Knowledge Acquisition from Multiple Experts Based on Semantics of Concepts

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Abstract. This paper presents one approach to acquire knowledge from multiple experts. The experts are grouped into multilevel hierarchical structure, according to the type of knowledge acquired. The first level consists of experts who have knowledge about the basic objects and their relationships. The second level of experts includes those who have knowledge about the relationships of the experts at the first level and each higher level accordingly. We show how to derive the most supported opinion among the experts at each level. This is used to order the experts into categories of their competence defined as the support they get from their colleagues.

1 Introduction

When an expert system is being build, knowledge is usually acquired from multiple knowledge sources. This knowledge usually includes inconsistencies, incompleteness, and incorrectness. These difficulties are often solved by selecting some part of knowledge as the only one to be saved into the knowledge base or by adding up some extra knowledge to be included to the collected ones into the knowledge base.

Distributed AI can be exploited in knowledge acquisition for modelling the experts (their cooperation and conflicts), the knowledge acquisition process and specially the cooperation during knowledge acquisition from a group of experts. Knowledge acquisition from several experts is an extremely difficult task. Turban and Tan [24] review the difficulties as well as the benefits involved in such an acquisition. Various research is being done on knowledge acquisition from multiple experts [9]: constructive modelling and elicitation [14], models of cognitive agents [10] for guiding knowledge acquisition [7], management and comparison of multiple viewpoints [20, 3], detection and solving of conflicts among several expertise models [16], comparison of knowledge graphs [6], generation of consensual rules among experts [18], architecture of cognitive agent [7], extension of CommonKADS [25, 5] for multi-expertise [8] and for multi-agent systems [3], cooperative knowledge evolution [22]. The types of cooperation depends on the organization of the agents: horizontal and vertical organizational structures can be distinguished. In non hierarchical societies, cooperation is based on sharing of tasks and results, while in a hierarchical society, it relies on commands, bids and competition [19].

One real application in the construction of knowledge-based systems is discussed by Gappa and Puppe [11]. The task description and knowledge sources were prepared and made available via the World Wide Web. The common knowledge material consisted of: transcripts of various reports and interviews of domain experts, partly formalised relational knowledge, pictures photos of the domain objects, and a database containing descriptions of the domain objects' samples. An essential knowledge engineering problem in such applications was discussed how to deal with the conflicting knowledge from the different experts. The authors tried to resolve the differences based on the consistency and frequency of the different expert opinions into one authoritative knowledge base. Another approach would be to build a special knowledge base for each expert and try to find the integration of the respective solutions to an overall solution. This might be done both by a majority vote or by a weighted majority vote.

One goal of our research is to develop formalisms to represent and reason with knowledge obtained from several knowledge sources. In this paper we present one formalism that is based on matrix representation of semantic networks and multilevel knowledge structure where the upper levels include knowledge about the relationships of the experts and domain objects, too.

We will use the formalism to handle three types of problems:

1) How to derive the most supported knowledge about basic domain objects and relations among the experts? This gives a user possibility to use "consensus" knowledge during reasoning process.

2) How to order the experts according to their supported competence concerning each domain relation and object? This order helps a user to select the most "competent" expert of each domain relation and object. We will name this 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 group experts into different levels? This helps a user both to evaluate the subjectivity of each expert and to select an expert whose knowledge he wants to be used during reasoning process. We will name this as deriving *multilevel vertical structure of experts*.

