Colleague-Oriented Interpretation of Knowledge Acquired from Multiple Experts

Seppo PUURONEN* and Vagan TERZIYAN**

* *University of Jyvaskyla, P.O.Box 35, SF-40351 Jyvaskyla, Finland*

** *Technical University of Radioelectronics, 14 Lenina av., 310726, Kharkov, Ukraine*

Abstract. *This paper presents an approach to derive a colleague-oriented interpretation of knowledge which is obtained from several sources and includes also knowledge about relations between experts and domain objects, relations between experts, and even an expert's opinion about himself. The method calculates the amount of support, which any knowledge source gets from his colleagues, and then it uses knowledge obtained from colleagues. The basic representation is the semantic network defined in a matrix-based way. The resulting representation is used to select the knowledge sources which have the best fit. This selection is presented in an abstract level and it is assumed to be used in an application-oriented way.*

1. Introduction

The general goal of our research is to develop formalisms to represent and reason with incomplete and inconsistent knowledge obtained from several sources. One formalism, we have presented in [3], derives and uses *competence* of knowledge sources measured by the support that they receive from other sources. We developed a method to calculate the amount of support, which any source gets from others, and thus to obtain order of knowledge sources according to their competence. We assumed that the most supported opinions belong to the most competent knowledge source. It is necessary to note that the most supported knowledge is not always the best one, of course. The most supported knowledge is often useful in applications that use voting-type technique [4] to refine knowledge of multiple experts.

In our research described in [3] we used this formalism to handle three types of problems:

1) How to derive the *most supported knowledge* among all the experts in the domain area?

2) How to order the experts according to their competence when the focuses are: domain objects, their relations, the use of concepts to present knowledge? We referred to this problem as deriving *horizontal order of experts* according to their competence.

3) How to use experts' opinions about relations between experts and domain objects, and between each other, to classify experts into different levels of expertise? We referred to this problem as deriving *multilevel vertical structure of experts*.

This paper is focused to develop formalisms to handle the problem: how to benefit knowledge obtained from several knowledge sources when we have derived the multilevel structure of experts? We refer to this problem as *colleague-oriented knowledge interpretation*.

The problem of knowledge base refinement is also closely connected with eliciting expertise from several experts. Could the overlapping knowledge, obtained from multiple sources, be described in a way that it is context independent? Taylor et al. give a negative answer [6]. Certainly there have been inference engines that were subsequently applied to related domains, but in general the sets of rules have been different. According to Mak et al. [1] the other researchers have found that if more than one expert are available, then we have either to select the opinion of the best expert or to pool the experts' judgements. Medsker et al. [2] distinguish three practical strategies for knowledge acquisition: use the opinion of only one expert, collect the opinions of multiple experts, but use them one at a time, or integrate the opinions. Roos [5] has described a logic for reasoning with inconsistent knowledge. The logic is suited for reasoning with knowledge coming from different knowledge sources. In this logic inconsistency may be resolved by considering the reliability of the knowledge sources used.

We present in this paper an approach in which knowledge about an expert and its relationships are used to assist in colleague-oriented knowledge interpretation when knowledge is obtained from several sources. The method calculates the amount of support, which any expert gets from others, and then it uses knowledge about an expert to derive resulting knowledge by the colleague-oriented way. The basic representation is a semantic network defined in a matrix-based way. The resulting representation is used to select the knowledge sources which have the best fit with user's context.

2. Basic Concepts

In this chapter, we introduce the basic concepts and the notation used in the paper.

