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How semantic memory structure and intelligence contribute to creative thought: a network science approach

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ABSTRACT
The associative theory of creativity states that creativity is associated with differences in the structure of semantic memory, whereas the executive theory of creativity emphasises the role of top-down control for creative thought. For a powerful test of these accounts, individual semantic memory structure was modelled with a novel method based on semantic relatedness judgements and different criteria for network filtering were compared. The executive account was supported by a correlation between creative ability and broad retrieval ability. The associative account was independently supported, when network filtering was based on a relatedness threshold, but not when it was based on a fixed edge number or on the analysis of weighted networks. In the former case, creative ability was associated with shorter average path lengths and higher clustering of the network, suggesting that the semantic networks of creative people show higher small-worldness.

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Associative and executive accounts of creativity

Current research on the creative process focuses on two seemingly competing accounts: The first account is the *associative theory of creativity* (Mednick, 1962). It argues that individual differences in semantic memory structure influence creative thought in a bottom-up manner (Gruszka & Neçka, 2002; Kenett, Anaki, & Faust, 2014; Mednick, 1962; Rossman & Fink, 2010; Schilling, 2005). It goes back to Mednick's (1962) theory, which assumes that creative individuals are characterised by "flat" (numerous and weakly related associations to a given concept) rather than "steep" (few, strong associations to a

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given concept) hierarchies in semantic memory. Rossmann and Fink (2010) concluded that creative individuals may have more associative links in their semantic memory and can activate remote associative relations faster than less creative individuals.

The second account is the *executive theory of creativity* (Beaty & Silvia, 2012; Benedek, Jauk, Sommer, Arendasy, & Neubauer, 2014; Dietrich, 2004; Martindale, 1995; Mendelsohn, 1976). This account argues for the importance of top-down cognitive control in the creative process, such as fluid intelligence, retrieval ability, and specific executive functions (Beaty & Silvia, 2012; Benedek & Neubauer, 2013; Benedek et al., 2014; Groborz & Neçka, 2003; Jauk, Benedek, & Neubauer, 2014; Lee & Therriault, 2013; Nusbaum & Silvia, 2011; Silvia, Beaty, & Nusbaum, 2013). According to this view, cognitive control supports creativity via top-down mechanisms that enable more effective memory retrieval and strategy implementation.

In both accounts, semantic memory is a key component (Abraham & Bubic, 2015; Benedek & Jauk, in press; Kenett, in press). Semantic memory is the system of human memory that stores concepts and facts, regardless of time or context (McRae & Jones, 2013). However, the way in which semantic memory is organised into categories and subcategories remains an open question (Jones, Willits, & Dennis, 2015). In regard to creativity, semantic memory is either directly related to creative ability via its structural properties (bottom-up account), or it is the basis upon which executive processes operate (top-down account). Currently, the few behavioural and computational studies that have examined the relation between semantic memory structure and creative ability have not been able to clarify in what way semantic memory affects creative thought. One potential reason for this is that previous studies have analysed differences in memory structure at the group level (i.e., low versus high creative individuals), which may conceal nuanced differences due to the necessary aggregation across individuals of a group. Therefore, in the present study, we propose a novel approach to represent semantic memory structure at the individual level and relate it to measures of creative ability and intelligence.

Semantic memory structure and creativity

Lately, there has been a growing amount of research empirically examining the relation between semantic memory structure and creative ability between low and high creative groups (Beaty, Silvia, Nusbaum, Jauk, & Benedek, 2014; Benedek & Neubauer, 2013; Kenett et al., 2014; Kenett, Anaki, & Faust, under review; Kenett, Beaty, Silvia, Anaki, & Faust, 2016). Benedek and Neubauer (2013) investigated Mednick's theory by computing associative hierarchies for groups of low and high creative individuals, which reflected the average association strength of the 10 most common responses to a set of cue words. No differences were found between the associative hierarchies of the two groups. However, high creative individuals showed higher association fluency (see also Benedek, Könen, & Neubauer, 2012) and thus were able to generate a higher proportion of uncommon associative responses within the same time. Based on these findings, Benedek and Neubauer concluded that low and high creative individuals do not differ in the structure of their associative hierarchies, but rather in the ability to fluently access semantic content. They also acknowledge the possibility that the differences in associative hierarchies between the two groups may be found in more weakly associated concepts. Yet, they claimed that the low frequency of these weak associative responses makes such an analysis difficult to conduct.

Kenett et al. (under review) took a similar approach, and examined the strength and latencies of associative responses generated by low and high creative individuals to a set of 96 cue words. The authors classified each of the associative responses generated to the cue words as a strong, medium, weak or unique associative response. This was done, for each group independently, based on the percentage of the group generating a specific associative response *x* as a response to a cue word *y* (Nelson, McEvoy, & Schreiber, 2004). The results of this study show that high creative individuals are faster in generating associative responses and provide a higher percentage of unique and lower percentage of strong associative responses than low creative individuals. Finally, they found a weak overlap between strong associative responses generated by the two groups.

Recently, Beaty et al. (2014) examined the involvement of bottom-up and top-down accounts to creative ability. The authors used latent semantic analysis (Landauer & Dumais, 1997) to compute semantic distance values of responses generated by participants during verbal fluency tasks to specific target words. Average semantic distance was considered as an index of the structural organisation of semantic memory. This measure, along with several measures of cognitive ability, was used to examine the contribution of both bottom-up and top-down processes in creative ability (i.e., divergent thinking). The authors found joint effects of average semantic distance and executive abilities, namely broad retrieval ability and fluid intelligence, on the fluency and creativity of divergent thinking responses. These findings suggest the contribution of both semantic structure and executive functions to creative thought.

Finally, a few studies have examined the relation of semantic memory structure to creativity through computational neural network models (Kajić, Gosmann, Stewart, Wennekers, & Eliasmith, 2016; Kajić & Wennekers, 2015; Marupaka, Iyer, & Minai, 2012; Marupaka & Minai, 2011; Olteţeanu & Falomir, 2015, 2016). For example, Marupaka and Minai (2011) demonstrate how a neural network model with small-world characteristics facilitates the most efficient search process that allows conceptual combinations. According to this model, conceptual combination arises through the co-activation of neural units, which leads to reorganisation of the semantic network (see Marupaka et al., 2012, for a full description of this model). Current neural network models have been developed to simulate the processes taking place while solving Mednick's Remote Associates Test (RAT) (Kajić et al., 2016; Kajić & Wennekers, 2015; Olteţeanu & Falomir, 2015). However, all of these models focus on specific tasks, such as conceptual combinations or the RAT. They do not account for any possible differences in semantic memory structure between low and high creative individuals.

The network science approach in the study of semantic memory, creativity and intelligence

Recent studies adopted methods from network science in order to obtain more differentiated measures of semantic memory structure (e.g., Faust & Kenett, 2014; Kenett et al., 2014). Network science is based on mathematical graph theory, providing quantitative methods to investigate complex systems as networks (Baronchelli, Ferrer-i-Cancho, Pastor-Satorras, Chater, & Christiansen, 2013; Borge-Holthoefer & Arenas, 2010; De Deyne, Kenett, Anaki, Faust, & Navarro, 2016). This approach has been applied in a variety of fields, including social sciences, biology, technology and infrastructure (Barabási, 2012, 2016). A network is comprised of nodes, which represent the basic unit of the system (e.g., semantic memory) and links, or edges, that signify the relations between them (e.g., semantic similarity). At the cognitive level, this approach is mainly applied to investigate complex systems of language and memory structure. For example, network science has identified mechanisms of language development through preferential attachment (Hills, Maouene, Maouene, Sheya, & Smith, 2009; Steyvers & Tenenbaum, 2005), has shown how specific semantic memory network parameters influence memory retrieval (Vitevitch, Chan, & Goldstein, 2014; Vitevitch, Chan, & Roodenrys, 2012; Vitevitch, Goldstein, & Johnson, 2016), and provides new insight on the structure of semantic network of second language in bilinguals (Borodkin, Kenett, Faust, & Mashal, 2016).