The area of eliciting expertise from one or more experts in order to construct a single knowledge base is still under great research interest. Could the overlapping knowledge obtained from multiple sources be described in such a way that it is context or even process independent? Taylor et al give a negative answer [23]. 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 [15] the other researchers have found that if more than one expert are available, then one must either select the opinion of the best expert or pool the experts' judgements. It is assumed that when experts' judgements are pooled, collectively they offer sufficient cues leading to the building of a comprehensive theory. Medsker et al [17] 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, and integrate the opinions of multiple experts. It was assumed that the acquired knowledge has more validity if it is obtained from the consensus across experts. Mak et al [15] discuss about five knowledge classification techniques and make experimental evaluation of them. The elicited knowledge was aggregated using classical statistical methods, the ID3 pattern classification method, the k-NN technique, and neural networks. In aggregating knowledge, authors seek to identify the significance of each of the extracted factors and the functional inter-relationship among the relevant factors. They found that the neural net method outperformed the other methods in robustness and predictive accuracy. Arens et al [1] have described an approach which exploits semantic model of a problem domain to integrate the information from various information sources. They have in their SIMS project created a complete semantic model for data retrieval and integration from multiple dispersed knowledge sources. Roos [21] has described a logic for reasoning with inconsistent knowledge coming from different and not fully reliable knowledge sources. Inconsistency may be resolved by considering the reliability of the knowledge sources used. Since the relative probability is conditional on inconsistencies, information from one reliable source cannot be overruled by information from many unreliable knowledge sources. Goto et al [12] discuss three level structure of information distribution. The levels are brains, gatekeepers and end users. A brain has his specific field of knowledge. A gatekeeper does not have any specific area of knowledge - only general information. Each brain recognizes the other brains which create structure of knowledge by interacting with each other. The necessity to multiply brains appears only if the area of knowledge is too wide to be covered by a single brain. Gatekeepers may be interpreted as an intelligent interface between brains and end users. A gatekeeper knows to which brain (group of brains) address user's question. Gatekeeper in multi-brain human society was assumed to have a key role.

Current books in formal semantics widely use approaches based on fundamental conceptual research in philosophy and cognitive psychology. For example Larsen and Segal [13] study a particular human cognitive competence governing the meanings of words and phrases. Authors argue that speakers have unconscious knowledge of the semantic rules of their language. Knowledge of meanings is both the semantics of domain attributes (properties and relations) and learning technology how to derive semantics of inconsistent and incomplete meanings. A knowledge base is built upon the definition of a structured set of concepts, derived, for a large part, by the knowledge engineer from text analyses (transcriptions of discussions with an expert or technical documentation). The focus of knowledge acquisition is the conceptual organisation of knowledge fields from the study of terms representing concepts in texts as it was mentioned in methodological issue of Aussenac [2].

The rest of the paper is organised as follows. Section 2 introduces the basic concepts with an example that is used across the whole paper. In Section 3 we present the way to derive the most supported knowledge about objects and their relations from multiple opinions of experts. In Section 4 we introduce our method to derive horizontal order of experts according to their supported competence concerning each piece of knowledge. In section 5 we present the derivation of vertical hierarchy of expert competence. Section 6 concludes with a few future research topics.

2 Basic concepts

In this chapter, we introduce the basic concepts and notation used with an example.

Knowledge is an information about *properties* of *objects* and their *relations* and it is presented by a set of *semantic predicates*.

Object has unique identifier (for an object we use notation A with index) and zero, one or more *properties*.

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 index) and *source* from which the information about this *relation* was acquired (we will use notation Ex with index). For example, the fact: "Mary told that Bill contacted to his friend Tom by phone", is presented using two objects <Bill> and <Tom> , two relations defined by the concepts <to be friend> and <to contact by phone>, and the source <Mary>.

Property describes an *object* separately from other objects. It may be interpreted as a special *relation* where the two *objects* between which the *relation* holds are the same *object*. *Concept* in such *relation* is the name of *property*. For example, the fact: "Bill is forty years old black man", is described using one object <Bill> with three properties: <to be male>, <to be black>, <to be 40 years old>.

We will index objects using *s, t* = 1,...,*n* (*n* objects), concepts - using *i, j* = 1,...,*r* (*r* concepts), and sources using *k, l* = 1,...,*m* (*m* sources) with notation of sources.

