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CONCEPT MAPPING AND EXPERT SYSTEMS: EXPLORING SYNERGIES

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Abstract. Concept maps and expert systems are both in the soft toolbar of knowledge modelling. We have spent nearly two decades developing our expert system shell "Doctus". Several years ago we have seen the first concept mapping solutions and started using them very soon. Frequently we have found ourselves using both tools in a particular research or consultancy project and started to wander how the two could be combined to achieve synergies. We came up with several ideas, typically when we have faced a situation which called for one of the potential synergies. In this paper we present the first of these ideas in elaborated form of a conceptual model and we also mention few additional ideas as our plans for future research. In this first idea we combine different kinds of concept maps and our expert system in order to map organisational knowledge. The expert system here is used in machine learning mode, i.e. the resulting concept map will be capable of learning – this is our intelligent concept map.

1 Organisational Knowledge Map

Let's try to construct an organisational knowledge map. In the first part of it we will combine ideas from the various mapping approaches. The first is the cognitive mapping, a form of which has been developed by Eden (see Eden, 1988 for historical summary) based on Kelly's (1955) conception of personal psychological constructs and the Repertory Grid developed by Fransella and Bannister (1967). (See also Eden & Ackermann, 1998; Bryson et al., 2004) These cognitive maps can be, in a sense, considered as subsets of more extensive use of causal mapping, e.g. in the case we are mapping knowledge of a group of people. (Ackermann & Eden, 2004) A product related to this approach to cognitive mapping is Decision Explorer[1]; Eden and his colleagues typically use it for supporting managers in structuring their problems for better understanding. Those who developed the various approaches to mapping knowledge typically agree that our concepts form some sort of hierarchies. Buzan's (e.g. Buzan & Buzan, 1995) approach puts this feature into the focus; this is why his mind maps always branch out from a single central concept. He claims that this represents the natural organisation of the human memory, which assertion would be in line with the previous discussion about taxonomies. The product developed in by Buzan is called Mind Map[2]; it harnesses the full range of cognitive elements – words, images, numbers, logic, rhythm, colour and spatial awareness – into a single whole. The third approach we want to discuss here is a form of concept mapping pioneered by Novak (see e.g. Novak & Gowin, 1984; Novak, 1990). In concept maps we have one concept as a unit of the map and by connecting these concepts we get patterns of concepts that pretty much resemble Bateson's (op cit) conception of patterns. In this approach Novak (ibid: 29) defines the concepts *"... as a perceived regularity in events or objects, or records of events or objects, designated by a label."* The propositions formed by linking two or more concepts are personal psychological constructs. This means that in a sense Eden's cognitive maps and Novak's concept maps can be regarded as different level of description about the same sort of reality: a proposition here would be a unit of mapping in the previous. The tool associated with this approach is C-Map[3].

We start from a knowledge/problem area that we want to map (leftmost on **Error! Reference source not found.**). We give it a label and start breaking down hierarchically (as in a mind map); for clearer distinction we call the first level topics and the next ones keywords. The concepts in the left part of the map should be connected (similarly as Novak's concept maps) in a way to form propositions. This means that we will form semantic structures as described by Quillian (1968) based on previous work by Chomsky (1957).

For the sake of simplicity, we suggest using only nouns as concepts and only verbs as connections; we know that this is a limitation as we may be excluding such propositions as "grass is green". However, we believe that this less harmful than it may seem at first glance and also brings the great advantage of being simpler and faster. We argue that it will be less harmful than it seems because if "being green" is important for the particular knowledge area then "greenness" will also appear as a noun and thus it will be included as a concept in

[1] www.banxia.com
[2] www.mind-map.com
[3] cmap.ihmc.us

the map. This is how we can cover the existing knowledge in the area. Assume that the knowledge available at that part of the organisation where we are creating the knowledge map about the knowledge area is incomplete; in this case there will be keywords that are not covered. If we already know something about these keywords, we can describe them by attributes. In this case, however, we cannot define such sophisticated relationships between the concepts to develop semantic structures; we will only be able to identify implications. Implications will mean causal relationships and, as we can expect, these will not be very clear. We will be able to say that a particular keywords can be describe using such and such attributes but the more subtle nature of these relationships cannot be defined. Therefore this second part of the map is a causal map. In order to continue building the map we need to include the expert system – therefore in the following section we introduce the Doctus expert system and then apply it to finish the map.

