Comparing complex networks

An application to emergency managers mental models

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Abstract. This paper describes an exploratory work that aims to identify a semantic basis underlying a mental model from the field of emergency management using a collaborative approach.

An experimental application of the distance ratio measure was used to compare individual networks among themselves and to analyze the aggregated network representing the group mental model

The data was obtained by surveying a group of Civil Protection graduates and aggregating all the answers (shared mental model). The data allowed us to deepen the analysis of the resulting network in order to understand the main group concepts and their relations within this domain.

Keywords: complex networks, distance ratio, emergency management

1 Introduction

Complex networks are becoming more frequent as a framework for modeling and analyzing social, physical and biological phenomena. Each element is in these domains can be represented as a node (e.g., a person, a molecule, a gene) that is connected to one (or some) other node by a link (edge).

The density of links in and out from a node, the distance between two nodes, the groups of nodes somehow related provide information about the phenomena under study. Several tools and indicators have been developed that allow to understand key features and proprieties of networks. A good survey of the measures used in complex networks can be found in Rubinov (2010:1066).[1]

Sometimes, it is important to compare networks (e.g., from two groups that share common elements, or resulting from different moments in time). We need to know how two networks are similar (or dissimilar) and what the characteristics and elements present (or absent) are.

In the case of mental models comparing is a key issue since it is important to understand the degree of proximity between the parties involved. Analyzing and comparing mental models is especially important in the context of emergency manage-

ment because there are have multiple (and different) agents and agencies involved, which require a shared degree of similarity among the participants in the activities developed to guarantee better performance.

In this work we implement a methodology (distance ratio) to perform a comparison of networks that represent mental models elicited from a group of emergency management graduates, contributing to a better understanding of the differences and similarities among groups. This information may help to develop procedures for a better collaboration or identification of training requirements.

1.1 The distance ratio

In the literature there seems to lack a measure that can be used for the purpose of comparing complex networks. We will use an indicator from the realm of system dynamics, that has been applied in the comparison of causal maps and will apply it to complex networks.

The Distance ratio (DR), in its original application, was used to calculate to what extent two causal maps were similar. Causal maps in systems dynamics are a set of elements that influence each other in a sequence and with a level of intensity. In the language of system dynamics there are more than variables and links. It is possible to identify other constructs such as delayer links, non-linear links, stock variables or rate variables and also feedback loops. [12]

Since causal maps can be seen as a network where an element can be represented as a node, the influence to other elements are links and the level of intensity is the weight of that link, it is our belief that the DR measure can be extended and applied to complex networks.

The formula for distance ratio is presented below [5], [13]

$$\frac{\sum_{i=1}\sum_{j=1} diff(i,j)}{(\varepsilon\beta+\delta)v_c^2+\gamma'(2v_c(v_{ua}+v_{ub})+v_{ua}^2+v_{ub}^2)+\alpha\big((\varepsilon\beta+\delta)v_c^2+\gamma(v_{ua}+v_{ub})\big)} \quad (1)$$

Where

$$diff(i,j)\begin{cases} 0, \quad if\ i=j\ and\ \alpha=1\ (no\ self-loops) \\ \Gamma(a_{ij},b_{ij}), \quad if\ i\ or\ j\ \notin\ v_c\ \wedge i\ or\ j\ \in\ v_a\ or\ v_b \\ |a_{ij}-b_{ij}|+\delta, if\ a_{ij}*b_{ij}<0 \\ |a_{ij}-b_{ij}|, \qquad otherwise \end{cases} \quad (2)$$

and

$$\Gamma(a_{ij},b_{ij})\begin{cases} 0,\ if\ \gamma=0 \\ 0,\ if\ \gamma=1\ and\ a_{ij}=b_{ij}=0 \\ 1,\ otherwise \end{cases} \quad (3)$$

The result obtained by the formula can vary between 0 and 1, where 0 means completely similar and 1 totally different (distant).