Semantic predicate describes a piece of knowledge (relation or property) by expression: $P(A_s, L_i, A_t, Ex_k) = true$, if there is knowledge, acquired from the knowledge source Ex_k, that a relation with concept L_i holds between objects A_s and A_t, and $P(A_s, L_i, A_t, Ex_k) = false$, if there is knowledge acquired from source Ex_k that a relation with concept L_i does not hold between objects A_s and A_t.

For example knowledge about the statement*: "Pete says that Bill hates poor Mary"* can be formally represented as follows: Ex_1: <Pete> is the source of knowledge; A_1: <Bill> and A_2: <Mary> are the objects; L_1: <to hate>, L_2: <to be poor> are the concepts; $P(A_1, L_1, A_2, Ex_1) - < Bill\ hates\ Mary >$ is the relation; $P(A_1, L_2, A_2, Ex_1) - < Mary\ is\ pure >$ is the property; and the knowledge is:

$$P(A_2, L_1, A_3, A_1) \wedge P(A_3, L_2, A_3, A_1) = true\ .$$

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

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

Let us consider, as an example, some of the characters and their relationships in the film "Santa-Barbara". The characters and concepts to be considered are presented in Figure 1.

Objects and their ids.	Concepts 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 "Santa-Barbara" example

Let us suppose that three spectators express their opinions about relationships in this domain in the following way:

Spectator 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."

Spectator 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."

Spectator 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 expressed by each spectator (let us use word "expert") can be presented by the semantic networks in Figure 2 a-c.

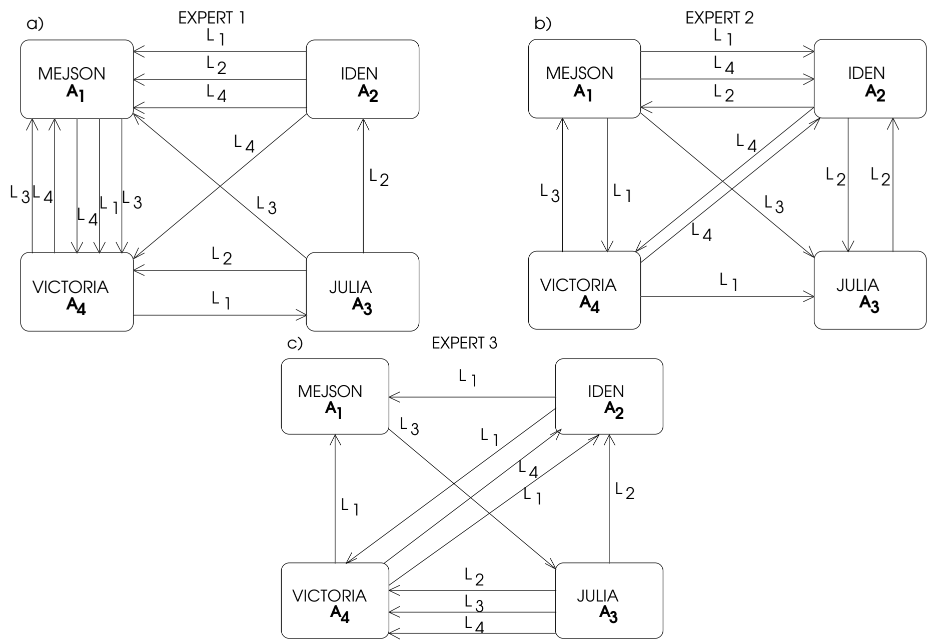

Fig. 2. Opinions of experts in the example presented by semantic networks

3 Deriving the most supported knowledge

In many cases as, in previous example, each expert interprets domain area by his own way. Without any co-ordination between experts, it is difficult to acquire useful information from their opinions. It is usual that information about one domain attribute is more in the area of expertise of one expert and another attribute is more in the expertise area of another expert. If one does not have such additional knowledge about expertise, then he has to select opinion of some of the experts. Another way is to use those pieces of knowledge that receive most support among all the experts.