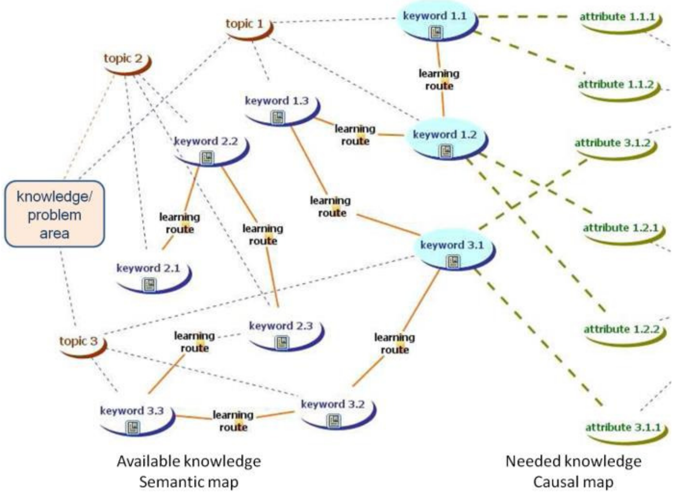

Figure 1: Organisational knowledge map - the first step

2 Doctus Expert System

We have been developing the Doctus knowledge-based expert system shell for nearly two decades. The term 'knowledge-based system' (KBS) indicates that there is a representation of knowledge in such systems; these representations are called knowledge bases. We also speak of 'expert systems' (ES) emphasizing that we build knowledge bases of experts' knowledge; we usually combine these two terms into the 'knowledge-based expert system' (KBES). Although the three terms differ in emphasis, in this paper they are used interchangeably. As we never believed that people think in numbers, we based Doctus on symbolic artificial intelligence (AI). Nobody thinks that the beautiful is 3.6 times better than the ugly. In symbolic AI the representation consists of concepts, acquired from the experts, which are connected by logical rules in «if... then» format. In this representation the concepts are treated as symbols hence the names 'symbolic logic' and 'symbolic AI' are used. During the nearly two decades of development we have used Doctus in over 140 consultancy project; the vast majority of these was providing support for top level executives. The process of building knowledge bases is called knowledge engineering and the person who facilitates it with the expert(s) is the knowledge engineer.

In deduction or rule-based reasoning (RBR) the expert articulates the aspects using which (s)he can describe the «cases». The «cases» can be anything the expert can describe from all relevant aspects; in the case of the organisational knowledge map we are developing, these will be the keywords. The aspects are described as «attributes» that have grades of satisfying, the «values». The «attributes» are then organized into a multi-level hierarchy called «rule-based graph» or RBG (**Error! Reference source not found.**); a set of «if... then» rules is defined in each node of the graph to connect the values of the attributes. As the last input step, the expert needs to define the «cases» using the «values» of the «attributes» – these are the «case features». Finally we can apply the previously defined rules to the «cases» to get an evaluation. Once the knowledge base is thus build, it need to be fine-tuned until the expert agrees with what the knowledge-based system represents and produces – i.e. all the evaluations as well apart from the components (s)he explicitly described.

In a sense the induction or case-based reasoning (CBR) is the opposite of deduction. The expert needs to articulate the «attributes», their «values» and the «cases» the same way as in deduction; only this time, apart from the «case features» (s)he also tells the outcome for each «case». Doctus uses a machine learning algorithm to infer the underlying rules that can describe all the cases from the expert's experience; this is based on a modified ID3 algorithm (Quinlan, 1986). The result is displayed in the «case-based graph» from which the rules can be read from the root of the graph towards each leaf. One of the important characteristics of induction is that the number of initial attributes (typically around 50 at the outset) is reduced (typically around 5-7 remain). Similarly to deduction, the last stage in induction is the fine-tuning and here it is even more important and less trivial than there.

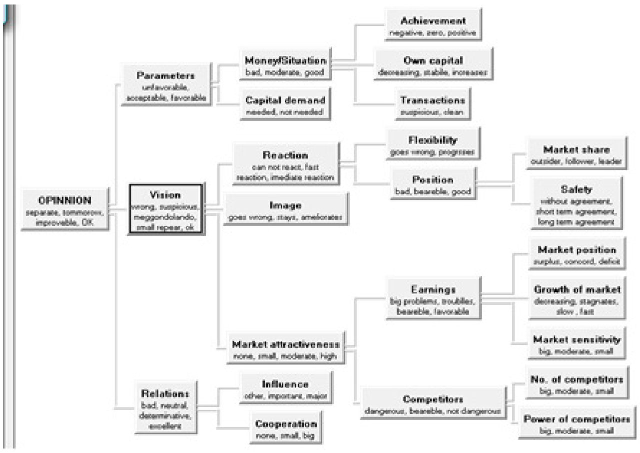

Figure 2: Rule-based graph in Doctus

Reduction is not a standalone reasoning type; it starts from an accomplished inductive knowledge base. It means taking the case-based graph and converting it into a single-level deductive knowledge base. The resulting deductive knowledge base will give the same outcome for all the cases as the expert articulated, only by using fewer «attributes»; thus the name of this type of reasoning, the number of attributes becomes reduced. We have found this type of reasoning particularly useful for supporting delegation of decisions and teaching novices about the most significant aspects of a knowledge area.