The distance ratio is used to compute to what extend two networks are close in terms of their constituents. Thus, an extended matrix A and B is used, where a_{ij} and b_{ij} are their elements. The adjacency matrix, with n variables, will form a n x n matrix with the strength of the links as cell values. [5]

A group of parameters are denoted by the Greek letters (α,β,γ,δ,ε) and are used to adjust the formula to different contexts. The α parameter can be set to 0 or 1, whether self-loops are allowed or not.

To reflect differences in weight between nodes in the networks we pass the max weight to parameter β.

ε accounts for the number of polarities in the matrix and it can take the value 1 or 2 (one polarity - only positive or negative or two polarities – positive and negative).

If δ=0, we do not differentiate situations where different weights create the same difference values. For instance, a difference between a weight of 4 and 1 is the same as for -2 and 1 as per equation 2. In the latter, since a negative and a positive value is involved, a value δ is added.

The parameter γ is set for how to interpret matrix cells for which one of the maps does not have an edge because there is a mismatch of nodes. In the context of concept maps the inexistence of a node is a result of the one that creates more difficulties. If we do not want to deduce anything from the absence of nodes, we will set γ=0. If we wish to assign meaning to the fact that one person as mentioned one concept (node) and another does not, the value of γ=1 signaling that this difference should be taken into account.

1.2 Mental models

Mental models are conceived of as a cognitive structure that forms the basis of reasoning and decision making, and can be seen as a network of associations between concepts in an individual's mind. Mental models have been described as a form of intuitive knowledge that serve as a frame of reference for interpretation of the world which forms the bases for reasoning and working with problems.[2]

They are built by individuals based on their personal life experiences, perceptions, and understanding of the world. Mental models provide the mechanism through which new information is filtered and stored. However, the ability to represent the world accurately is always limited and unique to each individual. [3]

There a variety of techniques for eliciting mental models, ranging from brainstorming, to interviews or text analysis. They include concept mapping, word association techniques, ordered recall, card sorting procedures, paired-comparison, and the ordered tree technique. [4–6]

They can be applied both individually or to a group of people. [4], [7] Most of procedures used are based on the assumption that an individual's mental model can be represented as a network of concepts and relations. Some procedures are designed to elicit a network representation of a mental model directly from the interviewee through a diagrammatic interview. Other procedures require the researcher to recreate, or infer, the network from interview data or questionnaire data. [3]

When working together people must share a part of the mental model to deal effectively with each other. Team mental models promote understanding among team members regarding information requirements, the need for communication and coordination. [8]

In the case of emergency management cycle the individuals involved need to have a common mental structure to deal with information issues. The lack of a common mental model is a common problem referred to in emergency management literature [9–11].

2 Methodology

To compute the DR we have built a network with the concepts that represent mental models of emergency management graduates. Although some ontologies for emergency management have been proposed [9], [14–16] they are mostly developed to be applied in contexts such as decision support systems or artificial intelligence applications.

The approach we propose merges both the power of collaborative web-based techniques and the use of social sciences methods (since it asks real people about what they knowledge about a particular issue) [17] in order to obtain the data that will allow to build the network.

In order to accomplish this we asked a group of graduate students to identify, organize and relate the concepts they recognized in the emergency management field.

To obtains a network, with a set of relations between concepts, an initial concept (Civil Protection) was defined. The survey group was asked to indicate a new level of concepts related to the initial one. For each of the concepts in this new group, a new sublevel of concepts was obtained. By iterating on the above mentioned steps, it is possible to build several levels of inter-related concepts (as represented in Figure 1). An individual structure is obtained representing the mental model of concepts of the respondents with the respective relations. This structure is representable as a network.

Figure 1 exemplifies the structure.

