Bachelor Thesis

Relation Between Semantic Relatedness Judgements and Creativity: Using Network Analysis to Compare More and Less Creative Individuals

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Abstract

There are many theories about creativity and where creative ideas come from. In this paper we focussed on theories that are grounded in memory structure. We used network analysis to mimic these structures and thereby relate test to theory. The main goal of this study was to find out if there are structural differences in the semantic networks of more and less creative individuals. To this end, we constructed individual semantic relatedness networks from a novel semantic relatedness task based on a commonly used task to measure creative potential, the alternative uses task (AUT). This way the relationship between the networks based on this task and the performance on it could be explored directly. 106 undergraduate psychology students were asked to rate the semantic relatedness between responses to the AUT; these judgement scores were used to generate individual semantic relatedness networks. The results did not show strong relationship between the structure of the semantic networks and creative potential. However, visualising the networks of the highest and lowest scoring individuals on the AUT, showed an indication that there are structural differences between the networks of more and less creative individuals. Variation in flexibility and fluency on the AUT were strongly related to the semantic network structure, even though creative potential was not. The results of this study were inconclusive, but the methods used, made it possible to relate both expected and unexpected results to different theories, and could help navigate further research on the relationship between of creativity and memory structure.

Keywords: creativity, network analysis, semantic networks, semantic memory

Are there differences in the semantic networks of more and less creative individuals?

Where do creative ideas come from? It is an interesting question with immensely many answers. Psychologists have been trying to get closer to the truth regarding the matter, but there is still a lot of uncertainty. One aspect that seems to be generally accepted, is the link to memory, especially semantic memory (Beaty, Silvia, Nusbaum, Jauk & Benedek, 2014; Necka, 2011; Abraham & Bubic, 2015; Kenett, Anaki & Faust, 2014). Mednick (1962) introduced the associative theory of the creative process and he stated that creative thinking is a process of forming new associations between elements. According to Mednick, creativity lies within the semantic distance between the elements used to make new useful combinations. He argues that people that are able to make associations between elements that further apart semantically are more creative. Not only do we want to know how creativity comes about, but we are also interested in the individual differences in creativity. How can we explain that one person is perceived as creative while another is not. In this paper I will try to answer that question by mapping the individual semantic networks of more and less creative individuals.

According to Mednick's theory, there are associative hierarchies that people differ in. In a task where people have to make associations to a certain word or object, a less creative person would make a lot of stereotypical associations in a short amount of time, but would run out of associations quickly. A more creative person would make more remote associations quite steadily after one another, not running out of associations as quickly as less creative individuals. More creative individuals would have a flat hierarchy whereas less creative individuals would have a steeper associative hierarchy. See Figure 1 for a graphical representation of Mednick's association hierarchies.

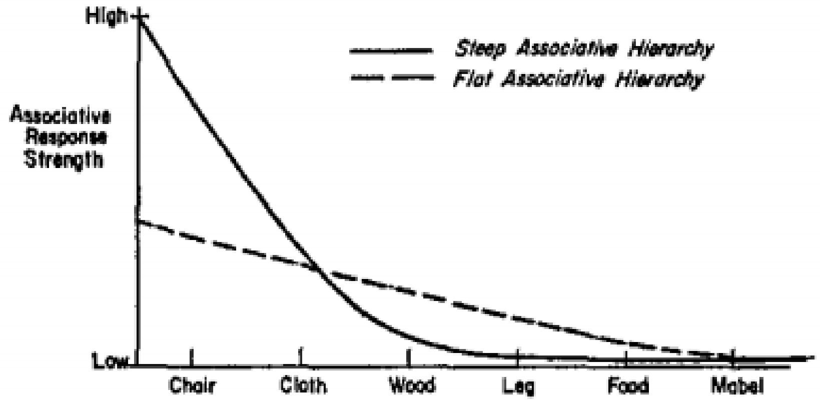

Figure 1. Association hierarchies for the concept “table” (adapted from Mednick, 1962, p. 223).