In this chapter, we present the way to derive the most supported knowledge and then we show how to discover knowledge sources that have given the pieces of knowledge included to the most supported knowledge.

In our example the semantics $L_1^k - L_4^k$ of concepts L_1 - L_4 according to the knowledge sources k = 1,2,3 is presented in Figure 3.

L^1_1	A_1	A_2	A_3	A_4
A_1	0	0	0	1
A_2	1	0	0	0
A_3	0	0	0	0
A_4	0	0	1	0

L^2_1	A_1	A_2	A_3	A_4
A_1	0	1	0	1
A_2	0	0	0	0
A_3	0	0	0	0
A_4	0	0	1	0

L^3_1	A_1	A_2	A_3	A_4
A_1	0	0	0	0
A_2	1	0	0	1
A_3	0	0	0	0
A_4	1	1	0	0

L^1_2	A_1	A_2	A_3	A_4
A_1	0	0	0	0
A_2	1	0	0	0
A_3	0	1	0	1
A_4	0	0	0	0

L^2_2	A_1	A_2	A_3	A_4
A_1	0	0	0	0
A_2	1	0	1	0
A_3	0	1	0	0
A_4	0	0	0	0

L^3_2	A_1	A_2	A_3	A_4
A_1	0	0	0	0
A_2	0	0	1	0
A_3	0	1	0	1
A_4	0	0	0	0

L^1_3	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^2_3	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_3	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	1
A_4	0	0	0	0

L^1_4	A_1	A_2	A_3	A_4
A_1	0	0	0	1
A_2	1	0	0	1
A_3	0	0	0	0
A_4	1	0	0	0

L^2_4	A_1	A_2	A_3	A_4
A_1	0	1	0	0
A_2	0	0	0	1
A_3	0	0	0	0
A_4	0	1	0	0

L^3_4	A_1	A_2	A_3	A_4
A_1	0	0	0	0
A_2	0	0	0	0
A_3	0	0	0	1
A_4	0	1	0	0

Fig. 3. Semantics of concepts in the example

Deriving the most supported semantics of concepts. We build a matrix $(CL)_{r\times m}$ by a following way:

$$(CL)_{i,k} = \sum_{s,t}^{n}((L_i^{k})_{s,t} \times \sum_{j,j\neq k}^{m}(L_i^{j})_{s,t}).$$

The formula gives to each element of the *CL* matrix an integer value that summarises the support that knowledge source gets among the experts using the concept to describe the relation. When the formula is applied to the example, we obtain the matrix in Figure 4. It shows that expert 1 gets most support among experts to the use of concept "to respect". It also shows that experts get equal support using the concept "to help".

CL	Ex_1	Ex_2	Ex_3
L_1	3	2	1
L_2	4	4	4
L_3	1	2	1
L_4	0	1	1

Fig. 4. Support to use concepts

The most supported knowledge about concepts is derived selecting only knowledge of most supported knowledge sources. We will use the concept *competent* and it is presented by matrix $(L_i^{m\sup})_{n\times n}$:

$$(L_i^{m\,sup})_{s,t} = sign(\sum_{\substack{k \\ \forall k (CL)_{i,k} = \max_l (CL)_{i,l}}} (L_i)_{s,t}^{k}).$$

When the formula is applied to the example, we obtain the matrixes of Figure 5.

L_1^{msup}	A_1	A_2	A_3	A_4
A_1	0	0	0	1
A_2	1	0	0	0
A_3	0	0	0	0
A_4	0	0	1	0

L_2^{msup}	A_1	A_2	A_3	A_4
A_1	0	0	0	0
A_2	1	0	1	0
A_3	0	1	0	1
A_4	0	0	0	0

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_4^{msup}	A_1	A_2	A_3	A_4
A_1	0	1	0	0
A_2	0	0	0	1
A_3	0	0	0	1
A_4	0	1	0	0

Fig. 5. The most supported opinion about each concept in the example

These matrixes of Figure 5 together present the most supported knowledge about concepts that describe domain relations. The semantic network presentation of it is in Figure 6.

