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rather than the *infinite array of values that the output of this function could take*. We might have contributed to this misunderstanding when claiming that a field is 'a quantity that has a magnitude for each point in space and time'. We should have clarified that the magnitude of a PPS measure can be seen as a specific sample from a field in the here and now rather than as a database containing all possible field values.

There is one further clarification we would like to make. Although all PPS measures reflect action value (at least under the perspective we propose), not all action values are reflected in PPS measures. The opinion of Noel and Serino about this issue is unclear because their title states that 'high action values occur near the body', implying that, for any type of action, action values *can only* be high when an object is near the body. However, they later specifically refer to contact creation/avoidance actions, implying that their title holds true only for this type of action. To be explicitly clear: our claim was that PPS measures reflect the value of only those actions which create or avoid contact with the body, and therefore are *in part* dependent on proximity to the body. There certainly are, however, action values which do not depend on body proximity. After all, it is undeniable that non-contact actions can be valuable, and that their value does not necessarily have anything to do with proximity: merely imagine tracking a distant cloud with your head to gather information about future storms.

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Forum

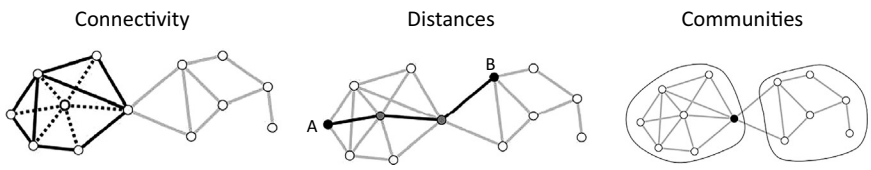
A Semantic Network Cartography of the Creative Mind

Yoed N. Kenett[1,*] and Miriam Faust[2,3]

The role of semantic memory in creativity is theoretically assumed, but far from understood. In recent years, computational network science tools have been applied to investigate this role. These studies shed unique quantitative insights on the role of semantic memory structure in creativity, via measures of connectivity, distance, and structure.

What do we need to know to have creative ideas? Embedded in theories on creativity is the notion that knowledge plays a role in one's ability to generate creative ideas. The main theory relating creative thinking to semantic memory – the memory system that stores concepts and facts – is the associative theory of creativity [1]. According to this theory, creativity involves the connection of weakly related, remote concepts into novel and applicable concepts. The farther apart the concepts are, the more creative the new combination will be. For this new combination to be applicable – to make sense – a broad enough body of knowledge is required. Thus, the structure of semantic memory plays an important role in the creative process. Furthermore, this theory argues that low and high creative individuals differ in their structure of semantic memory, with high creative individuals having a structure that facilitates such a process [1]. However, this theory has been challenging to investigate due to the complexity of modeling and representing semantic memory, which would allow examination of this theory. Recently, computational methods to study knowledge and memory structure in creativity are paving the way to uniquely examine their role in the creative process [2–4] and examine the associative theory of creativity [1]. Here, we outline one such approach, based on the application of network science methodologies [5].

Network science is based on mathematical graph theory, providing quantitative methods to investigate complex systems as networks [5,6]. A network is comprised of nodes that represent the basic units of a system (semantic memory) and edges that signify the relations between them (semantic similarity). While the application of network science methodologies has become a popular approach to study brain structure and function [7], it has been used to study cognitive phenomena to a lesser extent. This is despite classic cognitive theory in language and memory being highly related to a network perspective [5,6,8]. By structuring memory as a network [5], network science can directly and quantitatively examine classic cognitive theory and the operations of cognitive processes such as those taking place during memory retrieval and associative thought [8]. Such an approach provides powerful quantitative methods to examine the structure and dynamics of