According to the associative theory, creative individuals make more associations mover time. The associations that they make are also less common than those made by less creative individuals (Mednick, 1962). Mednick's theory in itself does not quite explain where these differences come from. Other psychologists building on Mednick's theory argue that the memory plays a big role in the individual differences in creativity.

Necka (2011) argues that there are two kinds of memory search or two different search strategies. There is local memory search and global memory search. Local memory search is narrow and well defined within the Long Term Memory (LTM). When searching locally, it is possible to get stuck within one domain and that leads to an uncreative process. Other maybe relevant information cannot be accessed because of the boundaries around the domain. When looking back at Mednick's theory, this could be the reason why the absolute number of associations made, are lower for less-creative individuals. When using global memory search, these boundaries can be crossed by using analogies for example. The crossing over to new domains makes for new, more distant associations and according to Mednick's definition, more creativity. The hypothesis Necka states, is that creative individuals are more inclined toward using global memory search than less creative people; they are more flexible when searching their memory.

Flexibility is also key concept in the Dual Pathway to Creativity Model by Nijstad, Dreu, Rietzschel, and Baas (2010). In this model there are two routes to achieve creativity; the cognitive flexibility route and the cognitive persistence route. The cognitive flexibility route is very similar to Necka's global memory search. When following the cognitive flexibility route, people explore more uncommon perspectives and will cross categorical boundaries, it leads to holistic and inclusive thinking (Dreu, Baas & Nijstad, 2008) and to making more remote associations (Nijstad et al, 2010). The cognitive persistence route is similar to Necka's local search process. In the cognitive persistence route systematic problem solving, hard work and more in-depth instead of cross-category thinking can lead to creative insights (Dreu et al, 2008). The cognitive persistence route can lead to creative fluency and originality within categories. Local memory search, or the cognitive persistence route, is not necessarily seen as a bad thing, or as something that limits creativity according to this Dual Pathway Model.

Creativity and Semantic Networks

As you can see, there is some variety between psychologists on how creativity and creative ideas come about, but memory seems to play an important role in the matter. Recently there has been more and more traction to the idea that the way the semantic memory is organised, influences the way people make creative associations (Kenett, Anaki & Faust, 2014, Benedek et al., 2017; Beaty, Silvia, Nusbaum, Jauk, & Benedek, 2014). Kenett, Anaki

& Faust (2014) investigated the structure of semantic networks in low and high creative persons by comparing networks constructed from one minute free association tasks with a target word. Benedek et al. (2017) used a different approach to construct such a network. They used a semantic relatedness task in which participants were asked to rate the semantic relatedness between concepts; these judgements were used to make individual semantic networks. The findings of both investigations suggest that semantic networks of more creative individuals do indeed differ from those of less creative individuals. The constructed networks consist of nodes and edges, nodes being the elements and edges the relation between the elements. The high creative individuals in Benedek's study showed shorter average path lengths (ASPL) between the elements. The ASPL value is the number of steps it takes to get from one node in the network to another when taking the shortest path between the two. The networks of highly creative individuals also showed higher clustering than the networks of less creative individuals. Clustering was measured with he clustering coefficient (CC), which refers to the probability that two neighbours of one node, will also be directly connected. The CC was also higher for more creative individuals than for less creative individuals.

Because the use of network analysis is still relatively new in Psychology, a lot more research on the relation between semantic networks and creativity needs to be done. It could give us a new and better understanding about creativity, what it is, and where individual differences come from.

The Present Study

When looking at the relation between people's semantic networks and creativity, separate methods are used to measure creativity and to create the semantic networks. In this study, we pull this closer together. To this end, we created semantic networks based on the Alternative Uses Task (AUT), which is often used as a measure of creative potential (Benedek, Mühlmann, Jauk & Neubauer, 2013; Gilhooly, Fioratou, Anthony & Wynn, 2007). In the AUT participants are presented with an everyday object and asked to come up with as many creative uses for that object as possible within a certain time limit (Guilford, 1956). Instead of constructing a semantic network from tasks not based on creativity, like the free association task (Kenett et al., 2014) or a semantic relatedness tasks that is not directly connected to creativity (Benedek 2017), we created a semantic relatedness task using the answers from AUTs. These responses were used to construct the individual semantic relatedness networks. The relation between creative potential and the explanation for the individual differences will be more direct in this way. Theoretically, the semantic relatedness networks should be more strongly connected for more creative individuals than for less creative individuals, making it easier for them to make remote and creative associations.