Of the various network models developed in network science theory, the network model that has been widely used to examine complex systems is the small-world network (SWN) model (Milgram, 1967; Watts & Strogatz, 1998). An SWN is a network that is characterised by both high local connectivity and short global distances between nodes, allowing for efficient transfer of information. This network type is known as a "small-world" network because every node is relatively close to other nodes. Analyses of different languages have consistently shown how different linguistic systems exhibit SWN characteristics (Arbesman, Strogatz, & Vitevitch, 2010; Borge-Holthoefer & Arenas, 2010; De Deyne & Storms, 2008). These SWN characteristics are now considered fundamental characteristics of linguistic systems, which allow for efficient and quick retrieval in linguistic information (Borge-Holthoefer & Arenas, 2010). Common parameters of network structure include the network's clustering coefficient (CC), the average shortest path length (ASPL), the "small-worldness" (S) and the modularity (Q).

The CC refers to the probability that two neighbours of a node will themselves be neighbours (i.e., a neighbour is a node *i* that is connected through an edge to node *j*). The ASPL refers to the average shortest number of steps needed to be taken between any two pair of nodes. An SWN is characterised by having a high CC and a short ASPL. To examine whether a specific network is an SWN, the statistical properties of empirical data are compared to those of a random null network with the same number of nodes and edges (Boccaletti, Latora, Moreno, Chavez, & Hwang, 2006). An additional measure, (S), quantifies the "small-worldness" of a specific network (Humphries & Gurney, 2008) by computing the ratio between the CC and the ASPL, and it reflects the extent to which a network is "small-worlded" (a value greater than one indicates that the network is "small-worlded"). Finally, a network's modularity, (Q), examines how a complex system comprised of many nodes and edges, breaks apart (or partitions) into smaller sub-networks (Fortunato, 2010; Newman, 2006). The larger the modularity measure, the more the network comprised of sub-networks (Newman, 2006). Current research is starting to highlight the role of modularity in typical and atypical cognitive networks (e.g., Kenett, Gold, & Faust, 2016; Siew, 2013).

Kenett et al. (2014) used network science methods to directly investigate Mednick's (1962) notion of the structural difference between low and high creative individuals. The authors applied a novel computational method to extract the semantic memory network organisation of 96 cue words in low and high creative individuals. This analysis showed that the semantic memory network of high creative individuals is less rigid than that of low creative individuals. The semantic memory network of the high creative individuals had a lower ASPL and Q values and a higher S value as compared to the network of low creative individuals (Kenett et al., 2014). Lower path lengths between concepts (ASPL) may facilitate a faster search for remote semantic concepts relevant for creative thought (Kenett & Austerweil, 2016; Rossman & Fink, 2010). Moreover, lower modularity (Q) of networks suggests that semantic networks do not strongly break apart in sub-communities, which conforms Mednick's (1962) notion that creativity should be characterised by flat rather than steep association hierarchies. Finally, a higher small-worldedness (S) indicates an effective balance of high network clustering (CC) and low ASPL, which allows highly efficient processing in semantic networks (Borge-Holthoefer & Arenas, 2010). These findings provide empirical network evidence for Mednick's theory by showing that high creative individuals have a more flexible semantic memory network structure. This structure may enable more efficient retrieval strategies when generating associations.

Kenett, Beaty, et al. (2016) examined the relation of fluid intelligence, creative ability and semantic memory structure. Participants completed a semantic verbal fluency task (name as many items as possible from a category, e.g., animals) and were divided into four groups based on their performance on intelligence and creativity measures. The semantic network representation of the animal category was compared for all groups. These results revealed that intelligence and creativity are differentially related to semantic memory structure: intelligence is more related to structural properties (higher ASPL and Q values) and creativity is more related to flexible properties (higher S value). Further, this study found that the semantic network of the high intelligence/high creative group has both properties.

Aims of the present study

The presented studies have provided novel and important insights on the creative process, and offer empirical support in favour of both the bottom-up, associative and the top-down, executive accounts of creativity. Clear conclusions on the role of bottom-up and top-down accounts, however, are complicated by the fact that individual differences in associative and executive processes may not be independent. On the one hand, individual differences in association fluency have been attributed to executive abilities facilitating effective retrieval from semantic memory (Benedek & Neubauer, 2013; Gilhooly, Fioratou, Anthony, & Wynn, 2007) and are commonly seen as indicator of the intelligence facet of broad retrieval ability (i.e., Gr; Carroll, 1993; Silvia et al., 2013). On the other hand, it was proposed that semantic memory structure may affect association fluency (i.e., flatter association hierarchies should be related to more fluent association; Mednick, 1962). Moreover, the computation of semantic network parameters is often based on free association behaviour and hence may be affected by association fluency itself. In order to further clarify the role of associative and executive processes in creativity, we need to consider both constructs together at the individual level. Previous research was primarily conducted at the group level – low versus high creative individuals. By representing semantic memory structure at the individual level and relating it to individual differences in creative ability and executive functions, this issue can be addressed more powerfully.

Currently, only one study has presented an approach to represent an individual's semantic network (Morais, Olsson, & Schooler, 2013). This approach was based on associative "snow-ball" sample collection, which is extremely time-demanding (between 30 and 60 consecutive days of data collection per participant). In this study, we take a step forward in this direction and propose a new, more efficient approach. Our approach makes use of network science tools to "reverse engineer" an individual's semantic network, based on semantic relatedness judgements. Kenett, Levi, Anaki, and Faust (in press) developed a novel semantic judgement task which quantifies semantic distance as measured with semantic network path length. Path length in a semantic network represents the amount of steps needed to traverse from one word in the network to the other. A series of studies examined how manipulation of path length affects performance in a semantic relatedness judgement task. These studies found a significant correlation between path length and subjective judgement of the relatedness strength of the word pairs. This significant correlation substantiates the relationship between semantic distance, as measured with path length, and subjective judgement of associative strength. The approach developed by Kenett et al. (in press) adds to a growing body of research that combines computational measures of semantic distance with neurocognitive approaches to examine semantic processing (Green, 2016; Green, Kraemer, Fugelsang, Gray, & Dunbar, 2010).

In the present study, we capitalise on this relation between semantic network distance and subjective judgement of relatedness from the opposite direction. We hypothesised that semantic relatedness judgements can serve as a proxy of semantic distance between concepts in the network of semantic memory. This rationale is consistent with previous approaches to construct semantic networks based on semantic proximity data such as in Pathfinder networks (Schvaneveldt, Dearholt, & Durso, 1988) and the Netscal algorithm (Hutchinson, 1989). As a notable difference, these previous approaches have been usually applied to group-based judgements of semantic similarity or word-association norms, whereas the present approach defines individual networks based on the semantic relatedness judgements of single participants. We hence defined a set of 28 concepts and asked participants to judge the semantic relatedness between all concepts. This resulted in a 28 $\times$ 28 semantic relatedness matrix for each participant, which was used to represent their individual semantic memory structure. Measures of semantic memory structure were then related to creative ability and intelligence.

The associative account of creativity would be supported by associations between creative ability and semantic memory structure. Specifically, we expect a positive correlation between creative ability and CC and S, and a negative correlation between creative ability and ASPL and Q (Kenett et al., 2014). The executive account of creativity would be supported by positive correlations between creative ability and intelligence. Importantly, by considering individual estimates of network structure and intelligence, we will be able to test whether they both represent independent predictors of creativity after controlling for mutual effects, thus providing a stringent test of associative and executive accounts of creativity.

Method

Participants

The sample of this study consisted of 89 participants (70% females) with an average age of 25 years (SD = 8.6). Participants were mainly undergraduate students (75%) enrolled in the local university, most frequently majoring in psychology (60%). All participants gave written informed consent.

Tasks and materials

Psychometric measures

Creative ability

Creative ability was assessed with measures of divergent thinking ability (Runco & Acar, 2012). Participants performed four alternate uses of tasks, a common measure of divergent thinking (DT), asking them to generate creative uses for a rope, a fork, a shoe, and a book. For each task they had two minutes and were instructed to name all the creative uses for the objects they could think of. As in our previous research, the task was devised and administered with MATLAB (e.g., Jauk et al., 2014). After the completion of all DT tasks, participants were asked to review their ideas and to select their three most creative ideas of each task. All ideas were rated for creativity by four trained raters on a scale from 0 (not creative) to 3 (very creative). The interrater-reliability ranged from ICC = .73–.79 for the four DT tasks. DT task performance was scored for fluency and creativity. DT fluency reflects the average number of generated ideas across tasks (Cronbach's $\alpha = .92$). DT creativity was scored with the subjective top-scoring method (Benedek, Mühlmann, Jauk, & Neubauer, 2013; Silvia et al., 2008). We computed a top-3 score, which reflects the average creativity of generated ideas from the self-selected three most creative ideas per task. When less than three ideas were generated in a task, missing ideas were assigned a creativity value of 0. The subjective top-scoring method was shown to avoid a necessary confound between DT creativity and DT fluency (Benedek et al., 2013; Silvia et al., 2008). The internal consistency of the top-3 DT creativity score was Cronbach's $\alpha = .72$.