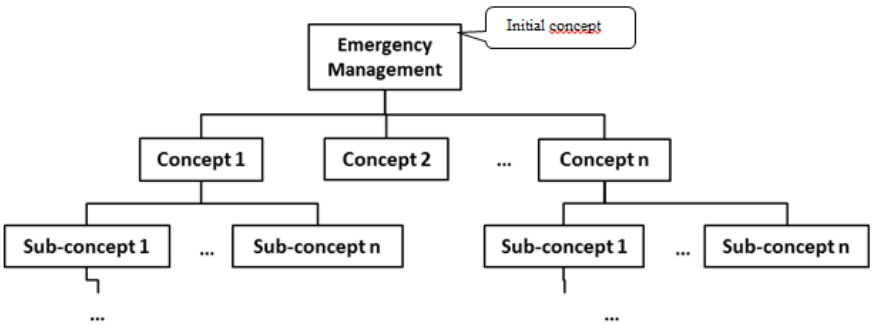

Fig. 1. Model of data gathering.

3 The study

To implement the structure of data gathering presented in Figure 1 above, a questionnaire was implemented, allowing to collect answers in a multilevel and relational format. The questionnaire was sent, by email, to 60 graduates in Civil Protection. Eleven answers were received (18 % of the sample).

As the concepts are words, several responses were verified for major spelling mistakes and typos. This is an important step to ensure that the same concept indicated by two different respondents was not coded as different ones because of an mistake. Finally, individual networks were grouped and processed to create a unique network with all the contributions.

This grouped network can be seen as a shared mental model [7]. In this network, we take into account the number of times a pair of concepts was mentioned by the respondents, because this stresses the importance of that relation within the group. That total was taken as a weight of the edge between concepts. In later extensions of this work we intended to introduce the weight of nodes, i.e. the number of different times an individual concept was mentioned.

The data was processed to transform the concepts identified in a network structure, where a node represents a concept and an edge represents a connection between two concepts. Moreover, for each pair of nodes the respective weight was indicated.

A file was created in the native format of *Pajek* software and this package was used to perform the analysis.

3.1 Results

In Table 1 are presented some basic measures about the aggregate network of concepts. The difference between the two columns is the consideration of the initial concept or not. As mentioned above, when collecting the data for the construction of the network, the initial question was: "What are the main concepts you relate to civil protection?". "Civil Protection" becomes the starting concept and, therefore, all other concepts propagate from this first one. It is important to analyze how the structure holds if we withdraw this concept.

Table 1. Summary of network data.

	With the starting concept	Without the starting concept
Nodes	262	261
Links	357	315
<k>	2.7251	2.4138
L	3.7275	4.2401
C	0.1183	0.0846

If the initial concept ("Civil Protection") is taken into account we have 262 different concepts and 357 links among them. The average degree (number of average links per node) is 2.7. Although the number of nodes (concepts) is high the average degree indicates that each was related to few other concepts. This can be due to the fact that only a small sample of individual responses was obtained.

The average path length (l) is 3.7 referring to average number of connections joining two randomly chosen nodes. The small value reflects the proximity between concepts but it may be justified with the dimension of the network.

If we remove the initial concept ("Civil Protection"), only one node is lost but some changes occur in the network. We notice a marked decrease in the number of links, meaning that the concept is strongly connected. It is also significant the increase in the average path length and the fact that some nodes became orphans (unconnected to the main core of the network).

In the analysis of the network we noticed the absence of references to mitigation and recovery as key concepts in the emergency management cycle and referred to in the Portuguese civil protection law. This can be due to lower emphasis given to these activities in common activities and decisions, while others like (prevention, rescue and planning) are given more importance as they are seen as main functions of emergency management in Portugal and are more present in the day-to-day practice, thus gaining more visibility.

3.2 Results of the Distance Ratio application

We will now present the results of the application of the distance ratio formula to the individual networks elicited in this study for each of the respondent subjects. We compute the DR for each of the networks among subjects. For the current application the parameters were set to:

- $\alpha = 1$, meaning self-loops were not taken into account, because in the case of complex networks a node do not link to itself directly[1];
- β=max weight, in the present case the value is one, meaning only that there is a link between two nodes;
- $\gamma=1$, because we want to take into account the fact that one network has a node and another has not, thus valuing the eventual link that can exist;
- $\delta=0$, not adding any value to differences, since we only have one polarity;
- $\varepsilon=1$, because in this case we only have one polarity. All link weights are positive.