To test this there are several hypotheses that need to be looked at; the first being that the distances between concepts within the semantic network influences the general ability to make associations. The shorter the distance between concepts, the easier it would be to make a lot of associations in a short amount of time, these don't necessarily have to be creative. The expectation is that people with shorter average length paths in their relatedness networks to show higher fluency on the AUT, they will have more valid responses than people with longer average length paths. Now this does not necessarily mean that they are more creative, for that it is necessary that more remote and original associations can be made, this is why flexibility is also important to look at.

If more creative individuals are indeed more inclined towards using global memory search, and show more flexibility in searching their memory, then this could be the result of the shorter distances between different concepts that are remote for less creative individuals. When the distances between concepts, especially concepts from different categories are smaller, it should be easier to switch domains as they're called by Necka (2011). Because of this, the second hypothesis I will test is that people who show more flexibility by switching categories on the AUT will also have less distance between the nodes in the semantic relatedness network. The AUT answers can be divided into different categories. For example, if the task is to name as many creative uses for a brick, there will be a category "weapon" for when people answer "to threaten someone" or "hit someone with it" and a category "play" for answers like "like a bowling ball" or "to play Jenga". This is why I expect there to be a negative relationship between flexibility, or the relative amount of category switches on the AUT, and the ASPL.

By visualising and analysing the semantic networks based on the AUT task, I hope to uncover one of the causes of these individual differences in creative potential and flexibility; the structure of the semantic memory. Based on earlier research, I would expect the networks of people that score higher on the AUT to show a higher clustering coefficient (CC), which means that the probability that two neighbours of a node will themselves be neighbours, is higher for more creative people than for less creative people. I also expect the ASPL will be shorter for people that score higher on the AUT than the people with lower scores. Apart from looking at the network measures, it's also informational to look at the relation between the explicit relatedness judgements and creativity, in this way we can find out if there are not just structural differences in the semantic networks, but also experience these differences.

In short, I want to know if a person's creative potential measured with the AUT is related to the connectedness of their semantic network based on AUT solutions. Because the goal is to understand what causes individual differences, I assume the direction of the relationship between the networks and creativity. This is why I look at the predictive ability of the network parameters and semantic relatedness judgements on the AUT performance.

Method

Participants

The sample consisted of 114 undergraduate psychology students from the University of Amsterdam. [no access to participant information such as gender and age yet, should be added when possible] The tasks administered for this research project were part of a mandatory test battery for first year psychology students. The study was approved by the University of Amsterdam's Social Science Research Ethics committee. All participants provided informed consent. Eight participants had to be excluded from the analyses because of missing data on one or more of the tasks, so in total the data of 106 participants was used for the analyses.

Instruments

Alternative Uses Task (AUT)

The Alternative Uses Task (AUT) was used to measure creative potential. We asked the participants to name as many creative uses for an object as possible. There was a two-minutes time limit per object. The objects used were "brick" and "paperclip". These were presented in the same order for each participant. Each valid response was judged on originality and given a score between one and five. The originality score per object was the average originality score of all responses for that object. The creativity score that was used for the analyses was the sum of the originality scores per object. This means that a participant that had an average originality score of 3.5 for the object "brick" and a 4.4 on "paperclip", the creative potential of this participant would be 7.9. Fluency per object was the number of valid responses. Flexibility per object was the number of category switches as described earlier.