Knowledge is information about *properties* of *objects* and their *relations* and it is presented by a set of *semantic predicates*. An *object* has unique identifier (for an object we use notation A with indexes s, t = 1,...,n; where n is the number of objects) and zero, one or more *properties*. A *relation* has four attributes. These are: the two objects between which the relation holds, the *concept* which indicates semantic contents of the named relation (we will use notation L with indexes i, j = 1,...,r; where r is the number of concepts) and the *knowledge source* from which the information about this relation was acquired (we will use notation Ex with indexes k, l = 1,...,m; where m is the number of knowledge sources, i.e. experts). A *property* describes an object separately from other objects, as a special relation which holds an object itself. A concept in such a relation is the name of a property. A *semantic predicate* $P(A_s, L_i, A_t, Ex_k)$ describes a piece of knowledge. $P(A_s, L_i, A_t, Ex_k) = 1$, if there is knowledge acquired from the source Ex_k that the relation named L_i holds between the objects A_s and A_t, and $P(A_s, L_i, A_t, Ex_k) = 0$, if there is knowledge acquired from the source Ex_k that the relation named L_i does not hold between the objects A_s and A_t.

We present the *semantics* of the named relation L_i acquired from the knowledge source Ex_k as a matrix $(L_i^k)_{n\times n}$ (n is the number of objects), where:

$$(L_i^k)_{s,t} = \begin{cases} 1, \ if \ \ P(A_s, L_i, A_t, Ex_k) = 1; \\ -1, \ if \ \ P(A_s, L_i, A_t, Ex_k) = 0; \\ 0, \ otherwise. \end{cases}$$

3. An Example

Let us consider, as an example, some of the characters and their relationships in the American TV-serial "Santa-Barbara". This example was used to describe the results of the three problems in [3]. The characters and concepts to be considered are presented in Figure 1.

Objects and their ids.	Named relations and their ids.
<Mejson> - A_1	<to respect> - L_1
<Iden> - A_2	<to help> - L_2
<Julia> - A_3	<to love> - L_3
<Victoria> - A_4	<to envy> - L_4

Fig. 1. Objects and concepts in the "Santa-Barbara" example

Let us suppose (as in [3]) that three experts (i.e. spectators acting as knowledge sources) express their opinions about relationships in this domain in the following way:

Expert 1: “Mejson loves, respects and envies Victoria. Iden respects, helps and envies Mejson. Iden envies Victoria. Julia loves Mejson, and she helps Victoria and Iden. Victoria loves and envies Mejson and she respects Julia.”

Expert 2: “Mejson envies Iden, he respects Iden and Victoria and loves Julia. Iden helps Mejson and Julia and envies Victoria. Julia helps Iden. Victoria loves Mejson and respects Julia.”

Expert 3: “Mejson loves Julia. Iden respects Mejson and Victoria. Julia helps Iden, and she helps, loves and envies Victoria. Victoria respects Mejson and Iden and envies Iden.”

The knowledge of each expert is presented in Figure 2a-c using semantic networks.

