ON THE ARCHITECTURE OF SEMANTIC NETWORKS: A QUANTITATIVE ASSESSMENT OF SUBJECTIVE REPRESENTATIONS

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ABSTRACT: *The increased use of computer aided qualitative data analysis software in social research fields profit from the semantic networks (SN) for the data organization and analysis. However, the validation and scope of these methodologies remains as an open discussion. In the other hand, graph theory methods are a growing field on mathematics but is becoming also important in most research fields, such as social and human sciences. Regardless the similarity between SN and graph theory, no studies have accessed the quantitative architecture of the SN. Here, we explored by quantitative means the subjective component of SN architecture. Overall, differences in the metrics of the SN graphs and loss of global correlation across experts suggested that the topology of SN include a subjective component, important in differentiating cognitive processes between persons. Furthermore, the results suggest that methods such as triangulation should be considered in the analysis of qualitative data.*

KEYWORDS: semantic networks, graph theory, subjectivity assessment, atlas.ti, semantic fields.

INTRODUCTION

Social sciences commonly assess qualitative subjects, occasionally via constructivist research paradigms –also called interpretivism– (Ang, Embi, & Md Yunus, 2016). These paradigms are sometimes considered flexible and context sensitive (Carcary, 2009). Furthermore, most of these types of studies use linguistic instead of cognitive based approaches (Borge-Holthoefer & Arenas, 2010), creating debates about their validity and trustworthiness (Bassett, 2004).Computer Aided Qualitative Data Analysis Software (CAQDAS) aim to reduce the gap between the qualitative nature of these problems and the quantitative standard solutions given by other research paradigms such as positivism (Alexa & Zuell, 2000). Since the late eighties, CAQDAS have been widely used to facilitate the building of theories and hypothesis in a user-friendly approach (Evans, 1996; Lee & Esterhuizen, 2000; Burnap, et al., 2013). Some of the most currently employed CAQDAS are the so-called semantic network methodologies to address qualitative questions in many research areas (García-Sánchez et al., 2018; Rivera-Largacha, Prieto, & Londoño, 2018; Weise & Monereo, 2018).

THEORETICAL UNDERPINNING

A semantic network is a graphical structure for representing knowledge in patterns of interconnected nodes, called concept fields, by means of semantic relations (Sowa & Zachman, 1992). In other words, they are a web-like approach that graphically represent knowledge (Doerfel, 1998). Also, semantic network methodologies, in social and human sciences, allow to easily and rapidly model qualitative content from techniques such as interviews, focus groups, field diary, life stories, thematic stories, among others (Borge-Holthoefer & Arenas, 2010).

However, some authors reject the use of semantic networks due to possible loss of depth in analysis and relation to the source data (Bassett, 2004). In particular, semantic networks CAQDAS for qualitative research may poorly represent the information with arbitrary relations. In addition, these approaches lack content expressiveness and use unclear semantics that are difficult to implement, or to control the associations (Marinov & Zheliazkova, 2005), which can lead to subjectivity problems.

In contrast, current literature supports the use of computer supported semantic networks methodologies for qualitative research (Ang, et al., 2016; Hwang, 2008). Indeed, novel technologies and the ability to produce and gather exceptional amounts of data from social and inherent-qualitative spheres such as hermeneutics open analysis opportunities via computational and mathematical methods (Conte et al., 2012). In particular, one current mathematical subject resembles the qualitative shape of semantic network techniques, the so-called graph theory field (Vitevitch, 2008). A graph is an integer set of elements called nodes, or vertices, connected by a second set of elements, called edges, that create a network-like topological mathematical object (Börner, Sanyal, & Vespignani, 2007). The architecture of graphs describes the organization of different types of complex systems such as natural and social phenomena (Watts, 2004). Indeed, graph theory originated in the fields of discrete mathematics and dynamic systems, but is currently used in almost all natural and social sciences (Watts, 2004).

By these definitions, it is easy to appreciate the similarity between the semantic networks and graphs. Actually, graph theory analysis has been proposed as a valuable tool for the analysis of mental organization of language (Vitevitch, 2008). A referent in this matter is Ricard Solé who has studied the language structure and dynamics using the under the scope of graph theory methods (Ferrer i Cancho & Solé, 2001; Solé, Corominas-Murtra, Valverde, & Steels, 2010). In human language, a graph is constructed by the depiction of words as the nodes of the network connected by its chronological linear appearance (Ferrer i Cancho & Solé, 2001). The quantity of edges in a node represents the number of times a word is used in the text, conversation or any other communication type. Actually, in most human languages this organization of graphs leads to a network architecture known as small-world (Dorogovtsev & Mendes, 2001). In this architecture, most network connections are made from a small group of nodes, frequently connected words, whereas the majority of nodes are less connected, creating a so-called power-law topology (Vitevitch, 2008).