Fluid intelligence and broad retrieval ability

We assessed fluid intelligence (Gf) and broad retrieval ability (Gr), two highly relevant intelligence facets in creativity research (Jauk, Benedek, Dunst, & Neubauer, 2013; Silvia et al., 2013). Gf was measured with a paper–pencil version of the Raven Advanced Progressive Matrices test (RAPM; Raven, Raven, & Court, 1998). Participants had 20 minutes to solve the 36 tasks (Set II), which was shown to be a valid and more adequate task time to avoid ceiling effects in student samples (Hamel & Schmittmann, 2006). The data of two participants had to be excluded because they failed to perform the task according to the instructions. The internal consistency of this task was good (Cronbach's $\alpha = .82$). Gr was assessed with two letter fluency tasks (F and S) and two category fluency tasks (occupations and names). Task time was two minutes per task. The average number of responses across the four tasks was used as estimate of Gr (Cronbach's $\alpha = .84$).[1]

Individual semantic networks

Semantic relatedness task

For the estimation of individual semantic networks, we devised a novel method based on relatedness judgements obtained from a semantic relatedness task. A semantic network is commonly represented by a set of concepts (i.e., the network vertices or nodes), and the semantic relatedness between these concepts is reflected by links (i.e., network edges) between them. In this study, we constructed individual semantic networks consisting of 28 concepts that were represented by single words. To ensure a wide variation of semantic relatedness between concepts, they were selected to cover seven different semantic categories with four category members each (see Appendix for a full list of concepts and their category attribution). The strength of relatedness between these concepts was inferred from self-reported semantic relatedness judgements (Kenett et al., in press). To this end, participants evaluated the semantic relatedness of all possible pairings between two different words, resulting in a total of 378 individual judgements.

The semantic relatedness task was administered with MATLAB. In each trial, a word pair was randomly selected from the pool of word pairs that had not yet been evaluated by the participant and that did also not involve a word that had been evaluated in the preceding trial. The word pair was presented in the middle of the screen with random order of the two words within the pair. Below the word pair, a visual analogue scale with a slider was presented with the poles defined as *unrelated* and *strongly related*. The slider could be freely moved with the computer mouse within the scale to indicate the perceived degree of semantic relatedness between concepts. In each trial, the slider was initially positioned in the middle of the scale. Participants were instructed to give a quick, intuitive judgement regarding semantic relatedness and to avoid extended rationalising. The evaluation was confirmed with

[1]For exploratory reasons, we also assessed personality structure with the German Big-Five inventory Neo-FFI (Borkenau & Ostendorf, 1993), which measures five personality factors (i.e., neuroticism, extraversion, openness, conscientiousness, and agreeableness) with a total of 60 items. As expected openness was positively correlated with creativity and intelligence measures, but personality was largely uninformative with respect to network parameters. For the sake of clarity and focus personality measures were thus not considered in the main analyses.

a mouse button press. The final slider position corresponded to a semantic relatedness value ranging from 0 to 1.

Given that these semantic relatedness judgements correspond to semantic distance in a participants' semantic memory network (Kenett et al., in press), these 28×28 semantic relatedness judgements can be studied as an adjacency matrix of a weighted, undirected semantic network. An adjacency (also known as connectivity) matrix is a means of representing which nodes are adjacent to which other nodes in the network. That is, we created an $n \times n$ matrix in which n represents the number of nodes (i.e., 28 concepts), and each cell represents the relation (i.e., semantic relatedness) between two concepts.

Network filtering. Since most of the edges have small values (weak relatedness judgements), the relevant information about the network can be obscured. Several methods have been developed to overcome this obstacle, either by constructing a sub-graph that captures the most relevant information embedded in the original network or by analysing weighted networks. For this novel type of semantic networks based on relatedness judgements, there is not yet an established method of network filtering. Previously, we used the Planar Maximally Filtered Graph (PMFG) method (Kenett et al., 2014; Tumminello, Aste, Di Matteo, & Mantegna, 2005). In the PMFG method, all edges are sorted according to the edge weights (in our case, semantic relatedness) and then edges are iteratively included (starting from highest) if the resulting network remains planar up to a total of $3(n - 2)$ edges. However, since the semantic relatedness network is quite sparse (i.e., shows a substantial amount of zero judgements), the double criterion of the PMFG method (i.e., maintain $3(n - 2)$ non-zero edges as well as planarity of the network) was only met by less than half of the participants' data, and the PMFG method thus seemed inappropriate for our data. Instead, we considered three different straightforward methods of network filtering.

The *fixed edge number* (FEN) method aims to maintain a fixed, high number of edges in all networks. We chose to maintain the 100 strongest semantic relatedness judgements (out of the total of 378) as edges. The criterion of 100 non-zero relatedness judgements was met by 90% of participants (i.e., 80) and hence only excluded those nine participants who rarely ever provided non-zero judgements. Notably, this method implies that the actual threshold of minimum relatedness (leading to a network edge) varies across participants. Since it may also seem reasonable to employ the same relatedness threshold across the whole sample, we implemented a second method of network filtering that required a *fixed minimum relatedness* (FMR) of 0.5. This criterion ensures that edges always correspond to high semantic relatedness, that is, above the mean of the scale. As a consequence, however, this method leads to a variable number of edges across participants. We kept all participants with at least 50 edges meeting the minimum relatedness criterion ($n = 79$) to ensure robust estimation of network parameters. In the FEN and FMR methods, the networks were binarised such that all selected edges were converted to a uniform weight = 1, and then analysed as unweighted, undirected networks. As a third method, we also analysed the structure of *weighted*, *undirected networks* (WUN). Here, all 378 edges were kept but edges are weighted by their judged relatedness. This method corresponds to an implicit way of network filtering that avoids some of the arbitrariness of deciding what counts as an edge. A comparison of findings across these three methods of network filtering (FEN, FMR and WUN) should be informative about the robustness of findings, and eventually help to determine which method is most appropriate for this novel semantic network approach based on relatedness judgements.

Network parameters. Analyses were performed with the Brain Connectivity Toolbox for MATLAB (Rubinov & Sporns, 2010). For each semantic network, the following parameters were calculated: the CC, the ASPL and the network modularity (Q) (Boccaletti et al., 2006; Newman, 2006). Finally, the S measure (Humphries & Gurney, 2008) was computed to quantitatively evaluate the small-world nature of the network (cf. Kenett et al., 2014).

Procedure

Participants were tested in groups of up to six people in a university computer lab. After giving informed consent and providing general biographical information, they performed the semantic relatedness task. This task involved 378 trials and was tiresome. Therefore, the task was divided into four equal blocks separated by short breaks. After the semantic relatedness task, participants performed the divergent thinking tasks, the RAPM and the word fluency tasks. The total experimental session took about 90 minutes. The procedure was approved by the local Ethics Committee.

Results

Table 1 presents descriptive statistics and correlations for psychometric trait measures, average semantic relatedness and network parameters for networks with FEN, FMR and WUN. The average semantic relatedness between concepts was 0.28 (SD = 0.11). As expected, the semantic relatedness judgements were much higher when evaluating concepts stemming from the same semantic category ($M = 0.60$, SD = 0.24; 42 within-category pairs) than when evaluating concepts coming from distinct semantic categories ($M = 0.24$, SD = 0.11; 336 cross-category pairs; $t[88] = 31.31$, $p < .001$). The average semantic relatedness rating showed a small positive association with DT fluency. Additionally, average relatedness showed substantial positive associations with edge number and further predicted higher CC and lower ASPL and Q in the FMR and WUN networks.

Table 1. Descriptive statistics and correlations.

