part of the PhD research of the first author in Bar-Ilan University, Israel.

References

Abbott, J. T., Austerweil, J. L., & Griffiths, T. L. (2015). Random walks on semantic networks can resemble optimal foraging. *Psychological Review, 122*(3), 558-569.

Baird, B., Smallwood, J., Mrazek, M. D., Kam, J. W. Y., Franklin, M. S., & Schooler, J. W. (2012). Inspired by distraction: Mind wandering facilitates creative incubation. *Psychological Science, 23*(10), 1117-1122.

Baronchelli, A., Ferrer-i-Cancho, R., Pastor-Satorras, R., Chater, N., & Christiansen, M. H. (2013). Networks in Cognitive Science. *Trends in Cognitive Sciences, 17*(7), 348-360.

Beaty, R. E., & Silvia, P. J. (2012). Why do ideas get more creative over time? An executive interpretation of the serial order effect in divergent thinking tasks. *Psychology of Aesthetics, Creativity and the Arts, 6*(4), 309-319.

Benedek, M., Jauk, E., Sommer, M., Arendasy, M., & Neubauer, A. C. (2014). Intelligence, creativity, and cognitive control: The common and differential involvement of executive functions in intelligence and creativity. *Intelligence, 46*, 73-83.

Bourgin, D. D., Abbott, J. T., Griffiths, T. L., Smith, K. A., & Vul, E. (2014). *Empirical evidence for markov chain monte carlo in memory search.* Paper presented at the Proceedings of the 36th Annual Conference of the Cognitive Science Society, Boston, MA.

Capitán, J. A., Borge-Holthoefer, J., Gómez, S., Martinez-Romo, J., Araujo, L., Cuesta, J. A., & Arenas, A. (2012). Local-Based Semantic Navigation on a Networked Representation of Information. *PLoS ONE, 7*(8), e43694.

Christoff, K. (2013). Thinking. In K. N. Ochsner & S. M. Kosslyn (Eds.), *The Oxford Handbook of Cognitive Neuroscience* (Vol. 2, pp. 318-333). Oxford: Oxford University Press.

Collins, A. M., & Loftus, E. F. (1975). A spreading-activation theory of semantic processing. *Psychological Review, 82*, 407-428.

Faust, M. (2012). Thinking outside the left box: The role of the right hemisphere in novel metaphor comprehension. In M. Faust (Ed.), *Advances in the Neural Substrates of Language: Toward a Synthesis of Basic Science and Clinical Research* (pp. 425-448). Malden, MA: Wiley Blackwell.

Galimberti, G., & Soffritti, G. (2011). Tree-based methods and decision trees. In R. S. Kenett & S. Salini (Eds.), *Modern Analysis of Customer Surveys* (pp. 283-307). Chichester, UK: John Wiley & Sons, Ltd.

Griffiths, T. L., Steyvers, M., & Firl, A. (2007). Google and the mind: Predicting fluency with PageRank. *Psychological Science, 18*(12), 1069-1076.

Henik, A., & Kaplan, L. (2005). *Content of categories: Findings regarding categories in Hebrew and comparison findings in the USA*. Ben-Gurion University.

Hills, T. T., Todd, P. M., & Jones, M. N. (2015). Foraging in Semantic Fields: How We Search Through Memory. *Topics in Cognitive Science, 7*(3), 513-534.

Jones, M. N., Willits, J., & Dennis, S. (2015). Models of semantic memory. In J. Busemeyer & J. Townsend (Eds.), *Oxford Handbook of Mathematical and Computational Psychology* (pp. 232-254).

Kenett, Y. N., Anaki, D., & Faust, M. (2014). Investigating the structure of semantic networks in low and high creative persons. *Frontiers in Human Neuroscience, 8*(407), 407.

Kenett, Y. N., Kenett, D. Y., Ben-Jacob, E., & Faust, M. (2011). Global and local features of semantic networks: Evidence from the Hebrew mental lexicon. *PLoS ONE, 6*(8), e23912.

Mednick, M., T., Mednick, S., A., & Jung, C., C. (1964). Continual association as a function of level of creativity and type of verbal stimulus. *Journal of Abnormal and Social Psychology, 69*(5), 511-515.

Mednick, S., A. (1962). The associative basis of the creative process. *Psychological Review, 69*(3), 220-232.

Milgram, R. N., & Milgram, N. A. (1976). Creative thinking and creative performance in Israel students. *Journal of Educational Psychology, 68*(3), 255-259.

Nevo, B., & Levin, I. (1978). Remote associates test: Assessment of creativity in Hebrew. *Megamot, 24*, 87-98.

Reali, F., & Griffiths, T. L. (2009). Words as alleles: connecting language evolution with Bayesian learners to models of genetic drift. *Proceedings of the Royal Society of London B: Biological Sciences*.

Rossman, E., & Fink, A. (2010). Do creative people use shorter association pathways? *Personality and Individual Differences, 49*, 891-895.

Runco, M. A., & Acar, S. (2012). Divergent thinking as an indicator of creative potential. *Creativity Research Journal, 24*(1), 66-75.

Sawyer, K. (2011). The cognitive neuroscience of creativity: A critical review. *Creativity Research Journal, 23*(2), 137-154.

Schilling, M. A. (2005). A "small-world" network model of cognitive insight. *Creativity Research Journal, 17*(2-3), 131-154.

Smith, K. A., & Vul, E. (2015). The Role of Sequential Dependence in Creative Semantic Search. *Topics in Cognitive Science, 7*(3), 543-546.

Zemla, J. C., Kenett, Y. N., Jun, K.-S., & Austerweil, J. L. (2016). U-INVITE: Estimating Individual Semantic Networks from Fluency Data, *Proceedings of the 38th Annual Meeting of the Cognitive Science Society*.