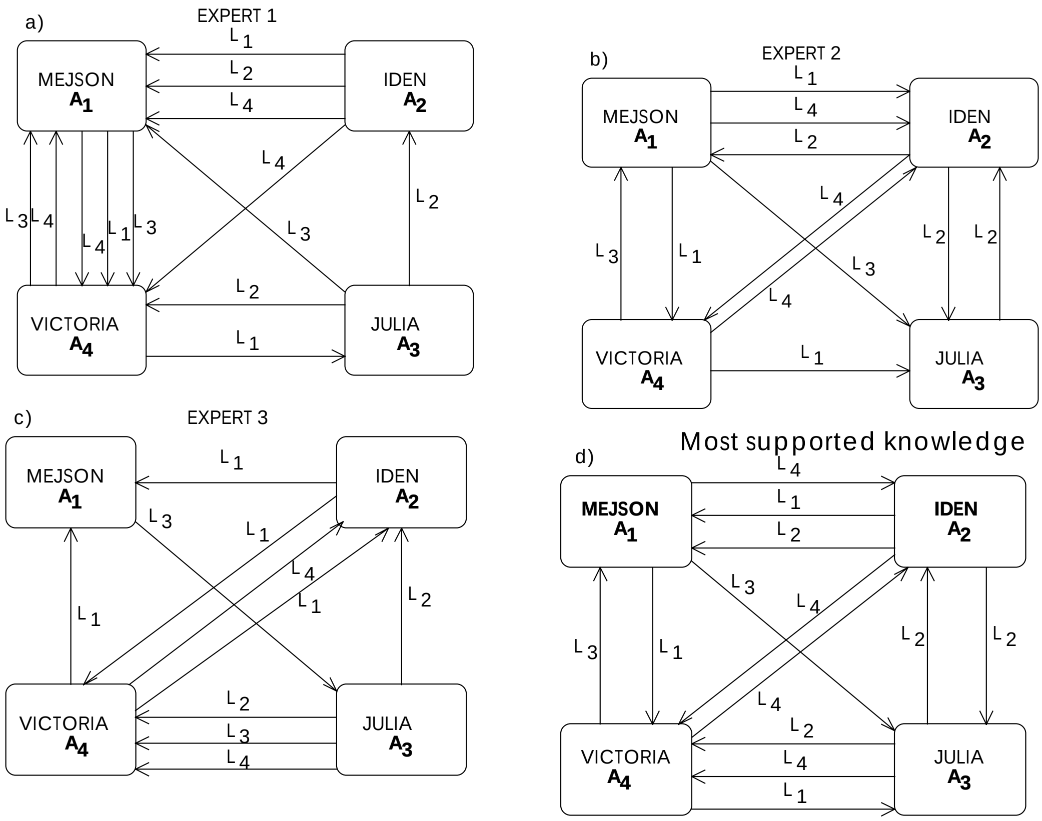

Fig. 2. Knowledge of experts and the most supported knowledge in the example

The *most supported knowledge* about named relationships used in the example is derived selecting only the knowledge of the most supported experts and presenting it as a matrix $(L_i^{m\,sup})_{n\times n}$ as in [3]:

$$(L_i^{m\,sup})_{s,t} = sign\Big(\sum_{\substack{k \\ \forall k (CL)_{i,k} = \max_l (CL)_{i,l}}} (L_i)^k_{s,t}\Big), \quad \text{where} \quad (CL)_{i,k} = \sum_{s,t}^{n} \Big((L_i^k)_{s,t} \times \sum_{j, j\neq k}^{m} (L_i^j)_{s,t}\Big).$$

The semantic network presentation of the most supported opinions, obtained using the last formula, is considered in Figure 2d.

4. Colleague-Oriented Knowledge Interpretation

When a knowledge-based system makes inferences with the most supported knowledge of the experts involved, who will interpret results? Often another, maybe less experienced expert.

However any person interprets knowledge from his own point of view because he has his own relationships to the domain attributes and to other experts. To be able to help a person to benefit the results, there is a need to know these relationships. Of course nothing can be done if there is no information about these relationships. We assume that something is known about these, and that any person feels inclined to interpret situation in a similar way as the experts who have similar kind of relationships to the domain attributes and other experts. We propose to select opinions of those experts with similar constituents and then derive the most supported knowledge using only the selected opinions.

We define colleague-oriented situation *Col* of the knowledge source Ex_k as follows:

$$Col(Ex_k) = \bigcup_i L_i, \forall i \exists Ex_l (P(Ex_k, L_i^{m\,sup}, Ex_l, *) = 1),$$

where $P(Ex_k, L_i^{m\,sup}, Ex_l, *)$ means that, according to the most supported knowledge, the expert Ex_k is connected with the expert Ex_l by the relation named L_i. For example, the statement $< to\_respect > \in Col(Ex_k)$ means that expert Ex_k respects some other expert (or possibly himself) from the most supported point of view.