	M	SD	*N*	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
1 DT creativity	1.10	0.33	89	1																		
2 DT fluency	6.20	2.94	89	**.33**	1																	
3 Gf	22.6	3.87	87	.10	.13	1																
4 Gr	25.7	4.59	89	**.41**	**.37**	.15	1															
5 Sem. Rel.	0.28	0.11	89	.06	**.21**	.06	.00	1														
6 CC (FEN)	0.43	0.06	80	−.06	−.17	.06	−.11	−.01	1													
7 ASPL (FEN)	1.84	0.09	80	.10	−.19	.00	.01	−.20	**.46**	1												
8 S (FEN)	1.58	0.19	80	−.11	−.11	.06	−.13	.08	**.93**	.09	1											
9 Q (FEN)	0.26	0.04	80	.13	.04	.06	.02	−.06	**.36**	**.48**	.20	1										
10 #E (FEN)	100.00	0.00	80	.00	.00	.00	.00	.00	.00	.00	.00	.00	1									
11 CC (FMR)	0.45	0.10	79	**.24**	.00	.03	.08	**.72**	**.45**	.08	**.45**	.11	.00	1								
12 ASPL (FMR)	1.85	0.27	79	**−.28**	−.08	.07	−.06	**−.83**	−.17	.09	−.19	.07	.00	**−.81**	1							
13 S (FMR)	1.69	0.41	79	−.18	−.11	.12	.01	**−.71**	.13	.09	.11	.09	.00	**−.46**	**.80**	1						
14 Q (FMR)	0.26	0.07	79	−.17	−.09	.11	.00	**−.75**	.01	.16	−.03	**.42**	.00	**−.61**	**.85**	**.74**	1					
15 #E (FMR)	108.14	36.25	79	**.25**	.13	−.04	.06	**.89**	.06	−.09	.09	−.07	.00	**.82**	**−.93**	**−.77**	**−.86**	1				
16 CC (WUN)	0.26	0.10	88	−.02	.14	.05	−.03	**.82**	.04	−.06	.08	−.01	.00	**.65**	**−.64**	**−.51**	**−.58**	**.75**	1			
17 ASPL (WUN)	2.84	1.50	88	−.07	−.16	−.11	−.04	**−.66**	−.02	**.25**	−.14	−.01	.00	**−.60**	**.68**	**.57**	**.48**	**−.61**	**−.51**	1		
18 S (WUN)	0.24	0.22	88	−.08	−.01	.06	.03	−.14	.10	.01	.11	.06	.00	.08	.09	.16	.14	−.04	**.37**	−.13	1	
19 Q (WUN)	0.20	0.10	88	.01	−.16	−.05	.02	**−.84**	**.24**	**.44**	.07	**.32**	.00	**−.41**	**.62**	**.57**	**.66**	**−.61**	**−.53**	**.64**	**.39**	1
20 #E (WUN)[a]	266.97	108.23	88	.11	.20	.07	.07	**.73**	−.08	−.18	−.01	.02	.00	**.38**	**−.51**	**−.45**	**−.43**	**.48**	**.29**	**−.45**	**−.63**	**−.83**

Note: DT, divergent thinking; Sem. Rel., average semantic relatedness rating; FEN, fixed edge number; FMR, fixed minimum relatedness; WUN, weighted, undirected networks; CC, clustering coefficient; ASPL, average shortest path length; S, small-worldness; Q, modularity; #E, number of edges. Correlation coefficients significant at $p < .05$ are depicted in bold face.

[a]This measure refers to the number of non-zero edges, while WUN principally considers all 378 edges.

DT creativity and DT fluency were both positively correlated with Gr but not with Gf. The relationship of creativity with network measures depended on the method of network filtering. When considering network parameter for FEN and WUN networks, we observed no significant correlations with creativity, besides a tendency towards small negative correlation between DT fluency and ASPL (FEN: $r = -.19$, $p = .09$; WUN: $r = -.16$, $p = .13$). Considering FMR networks, DT creativity was positively correlated with CC ($r = .24$, $p = .03$) and negatively with ASPL ($r = -.28$, $p = .01$). Furthermore, in line with the group-based analysis of Kenett et al. (2014), the correlation between FMR modularity and DT creativity exhibited a negative trend ($r = -.17$, $p = .13$). There were no significant correlations between DT fluency and FMR network measures. Figure 1 presents an example of the semantic network of a low creative participant and a high creative participant, based on the three different approaches. Networks were visualised using the *Cytoscape* network visualisation software (Shannon et al., 2003) spring-embedded visualisation algorithm. In these visualisations, nodes are presented as circles, and the lines represent the edges (either unweighted or weighted). The small size of the network (28 nodes) makes it hard to identify any differences between the networks. However, in all three networks of the high creative participant, the majority of nodes are more densely centred, indicating higher connectivity and lower path lengths (Figure 1).

As DT creativity was significantly predicted by network structure in FMR networks (CC and ASPL) as well as by the intelligence facet of retrieval ability (Gr), we examined whether the network measures remain significant predictors of DT creativity when the effect of Gr is taken into account. We hence computed a hierarchical regression analysis to predict DT creativity by network measures in a first step, and the intelligence facet Gr in a second step. Since semantic network measures are highly correlated (FMR: CC and ASPL: $r = -.81$, $p < .01$), they were entered stepwise in order to avoid issues with collinearity. In this first step, only ASPL was included as significant predictor of DT creativity (adj. $R^2 = .07$, $F[1,77] = 6.70$, $p = .01$; see Table 2). After entering Gr in the second step, ASPL and Gr both significantly predicted DT creativity (adj. $R^2 = .15$, $F[2,76] = 11.20$, $p < .001$; see Table 2). This finding suggests that semantic network structure defined by FMR and retrieval ability represent independent, complemental predictors of DT creativity.

From a methodological perspective, it is also interesting to consider the correlations between the same network measures among the three filtering methods (Table 1). These correlations were generally positive and ranged from .04 to .65 for CC, from .09 to .68 for ASPL, from .11 to .16 for S, and from .32 to .66 for Q. This suggests that the S parameter is most sensitive to the employed filtering method whereas the Q parameter may be more robust. Moreover, FMR and WUN methods generally showed the highest correlations between network parameters whereas correlations with the FEN method were lower.

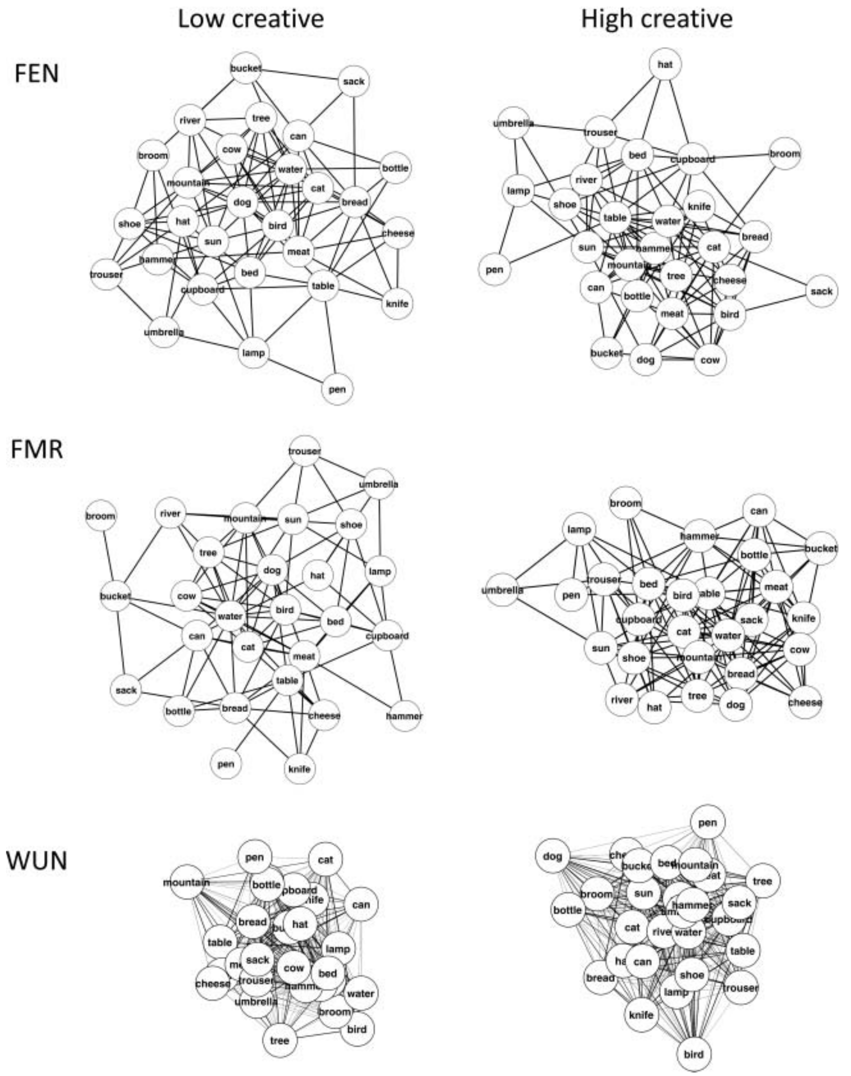

Figure 1. Network visualisation of example individual semantic networks for a low and a high creative person (left and right panels, respectively). Networks are represented for each of the three employed methods of network representation: based on the criterion of fixed edge number (FEN; top row), the criterion of fixed minimum relatedness (FMR; middle row), or weighted undirected networks (WUN; bottom row).