[1] We recall that the Distance Ratio formula is adapted from systems dynamics where self-loops are a normal situation.

Table 2. Distance Ratio between subjects.

		Subjects												
		1	2	3	4	5	6	7	8	9	10	11	Mean	SD
Subjects	1		0.027	0.019	0.013	0.029	0.044	0.02	0.022	0.017	0.023	0.045	0.026	0.0107
	2	0.027		0.018	0.013	0.024	0.029	0.018	0.019	0.016	0.019	0.026	0.021	0.0052
	3	0.019	0.018		0.012	0.018	0.02	0.017	0.017	0.015	0.017	0.017	0.017	0.0023
	4	0.013	0.013	0.012		0.013	0.013	0.014	0.013	0.012	0.013	0.012	0.013	0.0007
	5	0.029	0.024	0.018	0.013		0.032	0.019	0.02	0.016	0.02	0.029	0.022	0.0061
	6	0.044	0.029	0.02	0.013	0.032		0.02	0.022	0.017	0.024	0.07	0.029	0.0169
	7	0.02	0.018	0.017	0.014	0.019	0.02		0.018	0.017	0.019	0.019	0.018	0.0019
	8	0.022	0.019	0.017	0.013	0.02	0.022	0.018		0.015	0.019	0.02	0.019	0.0029
	9	0.017	0.016	0.015	0.012	0.016	0.017	0.017	0.015		0.016	0.015	0.016	0.0015
	10	0.023	0.019	0.017	0.013	0.02	0.024	0.019	0.019	0.016		0.022	0.019	0.0032
	11	0.045	0.026	0.017	0.012	0.029	0.07	0.019	0.02	0.015	0.022		0.028	0.0176

The values presented in Table 2 point to a low distance ratio since they are very close to 0, the lowest limit, meaning that networks are very similar among them. This can be due to the nature of the sample used. The subjects were all graduate students, with similar training and level of experience.

In spite of this fact, some differences can be perceived between subjects with some of them with more proximity with the others (subject 4) and lower deviation. Or with more relative distance (subject 6).

Table 3. DR from aggregated network and individual ones.

	Subjects												
	1	2	3	4	5	6	7	8	9	10	11	Mean	SD
Grouped Network	0.0055	0.0055	0.0056	0.0056	0.0054	0.0054	0.0059	0.0055	0.0055	0.0056	0.0052	0.0055	0.0001

If we compare the subjects with the group network with the starting concept (the aggregated network mentioned in table 1). We find a mean DR of 0.005 (with standard deviation of 0.0001). The value is lower than the values obtained between subjects (with mean of 0.02).

An possible explanation to this is that the aggregated network is constructed by adding all the individual contributions, therefore when we perform the distance ratio between the aggregated network and the individual ones, each one finds a “piece” of itself in the group network thus having a lower distance.

4 Conclusions

Network analysis seems to be a valid tool to study mental maps since the concepts and their relationships can be represented by nodes and links.

The application of the Distance Ratio to complex networks seems feasible but requires a broader sample that can increase potential differences. The sample used led to a low Distance Ratio, meaning that the mental models were very similar within the group under study. The distance ratio approach can be refined to take into account the ranking of concepts (node weight) in the case of aggregated networks.

Since this is an exploratory work that used a sample of graduates as the source of concepts, the computed differences between mental models were not very sharp. Future work will try to replicate this approach with professionals in the Civil Protection field, from different agencies and explore if greater dissimilarities exist.

The understanding resulting from that may be helpful to take decisions regarding training improvement and information sharing among individuals or groups in key organizations in the field.

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