This methodology has been recently used in many areas. Some examples include theoretical suggestions (Dorogovtsev & Mendes, 2001), the way language changes in psychiatric disorders (Bertola et al., 2014; Mota, Furtado, Maia, Copelli, & Ribeiro, 2014; Mota et al., 2012), and mental states (Bedi et al., 2014; Carrillo, 2017). However, given the increasing popularity of graph theory approaches in the context of language and cognitive research and the similarity between mathematical graphs and semantic networks, to our best of knowledge, there are no studies that assess problems of semantic networks quantitatively with graph theory methods.

The architecture of a semantic network is itself the reflection of the interpretation and organization of data in a subject; that is, a proxy of the subjective process of abstraction and association of categories. This process is a difficult concept to measure given its abstract nature. Therefore, the quantitative assessment of neural networks could provide novel insides of this subjective process. In this project, we suggest that graph theory metrics could supply additional information to semantic networks. Information that could be quantify. A property that offers a broad range of opportunities such as statistical comparisons of these subjective processes between and within subjects. With our research, we propose the use of graph theory metrics could be an additional framework to study semantic networks in quantitative bases.

The aim of this study is to evaluate the influence of subjective expert analysis in the architecture of the semantic networks constructed from complex interviews. In that respect, three experts built semantic networks based on interviews of children involved in war-related experiences. These networks were analysed using graph theory metrics to compare the topologies across experts. We found that the morphological measures of the graphs differ between subjects with a further lack of correlation between experts. These results suggest that the morphological properties of the graphs created from semantic networks depend on expert subjectivity.

METHODOLOGY

Interviews and interview transcripts

Semantic networks are considered as useful hermeneutical tools to assess implicit meanings and relations not easily observable in the data (Doerfel, 1998). Therefore, the data best suitable to this approach should be complex enough to have such implicit information (Fisher, 1990). Here, three experts phycologists with postgraduate level of education specialized in social research analysed fourteen transcript interviews of children, under 14 years of age, that were recruited in a Colombian guerrilla. This information was collected as part of the research project named: “Children and young people disconnected from the Colombian armed conflict” developed by Lucero Zamudio, Álvaro Toledo, and Diego-Mauricio Aponte from the centro de investigación sobre dinámica social (CIDS), from the Social and Human Sciences Faculty of the Universidad Externado de Colombia between 2004 to 2006. Depending on the child, the focus on different segments and descriptions of each experience produces high variability in the raw data, but with a

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common origin and nature. This variability of the raw data was relevant to assess the objective of the present study because not all transcriptions are equal in content, but the implicit information in them could be -or not- similar depending of the child.

Construction of semantic networks

We constructed the semantic networks with Atlas.Ti 7 software. An Open Coding exercise (Strauss & Corbin, 1998) was made for each transcript interview, which consist on a selection of highlight quotations along all text and the generation of conceptual categories (codes). Codes try to capture the semantic cores of each quotation and implies an hermeneutic interpretative work. Once all the codes were constructed, the next stage consisted on creating a conceptual representation model trough a relation map, sometimes called Axial Coding (Strauss & Corbin, 1998). The first step was importing codes into the field of the semantic network of the software, and distribute them in the two-dimensional space according to their potential conceptual proximity. After this, the expert had to create semantic links that allow them to connect each code with one another in a selective and specific way by using the software's tool named "Open Relation Editor". Finally, the expert arranged the network in order to avoid visual saturation of the space and get a clearer topology.

Construction of graphs

After the construction of the semantic networks, the concept fields and relations of the forty-two semantic networks were coded in nodes as a list of connections. Then, we transformed these connections into graphs suitable for analysis with the toolbox Graph and Network Algorithms from Matlab® (2015a). Here, we transformed the semantic networks in two different ways. First, we only included the concept fields or vertices of the semantic networks to create the graph. In the second approach, we also included nodes for the relations in the semantic network as shown in Figure 1. We later considered the differences in the way the experts related different abstractions from the transcriptions. Accordingly, we created two graphs, with or without relation nodes, per semantic networks. All further analysis were performed for both types of graphs separately.