To make a concept map intelligent, we need inductive reasoning – this is how we finish our previously started organisational knowledge map. We have started from the left to the right, from a knowledge area we identified topics and subsequently keywords, these were then connected into a semantic map. The last layer of keywords we described by attributes and these were connected into a causal map. Now in the last step, we can apply the inductive reasoning of Doctus. This will have the benefit of reducing the number of the attributes to what we call the most informative ones. If we assume, using Miller's limitation of the short term memory (Miller, 1956; Baddeley, 1994), 7±2 topics for the knowledge area, 7±2 keywords for each topics and 7±2 attributes for each keyword we will easily end up with more than two hundred, which appears to be another memory limitation (Davenport & Prusak, 2000); we can add to this that very frequently we will not be able to acquire such dense knowledge in the last keyword layer and thus will have significantly larger number of (redundant) attributes. So it can be really useful to reduce the number of these attributes. However, we can do more than this. By smartly formulating our cases we can also identify the occurrences of the attributes; these may be people, knowledge bases, document bases and even (although rarely) databases. This way, our organisational knowledge map is complete. (**Error! Reference source not found.**)

We can make further use of applying Doctus to our organisational knowledge map. If we apply the reductive reasoning to the attribute list got from induction and this way get a single-level deductive knowledge base. By fine-tuning this new inductive knowledge base we can gain sufficient understanding of the patterns to be able to connect the causally described concepts into a semantic network and go further to identify new keywords at the causal layer. Three things need to be noted for the end: (1) None of these processes will happen by only plugging in the machine; we will need the expert(s) and the knowledge engineer working on it. (2) When we fine-tune the reduced knowledge base and learn about our knowledge area enough to be able to extend the semantic network to our just described concepts original semantic map will usually also change – it is not a part of knowledge in the area that is changed but also the whole knowledge. (3) As it can by now probably be understood, this is a never-ending process: we restructure the semantic network and include the additional concepts, we define new causally described concepts, then we understand these better and include them into the semantic network, which is then again restructured and new keywords defined, and so forth.

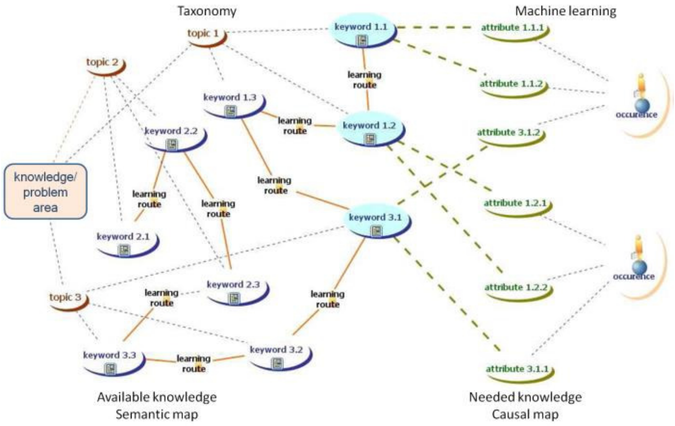

Figure 3: Organisational knowledge map - the complete picture

3 Conclusions

We have examined two branches of soft modelling tools using which we can support the achievement of meaning; we were interested how these two types of approaches and tools can be used together to achieve synergies. Particularly, we have examined one combination, the case of creating an organisational knowledge map; we say that by using the expert system we developed an intelligent concept map. We have a couple of further ideas which (more precisely some of which) make part of our forthcoming research. We outline three of these very briefly, only to set off imagination.

Almost trivially, we can use various concept mapping techniques to structure a problem and if this could be exported in a form to be importable into a knowledge-based system it would be possible to use the two tools in a sequential way. A more sophisticated way of doing this would be integrating the two tools. This is, however, not a scientific research problem but rather a software development project. Typically ES in deductive reasoning cannot contain recurrences/iterations as these would lead to infinite loops. To the contrary, we have noticed that 'concept mappers' become excited when they discover such loops in their diagrams as they usually mean something special. The two tools types could be combined or expert systems could simply learn from concept maps how to handle the positive, negative, or combined feedback loops for the benefit of the experts. Finally, the concept suggester component (Leake, Maguitman & Cañas, 2002; Leake et al., 2003) of the IHMC CMap Tools may probably also be enhanced by adopting an inductive and possibly inductive+reductive reasoning from expert systems. The idea for this research builds on the observation that there is no way of passing between lexicons, i.e. there is no translation due to context dependency. The context, however, can be described by the rules induced from cases and perhaps further enhanced during the fine-tuning in reduction.

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