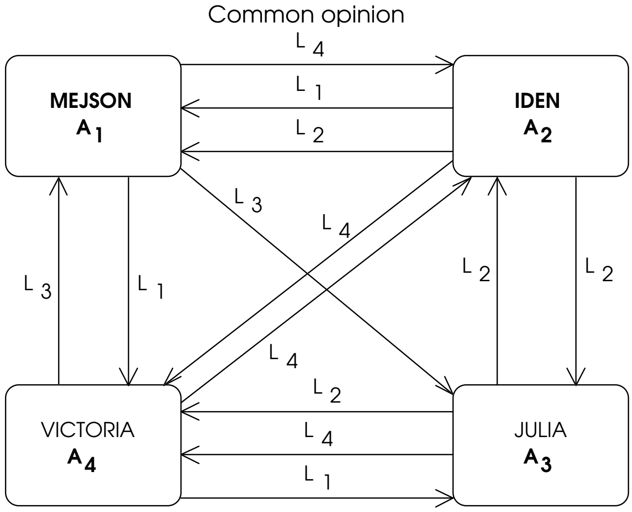

Fig. 6. The semantic network presentation of the most supported knowledge

4 Deriving horizontal order of experts

In this chapter we present how to order the experts according to their competence concerning each relation and object. This ordering is based on the most supported knowledge among the experts about concepts used to describe of domain relations. The amount of competence of an expert is measured by the support he receives to his opinions among experts. This is surely no absolute evaluation of competence and the result depends on the group of experts selected. In deriving expert's competence we firsts derive a numerical value for expert's competence concerning each possible relation and then use these values to order the experts according to their competence. After that, we order the experts according to their competence about objects using their competence about relations connected to each object.

The numerical value for expert's competence concerning each possible relation is derived as $(CR)_{n\times n\times m}$ array using the formula:

$$(CR)_{s,t,k} = \sum_{\substack{i, \\ (L_i^k)_{s,t}=(L_i^{m\,sup})_{s,t}}}^{r} (L_i^{m\,sup})_{s,t}\ , \text{ where } s,\ t = 1, ..., n;\ k = 1, ..., m.$$

Experts are grouped into categories of competence, relation by relation, according to the corresponding values of the CR-array. This can be described by the algorithm *A*:

Step 1: For each pair of objects A_s and A_t, (s, t = 1,...n) do step 2.

Step 2: Group the experts Ex_k, (k = 1,...,m) into categories $CEx_{s,t,l}$, (l = 1,..., n) so that the experts who have the same highest value of $CR_{s,t,k}$, (k = 1,...,m) belong to the first category $CEx_{s,t,1}$, the experts who have the same second highest value of $CR_{s,t,k}$, (k = 1,...,m) belong to the second category $CEx_{s,t,2}$, and so on until all experts have assigned into some category.

Step 3: Return the grouping of experts into categories as the result of this algorithm.

In our example above we receive CR-array presented in Figure 7.

	Ex_1				Ex_2				Ex_3			
CR	A_1	A_2	A_3	A_4	A_1	A_2	A_3	A_4	A_1	A_2	A_3	A_4
A_1	0	0	0	1	0	1	1	1	0	0	1	0
A_2	2	0	0	1	1	0	1	1	1	0	0	0
A_3	0	1	0	1	0	1	0	0	0	1	0	2
A_4	1	0	1	0	1	1	1	0	0	1	0	0

Fig. 7. CR-array for the example

The categories, obtained with algorithm *A*, are shown in Figure 8.