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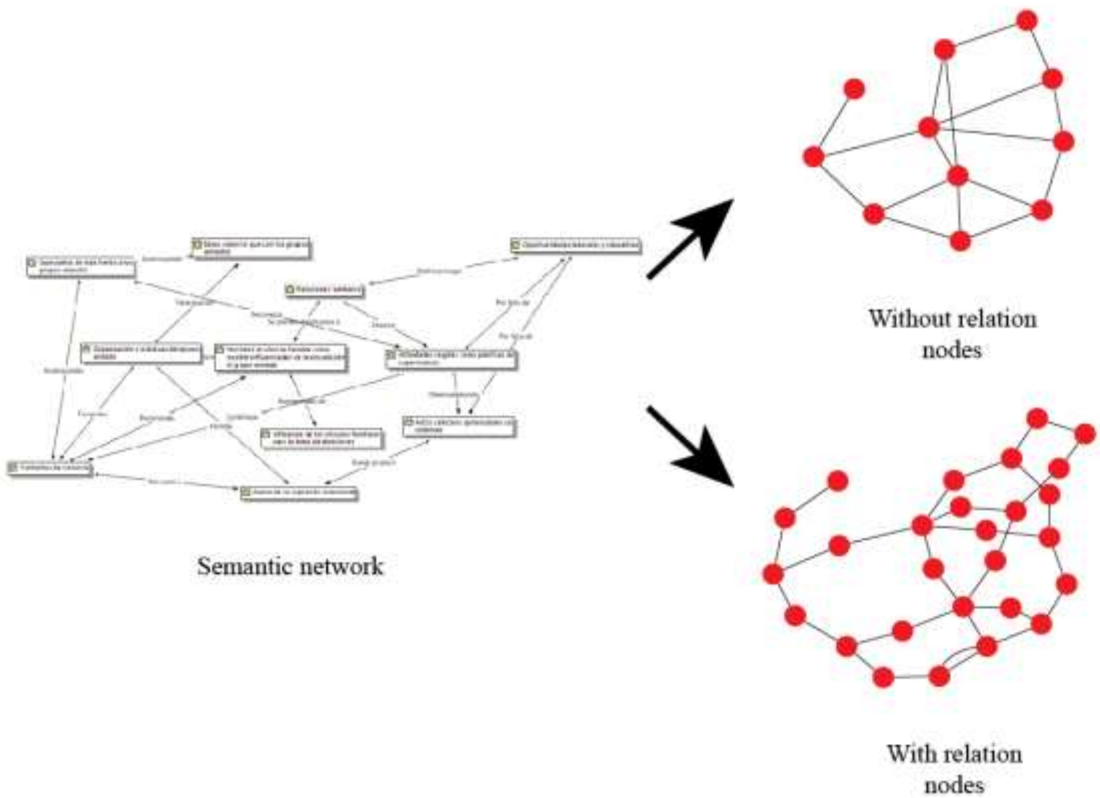

Figure 1. Construction of the graphs from semantic networks. After the expert creates the semantic network from an interview, two types of graphs were created: the first one includes only the conceptual fields in the nodes of the graph whereas in the second type also the relation nodes were included as nodes in the graphs**.**

Metrics

To assess the morphological complexity of these semantic networks, we calculated six features commonly used to describe the graph architecture (Mota, et al., 2012). Specifically, we calculated the total number of nodes (N) and edges (E), the average number of connections "from and to" any given node, a variable sometimes called Average total degree (ATD), and the density $De=2*E/(N*(N-1))$ as proposed Mota, et al., (2014). Finally, we calculated the diameter (Dm) of the network, known as the longest shortest path between all pairs of nodes, and the average shortest path (ASP) between nodes. We used the Matlab® (2015a) software and the Graph and Network Algorithms toolbox to perform the analysis, visualization and feature extraction of the networks.

Statistics

To test the relations in the architecture and complexity of the semantic networks across subjects, we divided the analysis in two questions and statistical approaches. First, we examined the effect of the subjective analysis in the complex architecture of the networks. We first tested for normality (Kolmogorov-Smirnov test) and homogeneity of variances between experts (Bartlett's test) for all the complexity variables. All tests showed a non-parametric behavior and therefore, we applied a Kruskal-Wallis test to assess the effect of the variable “Expert” in the networks architecture.

The second question was the reproducibility of the architecture and complexity of the networks between subjects. In other words, are the interviews of major complexity for a given expert also more complex for others? To test this, we performed a simple linear correlation test across subjects for all complexity features of the network, by means of Pearson test. We used Matlab® 2015a for all the statistical analysis. All statistical analysis were performed using $\alpha = 0.05/3$ to correct for the multiple comparisons.