Semantic Relatedness Judgements of AUT Responses Task

[No access to the task, screen-shot should be added here]

During this task, participants were asked to judge the relatedness of two responses to the AUT for the object "fork". The responses were actual answers people gave in previous studies using the AUT with the instruction: "Name as many creative uses for a fork as you can". We selected the following responses, all of which used consisted of single words and had similar originality scores: hairbrush, pitchfork, rake, toothpick, garbage picker, paintbrush, hammer, weapon and bottle opener. Participants first saw an instruction screen with a general explanation of the task and were instructed not to think about their answers too long, but to go with their first instinct. They were also made aware of the connection between the AUT and this task. The instruction was “How similar do you find the following two creative uses of a fork?”. Below this the participants saw a list of 45 unique combinations of ten AUT fork responses. They gave their ratings using a 7-point Likert scale from (1) “not similar at all” to (7)“the same“. The AUT fork response combinations were the same for each participant, but the order was randomised. The estimated duration of this task was 10 minutes. The similarity ratings for this task were used to construct the semantic networks.

Procedure

All tasks were administered by computer in a large examination room with other student during a testing session lasting 45 minutes. The test battery included numerous psychological tests and questionnaires, such as the Raven IQ test and the Big Five personality test. All task instructions were presented on the computer screen. The participants were first administered the Alternative Uses Task and then the Semantic Relatedness Task to make them aware of the connection between the two.

Statistical Analysis

Semantic Network Construction

To construct the semantic relatedness networks, the relatedness scores were converted to values between zero and one, this way the edges between nodes that were judged "not similar at all" were zeroed out. An adjacency matrix of the relatedness judgements of all answer combinations was made for every participant. The networks were constructed, visualised and analysed using the *qgraph* package in R (Epskamp et al., 2017). As discussed in the introduction, the network parameters chosen for the data-analyses were the Clustering Coefficient (CC) and the Average Shortest Path Length (ASPL). Both were also calculated with the *qgraph* package in R (Epskamp et al., 2017). In the study by Benedek et al., (2017), three filtering techniques were used to account for the large number of weak edges, but these networks were larger and were constructed using a continuous scale. This is why we decided against using any kind of filtering technique, so there would be no loss of information that could deform our data.The networks that were constructed in this study were weighted and undirected, meaning that the edges have different weights representing the relatedness scores.

Results

Descriptive statistics are presented in Table 1. The average semantic relatedness judgement score was 2.45 (SD = 0.76) on a 7-point scale. The average creativity score for the two AUT objects was 4.09 (SD = 0.89=7) with 5 being the highest possible rating for an AUT response, 10 being the highest possible creativity score. Table 2 shows a correlation matrix of all correlations between the different measurements.

Table 1

Descriptive Statistics

	Minimum	Maximum	Mean	SD
AUT creativity	1.09	6.20	4.09	0.87
AUT fluency	2	24.50	7.57	3.32
AUT flexibility	0.5	14.50	5.26	2.08
SR	1.07	5.16	2.45	0.76
NET CC	0.00	0.69	0.29	0.13
NET ASPL	0.04	7.18	3.71	1.32

n = 106. AUT, alternative uses task; SR, semantic relatedness; NET CC, network clustering coefficient; NET ASPL, network average shortest path length.

Table 2
Correlation Matrix

	AUT creativity	AUT fluency	AUT flexibility	SR	NET CC	NET ASPL
AUT creativity	1	0.08	0.51**	0.13	0.09	-0.06
AUT fluency		1	0.66**	0.34**	0.33**	-0.17
AUT flexibility			1	0.33**	0.24*	-0.16
SR				1	0.91**	-0.41**
NET CC					1	-0.32**
NET ASPL						1

n = 106. AUT, alternative uses task; SR, semantic relatedness; NET CC, network clustering coefficient; NET ASPL, network average shortest path length.
* p < .05 (2-tailed); ** p < .01 (2-tailed); Pearson correlation coefficients.

Table 2 shows that creativity and fluency on the AUT are not correlated. However, it does show a significant correlation between creativity and flexibility. This is a remarkable result since it demonstrates Necka's (2011) argument that people who are more creative are more inclined towards using global memory search and therefore need flexibility to cross domains or categories. The high correlations between the semantic relatedness and the network parameters was expected, since they were derived from the semantic relatedness scores.