Discussion

The present study employed a novel technique for estimating individual semantic memory structure, which allowed testing predictions according to the associative and executive accounts of creativity at the individual level. We will first discuss findings relevant to these examinations of creativity theory

Table 2. Hierarchical regression analysis predicting divergent thinking (DT) creativity by semantic network structure (FMR method) and trait measures.

	DT creativity	
	ΔR^2	β
Step 1	.08*	
ASPL		−.28
Step 2	.15**	
ASPL		−.26*
Gr		.39**

Notes: Step 1: Stepwise; Step 2: Enter. FMR, fixed minimum relatedness; ASPL, average shortest path length.
*$p < .05$; **$p < .01$.

and then turn to methodological considerations regarding the representation of individual semantic networks.

Testing predictions of associative and executive accounts of creativity

The associative account of creativity assumes that creativity is related to individual differences in semantic network structure (Kenett et al., 2014; Mednick, 1962). Using a novel method for constructing individual semantic networks based on relatedness ratings, parameters of semantic network structure were computed using three different filtering methods, either using a threshold criterion based on an FEN, based on FMR, and by analysing unfiltered WUN.

Considering the FMR method, DT creativity was positively correlated with CC and negatively with ASPL, which replicates previous findings by Kenett et al. (2014) using group-based networks. Furthermore, the correlation between FMR modularity and DT creativity exhibited an expected negative trend. These FMR findings suggest that the semantic networks of creative people are more strongly clustered and show shorter average distances between concepts and lower modularity in their semantic memory network. This kind of network structure is particularly indicative of a higher "small-worldness" (Humphries & Gurney, 2008) and hence suggests that semantic networks of creative people are more efficiently structured.

For the FEN and WUN networks, we observed only a trend where more fluent people have semantic networks with shorter ASPL. This notion was further evidenced by a small positive correlation between DT fluency and average semantic relatedness judgements. This finding is in line with previous work showing that more creative people perceive stronger semantic relationships especially between concepts that are largely unrelated (Rossman & Fink, 2010). Rossmann and Fink hypothesised that creative people might "use shorter associative pathways" (p. 891), a notion which receives first, albeit weak, empirical support in the present semantic network analyses. Taken together, we observed support for the associative account when considering

FMR networks, whereas associations were weak and non-significant for FEN and WUN networks.

The executive account of creativity assumes that creativity is related to individual differences in executive control and intelligence (Benedek et al., 2014; Dietrich, 2004; Martindale, 1995; Mendelsohn, 1976; Nusbaum & Silvia, 2011). This account was supported by significant positive correlations of broad retrieval ability (Gr) with both DT creativity and fluency, but there was no significant relationship with fluid intelligence (Gf) in this study. This missing Gf correlation was unexpected given the consistent relationship between Gf and creativity in the past research (Jauk et al., 2013; Nusbaum & Silvia, 2011). Regarding the DT test, an average number of six ideas and a low average subjective top-scoring rating are very common in this line of research (e.g., Jauk et al., 2014; Nusbaum & Silvia, 2011; Silvia et al., 2013). It reflects the difficulty to come up with creative ideas on the spot. This discrepant finding may possibly be due to the employed adapted version of the matrices task, which is more speeded, but which was proposed to be particularly adequate in academic samples (Hamel & Schmittmann, 2006).

The Gr finding is in line with previous research that consistently reported positive associations between Gr and DT ability (Beaty et al., 2014; Silvia et al., 2013), as well as with the creativity of generated drawings (Avitia & Kaufman, 2014) and metaphors (Beaty & Silvia, 2013). Gr is an established facet of the CHC model of intelligence reflecting the effectiveness and flexibility of memory retrieval (Carroll, 1993) and is commonly seen as an index of executive ability (Alvarez & Emory, 2006; Gilhooly et al., 2007). Previous studies found that people generate 12–20 responses in one minute (Gilhooly et al., 2007; Silvia et al., 2013), so the observed average response fluency of 26 seems reasonable for two-minute tasks. The findings hence corroborate the view that executive control (of memory) facilitates creative thought. As a potential alternative interpretation, Gr might also be seen to reflect the richness of semantic representations and hence be an indicator of semantic structure rather than executive ability. This view, however, was not supported in our data, as we observed no correlation between Gr and any of the network parameters, but only between Gr and creativity. Importantly, the employed DT creativity measure relied on a constant number of the three most creative ideas, which is largely uncorrelated with response fluency (Benedek et al., 2013).

We hence obtained partial support for the associative account (FMR networks, but not FEN or WUN networks) and the executive account of creativity (Gr, but not Gf) based on correlational findings. In the next step, we examined the possibility that associative and executive processes may not predict creative ability independently once their covariance is controlled. This examination was made possible due to the availability of network parameters at the individual level. A regression analysis revealed that ASPL and Gr indeed predict DT creativity independently. CC did not explain unique variance of DT creativity beyond these factors, which is likely due to the very high negative correlation between CC and ASPL. These findings suggest that associative and executive factors may contribute independently to creativity, even when accounting for their covariance. This is consistent with previous research (Beaty et al., 2014; Kenett, Beaty, et al., 2016), and extends it by using measures of individual semantic network structure based on network science. In semantic networks with shorter average path length and less clustering, the spreading of activation may more easily reach remotely related concepts (Kenett & Austerweil, 2016), while executive processes may facilitate the effective evaluation and selection of relevant concepts (Benedek, Franz, Heene, & Neubauer, 2012). Recent neuroscience research has already provided first insights in how this interplay can be manifested at the level of interacting brain networks (Beaty, Benedek, Kaufman, & Silvia, 2015; Beaty, Benedek, Silvia, & Schacter, 2016). This interpretation, however, is qualified by the fact that only one out of three methods for network estimation revealed significant associations between semantic network structure and creativity (besides a similar trend for the two other methods) and by a correlation only between Gr (and not Gf) and creativity in this study. The final conclusion depends on the validity of the network measures, which is further discussed in the next sections.

Methodological considerations

The associative account of creativity was only supported when using the FMR method, but not with the FEN and WUN methods. The ultimate decision on the validity of the semantic network structure findings hence depends on the appropriateness of the employed methods for network representation. In the FEN method, the number of edges is kept equal across networks. As a potential benefit of this method, it ensures that differences in network structure can be attributed to differences in the actual organisation of network edges rather than to their mere number. Network science commonly adheres to this method, and it was also employed in previous research on creativity using the PMFG filter (Kenett et al., 2014; Kenett, Beaty, et al., 2016; van Wijk, Stam, & Daffertshofer, 2010). In contrast, the FMR method relies on filtering based on an FMR threshold. This method ensures that edges in individual networks will always correspond to high semantic relatedness. This criterion, however, also implies that the number of edges varies across networks, and the edge count was found to be substantially correlated with all network parameters (see Table 1). As a consequence, network parameters are highly correlated with the average semantic relatedness for this method: a person giving higher average relatedness evaluations will have more significant edges in the FMR network, which results in higher CC and lower ASPL estimates.

We assumed that the third method, weighted undirected networks, might overcome some of the arbitrariness of the FEN and FMR methods. This method does not impose a specific threshold but instead considers the full available data in terms of weighted edges. The correlational data showed that WUN network parameters, similar to FMR, are again highly dependent on average semantic relatedness (see Table 1). This may also explain why WUN network parameters were substantially correlated with FMR parameters but not with FEN parameters. Even though WUN network representations appear more similar to FMR than to FEN, WUN did not replicate the significant correlations between network structure and creativity. Therefore, the relationship between creativity and network structure can be questioned in our data, because it was not observed with two out of three filtering methods. Future research is needed to determine whether FMR network representations are particularly sensitive to creativity-related aspects of network structure or whether this correlation was potentially due to type 1 error associated with the large number of tests when considering different network parameters and filtering methods. Such research should also examine alternative methods to collect semantic relatedness judgements, such as binary decisions (related/unrelated; e.g., Kenett et al., in press), or choosing a word that is the least similar to two other out of a triplet of words (Connolly, Gleitman, & Thompson-Schill, 2007; De Deyne, Navarro, Perfors, & Storms, 2016).