	First category				Second category				Third category			
CEx	A_1	A_2	A_3	A_4	A_1	A_2	A_3	A_4	A_1	A_2	A_3	A_4
A_1	Ex_1 Ex_2 Ex_3	Ex_2	Ex_2 Ex_3	Ex_1 Ex_2	∅	Ex_1 Ex_3	Ex_1	Ex_3	∅	∅	∅	∅
A_2	Ex_1	Ex_1 Ex_2 Ex_3	Ex_2	Ex_1 Ex_2	Ex_2 Ex_3	∅	Ex_1 Ex_3	Ex_3	∅	∅	∅	∅
A_3	Ex_1 Ex_2 Ex_3	Ex_1 Ex_2 Ex_3	Ex_1 Ex_2 Ex_3	Ex_3	∅	∅	∅	Ex_1	∅	∅	∅	Ex_2
A_4	Ex_1 Ex_2	Ex_2 Ex_3	Ex_1 Ex_2	Ex_1 Ex_2 Ex_3	Ex_3	Ex_1	Ex_3	∅	∅	∅	∅	∅

Fig. 8. The experts categories in the example

We group experts into categories according to their competence about objects using their categories according to their competence about relations connected to each object. For each object and expert, we calculate the *sum* of the numbers of categories, they are included to, concerning the connected relations. The more competent experts have smaller sum. This can be described by the algorithm *B*:

Step 1: For each object A_s, (s, = 1,...n) do step 2.

Step 2: For each expert Ex_k, (k = 1,...,m) do step 3.

Step 3: Calculate sum of the numbers l of the categories $CEx_{s,t,l}$, (t = 1,...,n) where the expert Ex_k belongs to and add up into the sum the numbers l of the categories $CEx_{t,s,l}$, (t = 1,...,n) where the expert Ex_k belongs to.

Step 4: Group the experts Ex_k, (k = 1,...,m) into categories $COEx_{s,l}$, (l = 1,..., n) so that the experts who have the same smallest value of sum calculated in the step 3 belong to the first category $COEx_{s,1}$, the experts, who have the same second smallest value of the sum, belong to the second category $COEx_{s,2}$, and so on until all experts have assigned into some category.

Step 5: Return the grouping of experts into categories as the result of this algorithm.

In the example above, we receive sum values and categories, that are presented in Figure 9.

Sum	Ex_1	Ex_2	Ex_3
A_1	10	9	12
A_2	11	9	12
A_3	11	10	10
A_4	10	10	12

COEx	First category	Second category	Third category
A_1	Ex_2	Ex_1	Ex_3
A_2	Ex_2	Ex_1	Ex_3
A_3	Ex_2, Ex_3	Ex_1	∅
A_4	Ex_1, Ex_2	Ex_3	∅

Fig. 9. Sum values and expert categories concerning objects of the example

Results of knowledge attributes' distribution among experts accordingly to their competence are presented as a graph in Figure 10.