To test whether the ASPL was a good predictor of fluency and flexibility a simple linear regression was calculated. The ASPL could not significantly explain the expected variance in fluency (R^2 = .03, F(1, 104) = 3.07, p = .08). The ASPL also could not significantly explain the variance in flexibility (R^2 = .03, F(1, 104) = 2.89, p = .09). Assuming the direction of the semantic relatedness network influencing the AUT performance, it would seem that, in this case, the distance between concepts is not a good predictor of the ability to make associations or to switch categories while associating. However, the CC did significantly explain the variance in fluency and flexibility (R^2 = .11, F(1, 104) = 13.13, p < .001 and R^2 = .06, F(1, 104) = 6.29, p < .05, respectively).

The CC, ASPL and the semantic relatedness judgement scores could not significantly explain the variance in creative potential (Table 3). This is an unexpected result and will be further discussed in the discussion.

Table 3

Regression Table of Creative Potential Predictors

	B	SE B	β	*t*	R^2	*F*(1, 104)	*p*
SR	0.15	0.11	.13	1.39	.02	1.92	.17
CC	0.60	0.63	.09	0.95	.01	0.90	.34
ASPL	-0.04	0.06	-.06	-0.58	.00	0.34	.56

n = 106. SR, semantic relatedness; CC, clustering coefficient; ASPL, average shortest path length

This is different when the creativity scores are calculated by taking the average of the sum of originality scores per object. This means that when a participant has an originality score of 15 for "brick " and 12 for "paperclip ", their average creativity score is 13.5. Note that this is not the common way of calculating this score. See the regression table below (Table 4).

Table 4

Regression Table of Creative Potential Predictors

	B	SE B	β	*t*	R^2	F(1, 104)	*p*
SR	3.44	0.91	.35	3.77	.12	14.6	<.001
CC	16.72	5.28	.30	3.17	.09	10.04	.002
ASPL	-1.12	0.55	-.20	-2.04	.04	4.15	.044

n = 106. SR, semantic relatedness; CC, clustering coefficient; ASPL, average shortest path length.
* Creative potential is the average of the sum of the originality scores per object

However, these values are heavily influenced by the fluency participants show on the AUT, and this is not necessarily what we are interested in. Even though the network parameters could not significantly explain the variance in creativity scores (Table 3), it is still useful to look at the structure of the networks when visualised. By taking average the network of the highest ten percent scoring participants on the AUT (creative potential), you can see that almost all nodes have a very visible edge between them (see Figure 2). Not all edges have the same weight, but the network is very connected. In contrast, the average network of the ten percent lowest scoring participants is less strongly connected and shows many sparse, almost invisible edges (see Figure 3). This shows that, at least in the extrema, there are structural differences in the semantic relatedness networks.