RESULTS

We first ask if the experts perceived the complexity of the interviews differently. That is, given two interviews, we ask whether two experts perceived the first of them always more complex than the second one. One way to quantify this is to measure the correlation of the complexity variables of the semantic networks between experts for the same interviews. Table 1 shows a significant linear correlation for the attributes nodes, edges, and density between the first two experts when analyzing the graphs constructed with or without the relations nodes. Correlations with the third expert were not statistically significant, for any of the studied variables.

Table 1. Correlation values for topological variables between pairs of experts.

Feature	With Connectors			Without connectors		
	S1-S2	**S1-S3**	**S2-S3**	**S1-S2**	**S1-S3**	**S2-S3**
Nodes	0.87 (2.64x10-4)	0.41 N.S	0.55 N.S	0.89 (9.14x10-5)	0.37 N.S	0.56 N.S
Edges	0.89 (1.11x10-4)	0.40 N.S	0.55 N.S	0.89 (1.14x10-4)	0.31 N.S	0.49 N.S
ATD	0.11 N.S	-0.17 N.S	-0.16 N.S	-0.59 N.S	0.20 N.S	0.43 N.S
D	0.78 (2.59x10-3)	-0.02 N.S	-0.01 N.S	0.85 (4.18x10-4)	-0.03 N.S	0.13 N.S
Dm	-0.02 N.S	-0.28 N.S	-0.40 N.S	0.10 N.S	-0.19 N.S	-0.49 N.S
ASP	0.14 N.S	-0.08 N.S	0.15 N.S	0.25 N.S	-0.41 N.S	-0.45 N.S

We applied a Kruskal-Wallis test across subjects for all architectural attributes of the graphs to test the influence of subjective evaluation in the architecture of the semantic networks. Given an interview, is the derived semantic network different across experts? With exception of the edges, the architectural measures of the graphs showed a significant effect of expert for the graphs constructed using only the concept fields or the ones including the relations (Figure 2), as the architecture of the graphs created from the same original information differed across subjects.

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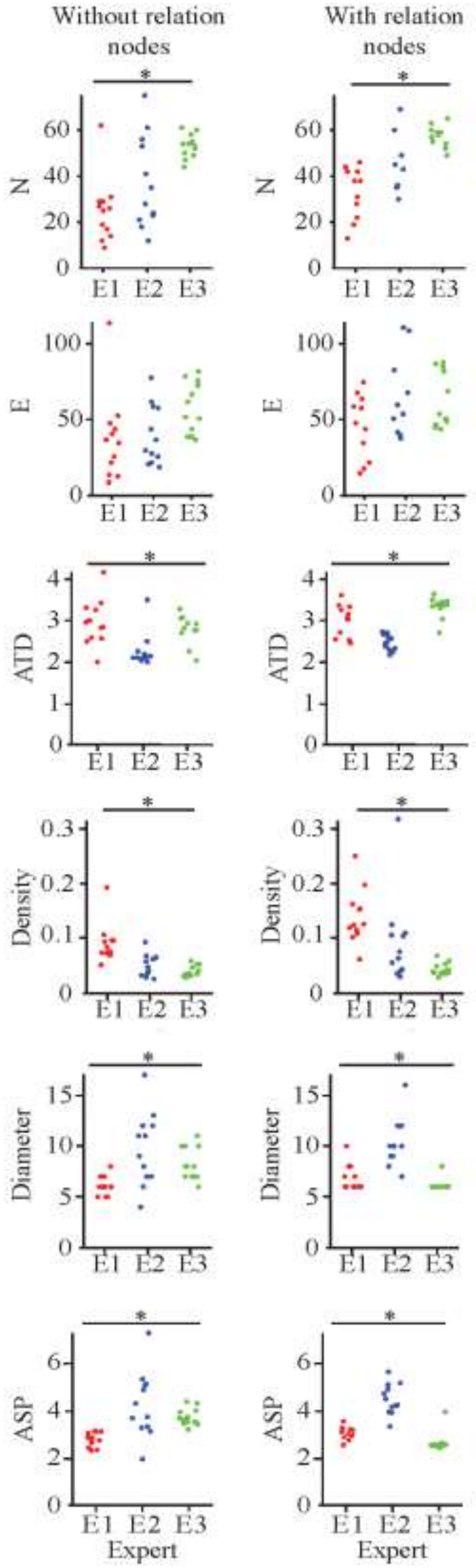

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Figure 2.Effects of the variable expert in the graph topological measures. Regardless of the use of relation nodes, most topological features of the semantic network-derived graphs show and effect of the variable expert in the distribution. N: Nodes. E: Edges. ATD: Average total degree. ASP: and the Average Shortest Path.