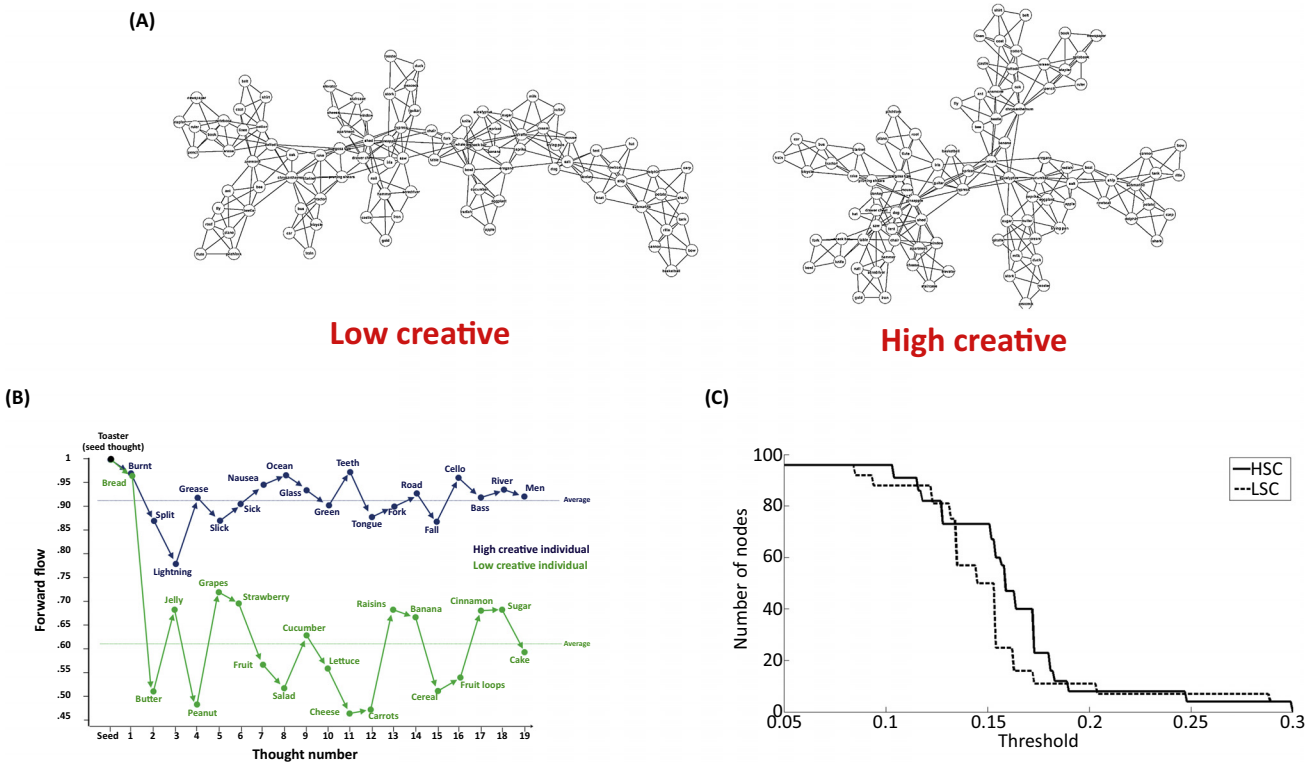


Trends in Cognitive Sciences

Figure 1. Examples of Main Network Measures Being Applied to Examine the Role of Semantic Memory in Creativity: Connectivity: The clustering coefficient of a network measures the extent to which two neighbors of a node in a network will themselves be neighbors (i.e., a neighbor is a node *i* that is connected through an edge to node *j*). Distances: the average shortest path length of a network measures the average shortest number of steps needed to be taken between any two pair of nodes in the network. Communities: The modularity measure of the network measures the extent to which the network can be partitioned into smaller sub-communities. Adapted from [7].

complex systems, quantitatively operationalizing issues of connectivity, distances, and community structure in such systems (Figure 1) [7].