We also explored some additional alternatives for network construction to examine the robustness of findings. First, we examined effects when filtering networks first with FEN or FMR and then performing weighted network analyses. These weighted analyses on FEN and FMR networks yielded essentially the same findings as the unweighted analyses: no significant association of network parameters with creativity measures for weighted FEN, and for weighted FMR, a significant negative correlation with ASPL and a positive correlation with CC (now by trend) remain. Second, we examined the effect of standardising semantic similarity ratings in WUN networks to account potential for individual differences in using the rating scale. To this end, the ratings of each participant were rescaled to show a minimum of 0 and standard deviation of 1. Again, this transformation did not affect findings for the WUN method, as all correlations with creativity measures remained non-significant. These explorative analyses corroborate the robustness of the effects for the different filtering methods, but since they did not contribute new findings, we only presented the main findings for FEN, FMR and WUN methods, which represent the most principled approach from different perspectives.

Limitations and future directions

Some potential limitations of this research need to be mentioned. First, the number of network nodes in this study was rather low. Previous research has used considerably larger networks of 96 concepts or more (De Deyne & Storms, 2008; Kenett et al., 2014; Kenett, Kenett, Ben-Jacob, & Faust, 2011; Morais et al., 2013). However, this was either done based on group data (Kenett et al., 2014), or for extensively collected individual data leading to non-identical network nodes (Morais et al., 2013). The present study employed 28 nodes which involved a total of 378 pairwise evaluations. If we wanted to use, for example, 96 nodes, the method of pairwise comparisons would already yield a total of 4560 evaluations per subject. Therefore, even though the novel method is efficient in directly estimating semantic networks from semantic relatedness ratings, it still becomes time-consuming when larger networks are considered. Future research should aim to further advance these approaches and examine semantic memory structure at the individual level in larger semantic networks (e.g., Zemla, Kenett, Jun, & Austerweil, 2016). Such research will contribute to our understanding of the relation between semantic memory structure and cognitive phenomena (De Deyne et al., 2016).

Second, we only examined linear associations between creative ability and network measures. However, it seems possible that extreme values in network characteristics are dysfunctional, and creativity is rather associated with moderate or somewhat increased expressions. For example, Faust and Kenett (2014) proposed a cognitive theory on the relation between the structure of semantic memory and typical and atypical thought processes. This theory proposes a cognitive continuum of semantic memory structure. On one extreme of this continuum lie rigid, structured semantic memory networks, such as those exhibited in individuals with Asperger syndrome (Kenett, Gold, & Faust, 2016). On the other end of this continuum lie chaotic, unstructured semantic memory networks, such as those conceptualised to characterise individuals with schizophrenia (Spitzer, 1997). According to this theory, efficient semantic processing is achieved via a balance between rigid and chaotic semantic memory structure (Faust & Kenett, 2014). Of course, nonlinear relationships could also be assumed for the association between creativity and intelligence (Abraham, 2014; Jauk et al., 2013; Karwowski et al., 2016). A powerful detection of nonlinear relationships with unknown inflection points can be achieved by means of the segmented regression analysis (Mueggo, 2008) or necessary condition analysis (Dul, 2016), but these methods require larger sample sizes in order to provide robust estimates. Future research hence may try to test theories on nonlinear relationships between semantic memory structure and typical vs. atypical modes of thought.

Third, future research may aim for a more differentiated assessment at the ends of executive ability. This study measured Gf and Gr, two proxies of executive control that are commonly employed in this line of research (Gilhooly et al., 2007; Jauk et al., 2013; Silvia, 2015). Regarding Gr, it cannot be excluded that retrieval abilities partially depend on the organisation of semantic networks, which would imply a confound between executive ability and network structure. While we did not find empirical support for this confound, this potential issue could be addressed in future research by assessing specific executive abilities such as working memory capacity, shifting ability or inhibition, which should be particularly informative of the role of executive control in creative thought (Benedek et al., 2014).

Finally, models of semantic network structure can only represent coarse approximations of the actual organisation of semantic memory (Jones et al., 2015). Concepts can be associated in many ways (e.g., phonological or visual associations) and the organisation of memory is a major source of individuality that is hardly captured by semantic network models. The present approach takes a step towards the acknowledgement of individuality of networks by modelling network structure based on individual judgements rather than group-based data.

Conclusions

The present study introduced a new, efficient approach for the representation of individual semantic networks based on relatedness judgements, which was applied to a test of associative and executive accounts of creativity. Using this novel approach, we found conditional evidence in support of both accounts of creativity: The role of associative processes was supported only for semantic networks based on FMR; the role of executive ability was supported by substantial correlations between DT ability and Gr. This study thus adds to the growing evidence on associative and executive contributions to creativity. Moreover, it demonstrates the feasibility and benefits of employing a network science approach in the analysis of individual semantic network structure, but also points to the need to further systematically examine and refine available methods for the representation of individual semantic networks.

Disclosure statement

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References

Abraham, A. (2014). Is there an inverted-U relationship between creativity and psychopathology? *Frontiers in Psychology, 5*. doi:10.3389/fpsyg.2014.00750

Abraham, A., & Bubic, A. (2015). Semantic memory as the root of imagination. *Frontiers in Psychology, 6*. doi:10.3389/fpsyg.2015.00325

Alvarez, J. A., & Emory, E. (2006). Executive function and the frontal lobes: A meta-analytic review. *Neuropsychology Review, 16*(1), 17–42. doi:10.1007/s11065–006-9002-x

Arbesman, S., Strogatz, S. H., & Vitevitch, M. S. (2010). The structure of phonological networks across multiple languages. *Entropy, 12*(3), 327–337.

Avitia, M. J., & Kaufman, J. C. (2014). Beyond *g* and *c*: The relationship of rated creativity to long-term storage and retrieval (*Glr*). *Psychology of Aesthetics, Creativity, and the Arts, 8*(3), 293–302. doi:10.1037/a0036772

Barabási, A.-L. (2012). The network takeover. *Nature Physics, 8*(1), 14–16.

Barabási, A.-L. (2016). *Network science*. Cambridge, UK: Cambridge University Press.

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. doi:10.1016/j.tics.2013.04.010

Beaty, R. E., Benedek, M., Kaufman, S. B., & Silvia, P. J. (2015). Default and executive network coupling supports creative idea production. *Scientific Reports, 5*, 10964. doi:10.1038/srep10964

Beaty, R. E., Benedek, M., Silvia, P. J., & Schacter, D. L. (2016). Creative cognition and brain network dynamics. *Trends in Cognitive Sciences, 20*(2), 87–95. doi:10.1016/j.tics.2015.10.004

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.

Beaty, R. E., & Silvia, P. J. (2013). Metaphorically speaking: Cognitive abilities and the production of figurative language. *Memory & Cognition, 41*(2), 255–267. doi:10.3758/s13421-012-0258-5

Beaty, R. E., Silvia, P. J., Nusbaum, E. C., Jauk, E., & Benedek, M. (2014). The roles of associative and executive processes in creative cognition. *Memory & Cognition, 42*(7), 1–12. doi:10.3758/s13421-014-0428-8

Benedek, M., Franz, F., Heene, M., & Neubauer, A. C. (2012). Differential effects of cognitive inhibition and intelligence on creativity. *Personality and Individual Differences, 53*(4), 480–485. doi:10.1016/j.paid.2012.04.014

Benedek, M., & Jauk, E. (in press). Spontaneous and controlled processes in creative cognition. In K. C. R. Fox & K. Christoff (Eds.), *The Oxford handbook of spontaneous thought: Mind-wandering, creativity, dreaming, and clinical conditions*. New York, NY: Oxford University Press.

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. doi:10.1016/j.intell.2014.05.007

Benedek, M., Könen, T., & Neubauer, A. C. (2012). Associative abilities underlying creativity. *Psychology of Aesthetics, Creativity and the Arts, 6*(3), 273–281.