DISCUSSION

In this study, we evaluated the influence of subjective expert analysis in the architecture of the semantic networks constructed from complex interviews. We found that the graphs created from the semantic networks differed in their general and global attributes between experts, regardless of the inclusion of the relations between concept fields as part of the nodes. In addition, only three classic complexity measures correlated between two experts without correlation for the other measures and with the third expert.

The growing use of CAQDAS in social and human science have opened a debate about the validity and trustfulness of the conclusions accomplished by these methods (Bassett, 2004; Lee & Esterhuizen, 2000). Furthermore, the use of quantitative approaches in inherently qualitative problems should be carefully considered because there might be intrinsic barriers when concrete examples are taken into account (Bryman, 2006).

However, social research profit from information technologies as a formalized framework that does not replace the researcher (Mikheyenkova, 2017; Lee & Esterhuizen, 2000). Instead, the computer becomes an assistant that helps in the conceptualization and testing of novel hypothesis and relations (Ang, et al., 2016). For instance, computer based semantic networks has been widely used in qualitative research in fields like travel industry (Xiang & Formica, 2007), health (Rivera-Largacha, et al., 2018; Shekhar, Prince, Finelli, Demonbrun, & Waters, 2018), education (Weise & Monereo, 2018), and economics (García-Sánchez, et al., 2018). In fact, Hwang (2008) argues for more transparent and replicable process with the use of Atlas.Ti based Semantic Networks. Moreover, recent studies encourage the use of Atlas.Ti as powerful tool in the analysis of qualitative data (Paulus, et al., 2018); particularly, the authors highlight the importance of training the limitations and capacities of the software.

In this study, the architectural features of the graphs created from semantic networks differs across experts. The latter suggest that the conceptualization and organization of the same information using semantic networks represent an inherent subjective organization of the concepts, at least to an architectural level. Indeed, some authors propose that subjective differences between semantic networks are an actual advantage of the technique for example in fields like education. For instance, it could help in the quick access to the cognitive process done by a subject exposed to a topic or field (Fisher, 1990).

Moreover, we observed a lack of correlation between variables across all experts. This suggests that, subjects perceive differently the complexity of the interviews. Given multiple sources of information such as interviews, two different subjects could create semantic networks with different levels of topological complexity. Nonetheless, the fact that two

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subjects show a linear correlation in some of the architectural features of their semantic networks, but not with a third expert, suggest that different pairs of people could also perceive similar complexity patterns in the phenomena.

Furthermore, the architectural differences of the semantic networks between experts supports the strategy of triangulation as a possible method to increase credibility, dependability and confirmability of qualitative research (Ang, et al., 2016). This technique consists in the use of multiple subjects, or methods, as sources of data analysis to reveal particular patterns (Wilson & Hutchinson, 1991). Although this technique has been widely used in the past to assess qualitative problems, it is still relevant in constructivist research to understand social phenomena and decision-making process (Shekhar, et al., 2018).

Yet, there are several technical and theoretical limitations in our approach. For instance, the sensitivity of the data restrains the number and expertise of experts that could access and examine the information. Second, not all the features of a graph are suitable to study the architecture of semantic networks. For example, recurrence attributes such as the cycles of one two or three nodes as well as the number of parallel edges are not present in the architectures of the graphs created from semantic networks and could then influence other measures such as density. Finally, the results do not refute the possibility that the complexity of a semantic network cannot be easily assessed by the general and global attributes of the graphs generated from them. Instead, it suggests a framework to quantify semantic analysis and organization of information given in a semantic network.

We proposed that graph theory analysis could generate additional information about the subjective process of categorization and association of the data given by the semantic networks. This quantitative approach could open a wide range of possibilities. For instance, this information could be statistically assessed, described using different approaches of numeric representation, used for research of a special population; e.g., comparing categorization within different cultures; or even for simpler academic purposes such as scoring the complexity of semantic networks of students. In the context of this study, we used the morphological metrics of the graphs, for the first time, to compare the complexity of the networks across subjects.

CONCLUSIONS

To our knowledge, this is the first time that general attributes of graphs generated from semantic networks are compared to estimate the subjective differences between experts. In other words, architectural features of graphs created from semantic networks of the same information sources differ between subjects. Moreover, the complexity of the information gathered from the subjects to create these networks might also be different between subjects. Indeed, one of the major advances of qualitative research has been the representation of knowledge in a grounded-theory based organized system, namely a semantic network (Caldeira, Lobao, Andrade, Neme, & Miranda, 2006; Yuen & Richards, 1994). This opened a link between two topological related techniques, the qualitative semantic network analysis and the graph theory mathematical architectures.

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