A growing number of studies have recently applied network science methodologies to study creativity, focusing on the role of semantic memory structure in the creative process. By briefly describing these studies, we aim to highlight the strength of applying network science to study high-level cognitive constructs such



Trends in Cognitive Sciences

Figure 2. Examples of Different Applications of Network Science Methodologies to Study the Role of Semantic Memory in Creativity. (A) Memory structure: the semantic networks of high creative individuals exhibit overall higher connectivity, lower distances, and lower communities than low creative individuals. Both networks are composed from free association response generated to the same 96 nodes (concepts) and the edges convey binary symmetric relation between pairs of nodes. Adapted from [9]. (B) Search processes: high creative individuals generate thoughts that are more distant from each other with a flatter distribution (black) than low creative individuals (green). This is measured via an accumulative measure of a textual corpora based co-occurrence semantic distance statistic (forward flow) between chained associates generated by the participant. X axis – thought number; Y axis – forward flow score. Adapted from [12]. (C) Flexibility: the semantic network of high semantically creative individuals (HSC) breaks apart slower than that of low semantically creative individuals (LSC). This is evident from a higher percolation integral (area under the curve of number of connected nodes in the giant component) for the HSC as edges with an increasing strength are removed from the network, compared to the LSC semantic network. Thus, the semantic network of the HSC group is more flexible than the LSC group. X axis – threshold of edge strength that are being removed; Y axis – number of nodes that stay connected in the giant component. Adapted from [13].

as creative thinking, and the unique empirical and theoretical insights these applications reveal.

Memory Structure

A recent study applied network science methods to directly investigate the associative theory of creativity [9]. In accordance with [8], the semantic networks of 96 cue words in groups of low and high creative individuals were estimated and compared. This was achieved using a continuous free association task (in 1 min generate all the responses you can think of) to the cue words. Edges between pairs of nodes were computed based on the overlap of the associative responses generated to them [8,9]. This analysis revealed that the semantic network of high creative individuals had higher connectivity, shorter distances between concepts, and fewer subcommunities in their network than low creative individuals (Figure 2A). The authors interpreted their findings as facilitating more efficient spread of information in the semantic network of high creative individuals, related to enhanced ability in connecting remote associations. However, by aggregating individuals into low and high creative groups [9], individual differences in semantic memory structure as related to creativity may be obscured. To address this issue, a novel method was developed to represent individual semantic networks based on semantic judgment ratings, and related these individual semantic networks to individual differences in creative ability [10]. The authors partially replicated the group-based findings of [9], finding a positive relation with connectivity, a negative relation with distance, and a trending negative relation with community measures of individual semantic networks and creativity. Thus, while further research is needed, network science methodologies are slowly elucidating the role of semantic memory structure in creativity, both at the group [9] and individual [10] levels.

Search Processes

Another prediction of the associative theory of creativity is that high creative individuals can reach further and weaker concepts while searching their memory [1]. This issue was investigated by simulating and comparing random walk models on the semantic networks of low and high creative individuals [11]. Starting at a particular node, a random walk moves to the next node according to a transition probability matrix. The authors hypothesized that the structure of the semantic network of high creative compared with low creative individuals enables them to use simple search processes that reach further and weaker connected concepts. The authors computed two 'creative measures' of the random walk simulations: the amount of unique visited nodes by the walk, as a measure of the breadth of the search; and the similarity between initial and final visited nodes, as a measure of the distance between connected concepts. In line with the associative theory of creativity, the authors found that random walks over the semantic network of high creative individuals visits more unique and weaker nodes.

A recent relevant study developed a method to quantify 'streams of thought' and examine how it tracks individual differences in creative ability [12]. This measure – forward flow – uses co-occurrence statistics of words in textual corpora (www.forwardflow.org) to compute the semantic distance between associative responses generated by participants in a chained free association task. In a series of studies, the authors show how this measure was positively correlated with individual differences of creativity across different groups, including performance majors, professional actors, and entrepreneurs. Importantly, in accordance with the associative theory of creativity, the authors found that high creative individuals reach farther distances than low creative individuals (Figure 2B). This study provides empirical support to the findings of [11], and further quantitative empirical evidence relating individual differences in semantic memory structure and creative ability.