Benedek, M., Mühlmann, C., Jauk, E., & Neubauer, A. C. (2013). Assessment of divergent thinking by means of the subjective top-scoring method: Effects of the number of top-ideas and time-on-task on reliability and validity. *Psychology of Aesthetics, Creativity and the Arts, 7*(4), 341–349. doi:10.1037/a0033644

Benedek, M., & Neubauer, A. C. (2013). Revisiting Mednick's model on creativity-related differences in associative hierarchies. Evidence for a common path to uncommon thought. *The Journal of Creative Behavior*, *47*(4), 273–289. doi:10.1002/jocb.35.

Boccaletti, S., Latora, V., Moreno, Y., Chavez, M., & Hwang, D. U. (2006). Complex networks: Structure and dynamics. *Physics Reports, 424*, 175–308.
Borge-Holthoefer, J., & Arenas, A. (2010). Semantic networks: Structure and dynamics. *Entropy, 12*(5), 1264–1302.
Borkenau, P., & Ostendorf, F. (1993). *NEO-Fünf-Faktoren Inventar (NEO-FFI) nach Costa und McCrae* [NEO five-factor personality inventory (NEO-FFI) according Costa and McCrae]. Göttingen: Hogrefe.
Borodkin, K., Kenett, Y. N., Faust, M., & Mashal, N. (2016). When pumpkin is closer to onion than to squash: The structure of the second language lexicon. *Cognition, 156*, 60–70. doi:10.1016/j.cognition.2016.07.014
Carroll, J. B. (1993). *Human cognitive abilities: A survey of factor analytic studies*. New York, NY: Cambridge University Press.
Connolly, A. C., Gleitman, L. R., & Thompson-Schill, S. L. (2007). Effect of congenital blindness on the semantic representation of some everyday concepts. *Proceedings of the National Academy of Sciences, 104*(20), 8241–8246. doi:10.1073/pnas.0702812104
De Deyne, S., Kenett, Y. N., Anaki, D., Faust, M., & Navarro, D. J. (2016). Large-scale network representations of semantics in the mental lexicon. In M. N. Jones (Ed.), *Big data in cognitive science: From methods to insights* (pp. 174–202). New York, NY: Psychology Press, Taylor & Francis.
De Deyne, S., Navarro, D. J., Perfors, A., & Storms, G. (2016). Structure at every scale: A semantic network account of the similarities between unrelated concepts. *Journal of Experimental Psychology: General, 145*(9), 1228–1254. doi:10.1037/xge0000192
De Deyne, S., & Storms, G. (2008). Word association: Network and semantic properties. *Behavior Research Methods, 40*(1), 213–231.
Dietrich, A. (2004). The cognitive neuroscience of creativity. *Psychonomic Bulletin and Review, 11*(6), 1011–1026.
Dul, J. (2016). Necessary condition analysis (NCA) logic and methodology of "Necessary but Not Sufficient" causality. *Organizational Research Methods, 19*(1), 10–52.
Faust, M., & Kenett, Y. N. (2014). Rigidity, chaos and integration: Hemispheric interaction and individual differences in metaphor comprehension. *Frontiers in Human Neuroscience, 8*(511), 1–10. doi:10.3389/fnhum.2014.00511
Fortunato, S. (2010). Community detection in graphs. *Physics Reports, 486*(3–5), 75–174. doi:10.1016/j.physrep.2009.11.002
Gilhooly, K., Fioratou, E., Anthony, S., & Wynn, V. (2007). Divergent thinking: Strategies and executive involvement in generating novel uses for familiar objects. *British Journal of Psychology, 98*(4), 611–625. doi:10.1348/096317907×173421
Green, A. E. (2016). Creativity, within reason: Semantic distance and dynamic state creativity in relational thinking and reasoning. *Current Directions in Psychological Science, 25*(1), 28–35. doi:10.1177/0963721415618485
Green, A. E., Kraemer, D. J. M., Fugelsang, J. A., Gray, J. R., & Dunbar, K. N. (2010). Connecting long distance: Semantic distance in analogical reasoning modulates frontopolar cortex activity. *Cerebral Cortex, 20*(1), 70–76. doi:10.1093/cercor/bhp081
Groborz, M., & Neçka, E. (2003). Creativity and cognitive control: Explorations of generation and evaluation skills. *Creativity Research Journal, 15*(2–3), 183–197. doi:10.1207/S15326934crj152&3_09
Gruszka, A., & Neçka, E. (2002). Priming and acceptance of close and remote associations by creative and less creative people. *Creativity Research Journal, 14*(2), 193–205.
Hamel, R., & Schmittmann, V. D. (2006). The 20-minute version as a predictor of the raven advanced progressive matrices test. *Educational and Psychological Measurement, 66*(6), 1039–1046. doi:10.1177/0013164406288169

Hills, T. T., Maouene, M., Maouene, J., Sheya, A., & Smith, L. (2009). Longitudinal analysis of early semantic networks: Preferential attachment or preferential acquisition? *Psychological Science, 20*(6), 729–739. doi:10.1111/j.1467-9280.2009.02365.x

Humphries, M. D., & Gurney, K. (2008). Network 'small-world-ness': A quantitative method for determining canonical network equivalence. *PLoS ONE, 3*(4), e0002051. doi:10.1371/journal.pone.0002051

Hutchinson, J. W. (1989). NETSCAL: A network scaling algorithm for nonsymmetric proximity data. *Psychometrika, 54*(1), 25–51.

Jauk, E., Benedek, M., Dunst, B., & Neubauer, A. C. (2013). The relationship between intelligence and creativity: New support for the threshold hypothesis by means of empirical breakpoint detection. *Intelligence, 41*(4), 212–221. doi:10.1016/j.intell.2013.03.003.

Jauk, E., Benedek, M., & Neubauer, A. C. (2014). The road to creative achievement: A latent variable model of ability and personality predictors. *European Journal of Personality, 28*(1), 95–105. doi:10.1002/per.1941

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). Oxford: Oxford University Press.

Kajić, I., Gosmann, J., Stewart, C. T., & Wennekers, T. & Eliasmith, C. (2016). *Towards a cognitively realistic representation of word associations*. Paper presented at the Proceedings of the 38th Annual Meeting of the Cognitive Science Society, Philadelphia, PA.

Kajic, I., & Wennekers, T. (2015). Neural *n*etwork *m*odel of *s*emantic *p*rocessing in the *r*emote *a*ssociates *t*est. Paper presented at the Workshop on Cognitive Computation: Integrating Neural and Symbolic Approaches, 29th Annual Conference on Neural Information Processing Systems (NIPS 2015), Montreal.

Karwowski, M., Dul, J., Gralewski, J., Jauk, E., Jankowska, D. M., Gajda, A., … Benedek, M. (2016). Is creativity without intelligence possible? A necessary condition analysis. *Intelligence, 57*, 105–117.

Kenett, Y. N. (in press). Going the extra creative mile: The role of semantic distance in creativity – Theory, research, and measurement. In R. E. Jung & O. Vartanian (Eds.), *The Cambridge handbook of the neuroscience of creativity*. New York, NY: Cambridge University Press.

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), 1–16. doi:10.3389/fnhum.2014.00407

Kenett, Y. N., Anaki, D., & Faust, M. (under review). Strength and latencies of associative responses generated by low and high creative individuals.

Kenett, Y. N., & Austerweil, J. L. (2016). *Examining search processes in low and high creative individuals with random walks*. Paper presented at the Proceedings of the 38th Annual Meeting of the Cognitive Science Society, Austin, TX.

Kenett, Y. N., Beaty, R. E., Silvia, P. J., Anaki, D., & Faust, M. (2016). Structure and flexibility: Investigating the relation between the structure of the mental lexicon, fluid intelligence, and creative achievement. *Psychology of Aesthetics, Creativity, and the Arts, 10*(4), 377–388. doi:10.1037/aca0000056

Kenett, Y. N., Gold, R., & Faust, M. (2016). The hyper-modular associative mind: A computational analysis of associative responses of persons with Asperger Syndrome. *Language and Speech, 59*(3), 297–317. doi:10.1177/0023830915589397

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. doi:10.1371/journal.pone.0023912

Kenett, Y. N., Levi, E., Anaki, D., & Faust, M. (in press). The semantic distance task: Quantifying semantic distance with semantic network path length. *Journal of Experimental Psychology: Learning, Memory, & Cognition*. doi:10.1037/xlm000039

Landauer, T. K., & Dumais, S. T. (1997). A solution to Plato's problem: The latent semantic analysis theory of acquisition, induction, and representation of knowledge. *Psychological Review, 104*(2), 211–240.