We derive colleague-oriented interpretation $L_i^{L_j}$ of the named relation L_i using knowledge of all experts, whose situation includes the named relation L_j, by the following formula:

$$L_i^{L_j} = L_i^{m\sup\{Ex\}} (\forall L_i \forall L_j \exists \{Ex\} (\forall Ex_l (Ex_l \in \{Ex\}) \,\&\, (L_j \in Col(Ex_l))),$$

where $L_i^{m\sup\{Ex\}}$ is the most supported knowledge about the named relation L_i obtained from the group $\{Ex\}$ of knowledge sources.

The results of interpretation of the same knowledge in different situations can be also different. For example, the statement: $< to\_love >^{<to\_be\_female>} \neq < to\_love >^{<to\_be\_male>}$ means that experts with property “to be male” and experts with property “to be female” interpret semantics of meaning “to love” in a different way at any level of expertise. It means that if one knows events of “Santa-Barbara” listening different opinions and wants to convey the main idea of this film to his wife, he needs to select only females’ opinions. To be understood he even has to select those females who have most similar situation with his wife. Using the “Santa-Barbara” example of the previous chapter, we show some results of colleague-oriented interpretation. Let us assume that the three experts (i.e. spectators), in addition to their knowledge about the basic domain, have also expressed their statements about relationships of each other in the following way:

$$P(Ex_1, L_2, Ex_2, Ex_1) \wedge P(Ex_1, L_3, Ex_2, Ex_1) \wedge P(Ex_2, L_3, Ex_2, Ex_1) \wedge$$
$$\wedge P(Ex_3, L_3, Ex_3, Ex_2) \wedge P(Ex_1, L_3, Ex_3, Ex_3) \wedge P(Ex_3, L_3, Ex_3, Ex_3) = 1.$$

It means that the opinions of the experts are the following:

Expert 1: “I help to the *Expert 2* and I love him but *Expert 2* loves himself ”;

Expert 2: “*Expert 3* loves himself ”;

Expert 3: “*Expert 1* loves me and I love myself”.

The most supported knowledge derived from the three last statements can be represented by the semantic network in Figure 3.

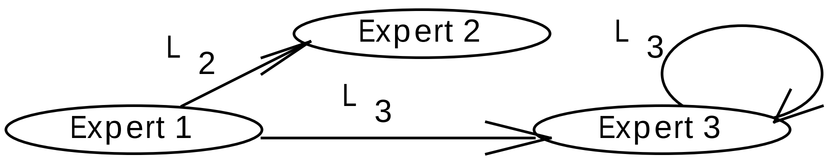

Fig. 3. The most supported opinion of experts about each other in the example

Let us use the most supported knowledge of experts about each other to interpret the named relation "to love". Using the above formulas, one can be convinced of differences between meanings: $< to\_love >^{msup} \neq < to\_love >^{<to\_help>} \neq < to\_love >^{<to\_love>}$.

The matrixes of Figure 4 include some results of colleague-oriented interpretation of semantic concepts for the term "to love" in the example.

L_3^{msup}	A_1	A_2	A_3	A_4
A_1	0	0	1	0
A_2	0	0	0	0
A_3	0	0	0	0
A_4	1	0	0	0

$L_3^{L_2}$	A_1	A_2	A_3	A_4
A_1	0	0	0	1
A_2	0	0	0	0
A_3	1	0	0	0
A_4	1	0	0	0

$L_3^{L_3}$	A_1	A_2	A_3	A_4
A_1	0	0	1	1
A_2	0	0	0	0
A_3	1	0	0	1
A_4	1	0	0	0

Fig. 4. Results of interpretation of the concept "to love" in the example

5. Conclusion

In this paper, we have presented how to refine our matrix-based presentation of knowledge acquired from multiple knowledge sources. The basic representation of knowledge behind is a semantic network with objects and their relations. Named relations are used to define the semantics of relationships that are interpreted. These can be used to select the opinions of the knowledge sources with the similar situation as the person who is going to apply the multiple experts' knowledge. We presented the result in an abstract level and it needs further application area oriented research efforts.

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