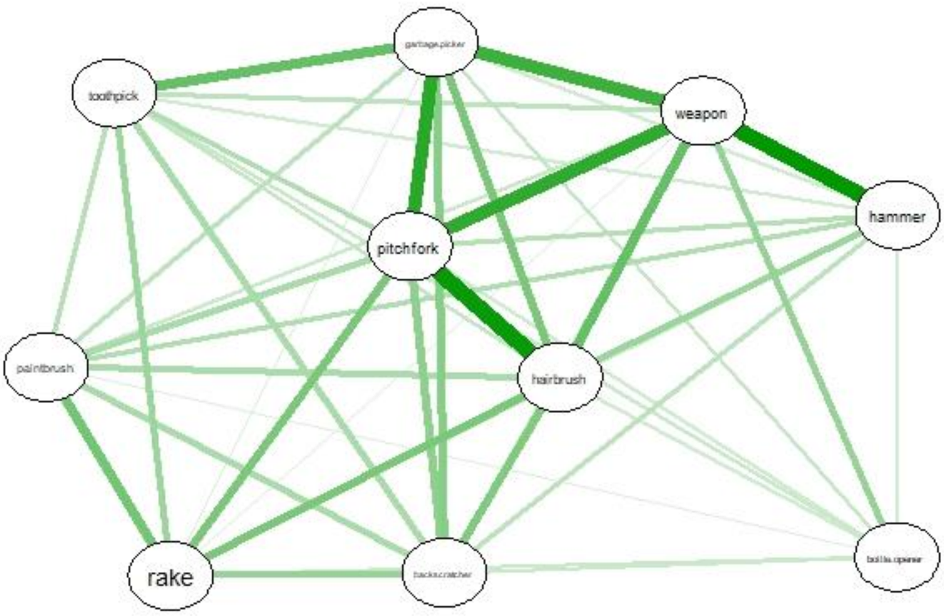

Figure 2. Network visualisation of the 10% highest scoring individuals on the creativity task.

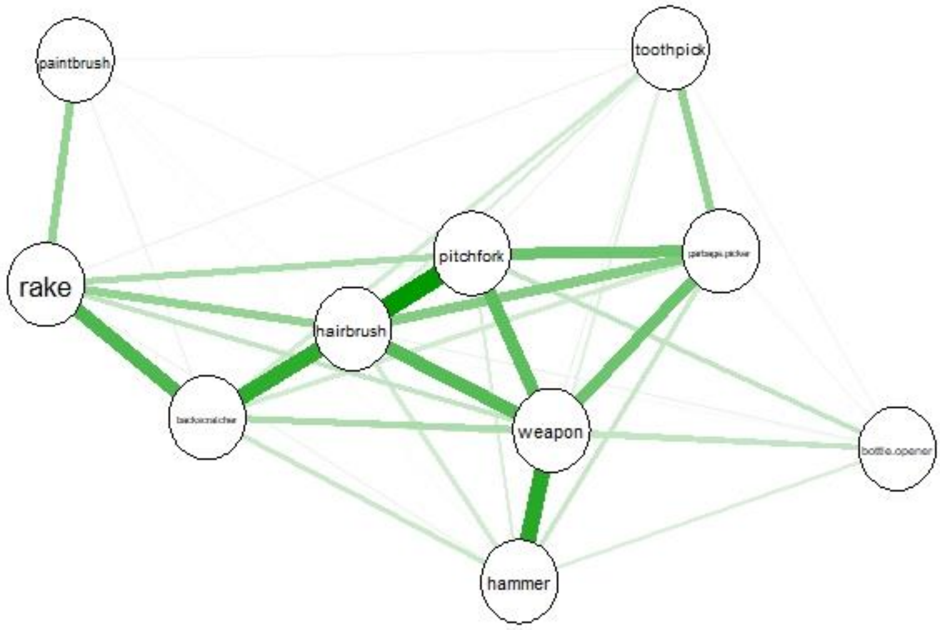

Figure 3. Network visualisation of the 10% lowest scoring individuals on the creativity task.

Discussion

This was an exploratory study on the relationship between people's semantic relatedness networks and creative potential, focussing on the Alternative Uses Task; a task often used to measure creativity in psychological research (Benedek et al., 2013; Gilhooly et al., 2007). This is why the semantic relatedness networks were constructed from a new task based on the AUT. In this way, we can directly relate the results of both tasks and get a more in depth look in what happens when people are presented with tasks like the AUT. Even though there was no clear relationship found between the network parameters, CC and ASPL, and creative potential, there are other results that are interesting to look at and that still give us valuable information. The distances between different concepts within the networks did not provide as much information as we expected based on earlier research, which showed that the ASPL was strongly related to fluency (Benedek et al., 2017, Kenett, Anaki & Faust, 2014). This is not what we found in this study; the ASPL had no apparent connection with fluency or flexibility. However, another network parameter, the clustering coefficient, did positively relate to people's ability to come up with valid answers on the AUT, as well as with the number of category switches people made.