Flexibility

A third line of prediction by the associative theory of creativity is that higher creative individuals have a more flexible memory structure [1]. However, currently flexibility in creativity is studied only through indirect behavioral means [13]. A recent study proposed a quantitative operationalization of flexibility of memory structure, based on percolation theory [13]. Percolation theory examines the robustness of complex systems to targeted attacks or random failures, based on the notion that the greater the robustness of the system, the more flexible it is [13]. Thus, the higher the robustness of a semantic network to attack, the higher its flexibility. This study found that the semantic network of high creative individuals is more robust to network percolation, as exhibited by a higher robustness as indicated by a slower breaking of their network (Figure 2C). Importantly, the authors show how the difference in robustness between the two groups is uniquely related to differences in the structure of their semantic networks. Thus, this study further supports the associative theory of creativity, by quantitatively linking creativity, flexibility and semantic memory.

Concluding Remarks

Our aim here was to highlight the strength of applying network science methodologies to study high-level cognitive constructs, by reviewing recent cognitive network research on the role of semantic memory in creativity. These studies quantitatively show how the semantic memory structure of high creative individuals is more connected and more flexible, allowing for broader search over such a semantic network structure.

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The application of network science to study cognitive phenomena is slowly developing, providing quantitative means to study the structure and dynamics of cognitive systems. Such an approach is especially relevant in studying aspects of memory and language [8]. However, it is important to acknowledge a critical open debate on whether semantic networks can be investigated independently from the retrieval processes taking place in producing the behavioral output used to estimate the semantic networks [5,14]. To study semantic memory structure and how it may relate to higher-level cognition, future studies must develop methods to disentangle such retrieval processes from structure [5].

In closing, network neuroscience methodologies have greatly advanced our understanding of brain structure and dynamics. Similarly, such applications at the cognitive level allows directly examining, expanding and evolving classic cognitive theories, grounding these theories in quantitative measures in the process.

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Forum

A Dopaminergic Basis for Fear Extinction

Raffael Kalisch,[1,2,*] Anna M.V. Gerlicher,[3] and Sevil Duvarci[4]

It is a joyous relief when an event we dread fails to materialize. In fear extinction, the appetitive nature of an omitted aversive event is not a mere epiphenomenon but drives the reduction of fear responses and the formation of long-term extinction memories. Dopamine emerges as key neurobiological mediator of these related processes.

One of the great breakthroughs in the study of appetitive learning was the insight that the unexpected occurrence of a rewarding stimulus is signaled by a phasic release of dopamine (DA) in the nucleus accumbens (NAcc) from neurons originating in the ventral tegmental area (VTA) [1]. Specifically, the DA signal in appetitive learning encodes the prediction error (PE), or mismatch, between one's reward expectation (usually zero at the beginning of learning) and the actual reward obtained. The DAergic PE thereby constitutes the critical learning signal that allows reward-contingent neutral stimuli to become reward predictors, that is, conditioned stimuli (CSs) that by themselves evoke reward-anticipatory behaviors [1].

In fear extinction, a CS that was previously paired with an aversive stimulus (unconditioned stimulus, US) is repeatedly presented in the absence of that stimulus, such that the subject eventually recognizes the CS as safe and ceases producing conditioned fear responses (CRs). Hence, extinction constitutes an instance of new learning, in which the CS is associated with information about its safety (the absence of the US). The PE signal that drives this learning has, however, remained elusive. Proponents of the idea that the appetitive and aversive motivational systems inhibit each other antagonistically have long suspected that the unexpected omission of an aversive US in fear extinction effectively is a rewarding event that activates the appetitive system and, as a consequence, suppresses the expression of conditioned fear [2,3]. This hypothesis has recently received substantial support by experiments showing that fear extinction in fruit flies requires the same distinct population of DA neurons that also mediates reward, but not fear, learning [4].

Now, two recent studies in rodents provide independent evidence suggesting that a key function of DA neurons in extinction is to signal when the outcome is better than expected (there is no US following the CS) and that this quasi-appetitive PE signal is required for