Lee, C. S., & Therriault, D. J. (2013). The cognitive underpinnings of creative thought: A latent variable analysis exploring the roles of intelligence and working memory in three creative thinking processes. *Intelligence, 41*, 306–320.

Martindale, C. (1995). Creativity and connectionism. In S. M. Smith, T. B. Ward, & R. A. Finke (Eds.), *The creative cognition approach* (pp. 249–268). Cambridge, MA: The MIT Press.

Marupaka, N., Iyer, L. R., & Minai, A. A. (2012). Connectivity and thought: The influence of semantic network structure in a neurodynamical model of thinking. *Neural Networks, 32*(0), 147–158. doi:10.1016/j.neunet.2012.02.004

Marupaka, N., & Minai, A. A. (2011). Connectivity and creativity in semantic neural networks. *Paper presented at the 2011 International Joint Conference on Neural Networks (IJCNN)*. San Jose, CA.

McRae, K., & Jones, M. N. (2013). Semantic memory. In D. Reisberg (Ed.), *The Oxford handbook of cognitive psychology* (pp. 206–219). Oxford: Oxford University Press.

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

Mendelsohn, G. A. (1976). Associative and attentional processes in creative performance. *Journal of Personality, 44*(2), 341–369. doi:10.1111/j.1467-6494.1976.tb00127.x

Milgram, S. (1967). The small world problem. *Psychological Today, 1*, 62–67.

Morais, A. S., Olsson, H., & Schooler, L. J. (2013). Mapping the structure of semantic memory. *Cognitive Science, 37*(1), 125–145. doi:10.1111/cogs.12013

Mueggo, V. M. (2008). Segmented: An R package to fit regression models with broken-line relationships. *R News, 8*(1), 20–25.

Nelson, D. L., McEvoy, C. L., & Schreiber, T. A. (2004). The University of South Florida free association, rhyme, and word fragment norms. *Behavior Research Methods, Instruments, & Computers, 36*(3), 402–407. doi:10.3758/BF03195588

Newman, M. E. J. (2006). Modularity and community structure in networks. *Proceedings of the National Academy of Sciences USA, 103*(23), 8577–8582. doi:10.1073/pnas.0601602103

Nusbaum, E. C., & Silvia, P. J. (2011). Are intelligence and creativity really so different? Fluid intelligence, executive processes, and strategy use in divergent thinking. *Intelligence, 39*(1), 36–45.

Olteţeanu, A.-M., & Falomir, Z. (2015). comRAT-C: A computational compound Remote Associates Test solver based on language data and its comparison to human performance. *Pattern Recognition Letters*, *67*(Part 1), 81–90. doi:10.1016/j.patrec.2015.05.015

Olteţeanu, A.-M., & Falomir, Z. (2016). Object replacement and object composition in a creative cognitive system. Towards a computational solver of the Alternative Uses Test. *Cognitive Systems Research, 39*, 15–32. doi:10.1016/j.cogsys.2015.12.011

Raven, J., Raven, J. C., & Court, J. H. (1998). *Advanced progressive matrices*. Oxford: Oxford Psychologists Press.

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

Rubinov, M., & Sporns, O. (2010). Complex network measures of brain connectivity: Uses and interpretations. *NeuroImage, 52*(3), 1059–1069. doi:10.1016/j.neuroimage.2009.10.003

Runco, M. A., & Acar, S. (2012). Divergent thinking as an indicator of creative potential. *Creativity Research Journal, 24*(1), 66–75. doi:10.1080/10400419.2012.652929

Schilling, M. A. (2005). A "small-world" network model of cognitive insight. *Creativity Research Journal, 17*(2–3), 131–154. doi:10.1080/10400419.2005.9651475

Schvaneveldt, R. W., Dearholt, D. W., & Durso, F. T. (1988). Graph theoretic foundations of pathfinder networks. *Computers & Mathematics with Applications, 15*(4), 337–345. doi:10.1016/0898-1221(88)90221-0

Shannon, P., Markiel, A., Ozier, O., Baliga, N. S., Wang, J. T., Ramage, D., … Ideker, T. (2003). Cytoscape: A software for integrated models of biomolecular interaction networks. *Genome Research, 13*(11), 2498–2504. doi:10.1101/gr.1239303

Siew, C. S. Q. (2013). Community structure in the phonological network. *Frontiers in Psychology, 4*. doi:10.3389/fpsyg.2013.00553

Silvia, P. J. (2015). Intelligence and creativity are pretty similar after all. *Educational Psychology Review, 27*(4), 1–8. doi:10.1007/s10648-015-9299-1

Silvia, P. J., Beaty, R. E., & Nusbaum, E. C. (2013). Verbal fluency and creativity: General and specific contributions of broad retrieval ability (Gr) factors to divergent thinking. *Intelligence, 41*(5), 328–340. doi:10.1016/j.intell.2013.05.004

Silvia, P. J., Winterstein, B. P., Willse, J. T., Barona, C. M., Cram, J. T., Hess, K. I., … Richard, A. C. (2008). Assessing creativity with divergent thinking tasks: Exploring the reliability and validity of new subjective scoring methods. *Psychology of Aesthetics, Creativity, and the Arts, 2*(2), 68–85.

Spitzer, M. (1997). A cognitive neuroscience view of schizophrenic thought disorder. *Schizophrenia Bulletin, 23*(1), 29–50.

Steyvers, M., & Tenenbaum, J. B. (2005). The large scale structure of semantic networks: Statistical analysis and a model of semantic growth. *Cognitive Science, 29*(1), 41–78.

Tumminello, M., Aste, T., Di Matteo, T., & Mantegna, R. N. (2005). A tool for filtering information in complex systems. *Proceedings of the National Academy of Sciences of the United States of America, 102*(30), 10421–10426. doi:10.1073/pnas.0500298102

van Wijk, B. C. M., Stam, C. J., & Daffertshofer, A. (2010). Comparing brain networks of different size and connectivity density using graph theory. *PLoS ONE, 5*(10), e13701. doi:10.1371/journal.pone.0013701

Vitevitch, M. S., Chan, K. Y., & Goldstein, R. (2014). Insights into failed lexical retrieval from network science. *Cognitive Psychology, 68*, 1–32. doi:10.1016/j.cogpsych.2013.10.002

Vitevitch, M. S., Chan, K. Y., & Roodenrys, S. (2012). Complex network structure influences processing in long-term and short-term memory. *Journal of Memory and Language, 67*(1), 30–44. doi:10.1016/j.jml.2012.02.008

Vitevitch, M. S., Goldstein, R., & Johnson, E. (2016). Path-Length and the Misperception of Speech: Insights from network science and psycholinguistics. In A. Mehler, A. Lücking, S. Banisch, P. Blanchard, & B. Job (Eds.), *Towards a theoretical framework for analyzing complex linguistic networks* (pp. 29–45). Berlin, Heidelberg, Berlin: Springer.

Watts, D. J., & Strogatz, S. H. (1998). Collective dynamics of 'small-world' networks. *Nature, 393*(4), 440–442.

Zemla, J. C., Kenett, Y. N., Jun, K.-S., & Austerweil, J. L. (2016). *U-INVITE: Estimating individual semantic networks from fluency data*. Paper presented at the Proceedings of the 38th Annual Meeting of the Cognitive Science Society, Austin, TX.

Appendix

Table A1. Stimulus words used in the semantic relatedness task (English translation of German stimuli in brackets).

Category	Concepts
Animals	Hund, Katze, Vogel, Kuh (dog, cat, bird, cow)
Nature	Berg, Baum, Fluss, Sonne (mountain, tree, river, sun)
Food	Fleisch, Käse, Wasser, Brot (meat, cheese, water, bread)
Tools	Hammer, Besen, Stift, Messer (hammer, broom, pen, knife)
Furniture	Bett, Tisch, Kasten, Lampe (bed, table, cupboard, lamp)
Clothes	Schuh, Hose, Hut, Schirm (shoe, trouser, hat, umbrella)
Container	Eimer, Flasche, Sack, Dose (bucket, bottle, sack, can)