First, we take a look at why we did not find a relationship between creative potential and the CC and ASPL. From the literature we would expect there to be a strong relationship (Kenett, Anaki & Faust, 2014, Benedek et al., 2017; Beaty,et al., 2014). Especially according to Necka’s (2011) theory, the current findings are unexpected. The ability to make creative associations, and perform better on the AUT, is dependent on the ability to switch domains. The switching of domains is facilitated by the semantic memory structure. If this is the case there should be a clear relationship between creative potential and the CC and ASPL. The current findings are not as unexpected when looking at the Dual Pathway to Creativity Model by Nijstad et al. (2010), which does not state that domain-switching is a necessity for making creative associations. Creative associations can also be acquired by cognitive persistence, so this model does not require these structural differences in people’s semantic networks. However, these results might be a consequence of the manner in which creative potential was measured. The participant’s fluency had no influence on the creativity score, to keep these two measurements independent from one another. However, this means that when one participant gave one response with a score of five, and another participant gave twelve responses with a score of four, the latter would get a lower creativity score. A lot could be said against this approach. This is why another analysis was done where this was not the case; fluency had a big impact on these creativity scores. These results, however, did show a strong relationship between the network parameters, semantic relatedness judgements and creative potential. An argument could be made for both approaches, but it would also be valuable to find a compromise between the two, so that fluency is included, but does not weigh that heavily.

The visualisation of the networks shows that there is a difference in the strength of connectedness in the networks of the highest and lowest scoring individuals on the AUT. Even though this was not found in general, the obvious difference in network structure seen between these groups, indicate that there is value in looking at the connection between creativity and the semantic network structure. Dividing the participants into groups based on their creativity scores could tell us more about where we can and cannot see these structural differences and explore the accompanying implications.

The ASPL was uninformative in this study, we expected it to be strongly related to both fluency and flexibility, but this is not what was found. The CC however, did better at explaining the variation in fluency and flexibility. The result that the probability that two neighbours of one node are also connected relates to the participants‘ ability to make associations and switch categories, does not go against our expectations. A high CC indicates that a network is connected more strongly, that is why it makes sense that this would facilitate both fluency and flexibility. These findings are in accordance with Necka’s theory of memory search (2011). Another result that corroborates Necka’s theory is the strong connection between creativity and flexibility; creative people switch more often between domains than less creative people do, indication that they might me more inclined towards global memory search.

Since this was a relatively small exploratory study, there were many limitations. We did find some interesting results, but to further validate these results, more research needs to be conducted. It would be valuable to test if the results we found are influenced or mediated by other variables, such as intelligence, overall task performance, motivation and mood. As mentioned earlier, it would also be informative to take another look of the scoring of the AUT task; the scoring of the AUT was done by protocol in this study to optimize objectivity. However, even when using the protocol, many responses could be interpreted in different ways. That is why it is useful to look at different scoring methods, such as a Top 2 scoring method where the participants choose the two responses they find most creative, which in turn will be evaluated by the raters (Silvia et al., 2008). In this way, unoriginal answers would not bring down the average creativity score as it did in the current study. An important limitation of the current study is that the direction of the relationship between the semantic relatedness networks and creative potential is assumed, not tested. This is a very difficult task but is important to keep in mind when conducting further research. Another, and more practical direction for further research, is to test whether the structure of the semantic relatedness networks is also connected to less language-based creativity tasks, or if it is limited to language based creativity.

The results found in this exploratory study were inconclusive but did provide valuable information of the worth of using a novel semantic relatedness judgement task based on the AUT to construct individual semantic relatedness networks. By minimizing the distance between the task used to measure creative potential and the task used to construct the networks, the results are easier to interpret and to apply to various theories about memory search such as those by Necka (2011) and Nijstad et al. (2010). The visualisation of the semantic relatedness networks facilitate this as well. In conclusion, we argue that it is valuable to continue down this road of using existing creativity tasks to construct, analyse and visualize semantic relatedness networks. This way we will be able to test the substantiation of different theories on the same subject and figure out which one(s) explain the phenomena we see in real life and in psychological science best.

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