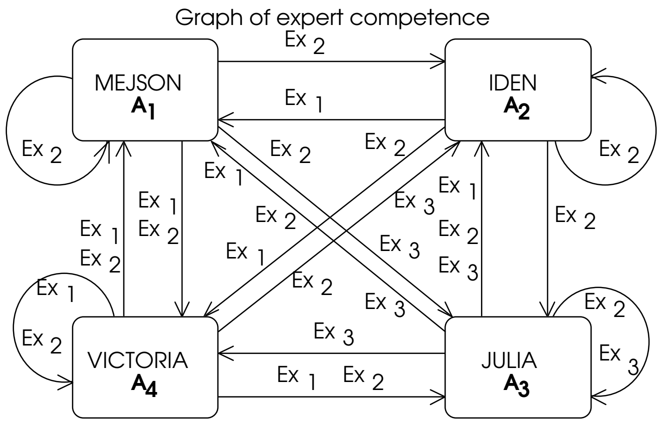

Fig. 10. Graph of horizontal competence of experts in the example

5 Multilevel vertical structure of experts

In this chapter we describe how to derive vertical hierarchy of experts. In our approach we suppose that experts give statements about the other experts (and even themselves) using the same relations of the basic level. We use the content of these statements to locate experts (and their statements) in different levels. The experts who give statements are both the experts who have given basic level knowledge of the domain area and experts who give only statements about the relations of the other experts. Figure 11 presents an example of cross-expertise professor-student. Student has his own opinion (a) about his own level of learning some course of lectures given by professor. Professor contacting with student forms his opinion (b) about student's level. Student has an opinion (c) about quality of lectures. Professor gives his own appreciation (d) of himself as lecturer. It seems reasonable to take into consideration all (a-d) opinions to derive resulting opinion concerning student. Experts in such situation represent multilevel structure of expertise. It is possible that some of experts are present at the different levels in the same structure. We can be at one level of competence when we evaluating a student and we are certainly at another level when we discussing the policy of a president.

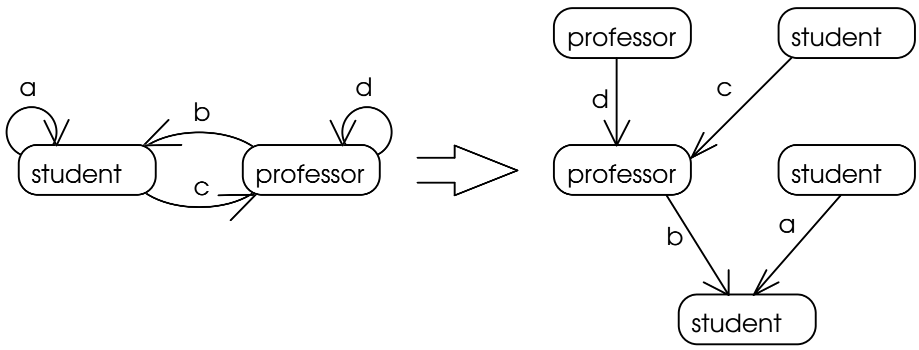

Fig. 11. Vertical hierarchy of competence

We introduce a new relation *Exp* that can exist between any two experts and it has the meaning that the first expert in the relation has expressed a statement about the second expert's relation with domain objects or himself. When the notion of object is allowed to represent also an expert then this can be described by formula:

$$\forall k, l \exists i, t (P(Ex_l, L_i, A_t, Ex_k) \vee P(A_t, L_i, Ex_l, Ex_k) \vee$$
$$\vee P(Ex_l, L_i, Ex_l, Ex_i)) \Rightarrow P(Ex_k, Exp, Ex_l, Ex_k).$$

We construct a multilevel structure of experts in the following way. The zero level of the structure, marked D^0, includes only basic domain objects and their relations. The first level of the structure includes *Exp*-relations that are statements of experts about the other experts and/or their relations at the zero level D^0. The next level of the structure includes *Exp*-relations that are statements about experts that gave statement at the previous level and so on. There is a need to prevent infinite formation of levels in the case when statements form a circular structure. The formation of the upper levels of the structure can be described by:

$$\forall q(0 < q < 3)\forall A_k \exists A_l((A_l \in D^{q-1}) \wedge P(A_k, Exp, A_l, A_k)) \Rightarrow (A_i \in D^q), \text{ and}$$

$$\forall q(q \geq 3)\forall A_k \exists A_l((A_l \in D^{q-1}) \wedge P(A_k, Exp, A_l, A_k) \wedge \neg\exists p((0 \leq p \leq q-2) \wedge$$
$$\wedge Connect(A_l, q-1, A_k, p))) \Rightarrow (A_k \in D^q),$$

where *Connect* is a predicate that defines connection between the objects of different levels of the structure through circular chain of *Exp*-relations as:

$$\forall p \forall A_l(A_l \in D^p)\forall q(q \leq p-2)\forall A_k(A_k \in D^q)\exists A_{d_1}, A_{d_2}, \dots, A_{d_{p-q-1}}(((A_{d_1} \in$$
$$\in D^{p-1}) \wedge (A_{d_2} \in D^{p-2}) \wedge \dots \wedge (A_{d_{p-q-2}} \in D^{q+2}) \wedge (A_{d_{p-q-1}} \in D^{q+1})) \wedge$$
$$\wedge (P(A_l, Exp, A_{d_1}, A_l) \wedge P(A_{d_1}, Exp, A_{d_2}, A_{d_1}) \wedge \dots$$
$$\dots \wedge P(A_{d_{p-q-1}}, Exp, A_k, A_{d_{p-q-1}}))) \Rightarrow Connect(A_l, p, A_k, q).$$

To continue our previous example we assume that the three experts have expressed their statements about competence of each other in the following way:

$$P(Ex_1, L_1, Ex_1, Ex_1) \wedge P(Ex_1, L_2, Ex_2, Ex_1) \wedge P(Ex_1, L_3, Ex_2, Ex_1) \wedge$$
$$\wedge P(Ex_2, L_1, Ex_1, Ex_1) \wedge P(Ex_2, L_3, Ex_2, Ex_1) \wedge P(Ex_3, L_3, Ex_3, Ex_2) \wedge$$
$$\wedge P(Ex_3, L_1, Ex_3, Ex_2) \wedge P(Ex_1, L_1, Ex_1, Ex_3) \wedge P(Ex_1, L_3, Ex_3, Ex_3) \wedge$$
$$\wedge P(Ex_3, L_1, Ex_1, Ex_3) \wedge P(Ex_3, L_1, Ex_3, Ex_3) \wedge P(Ex_3, L_3, Ex_3, Ex_3) = 1.$$

Using definition of *Exp*-relation it is possible to write:

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

These relations form the graph of cross-expertise in the way that is shown in Figure 12. Arrows mean *Exp* - relations.

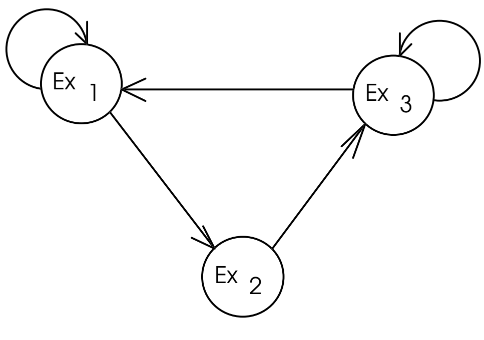

Fig. 12. Graph of cross-expertise

Using the above description, it is possible to unfold this graph into the multilevel vertical structure of experts presented in Figure 13.

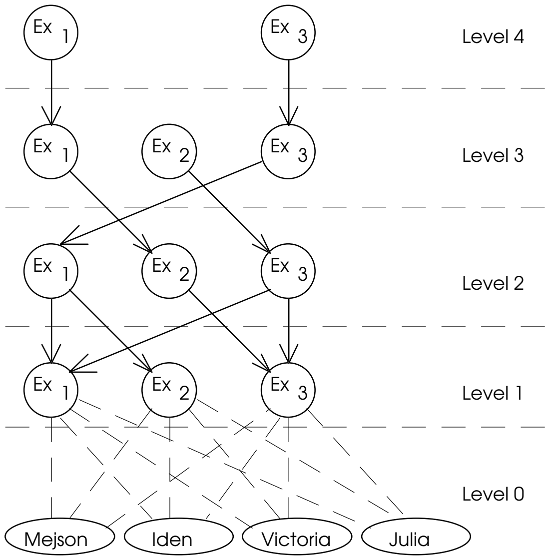

Fig. 13. Multilevel vertical structure of experts in the example

The method of deriving horizontal order of experts can be used to derive the most supported knowledge at each level. In the example the levels 1, 2 and 3 are as in Figure 14.

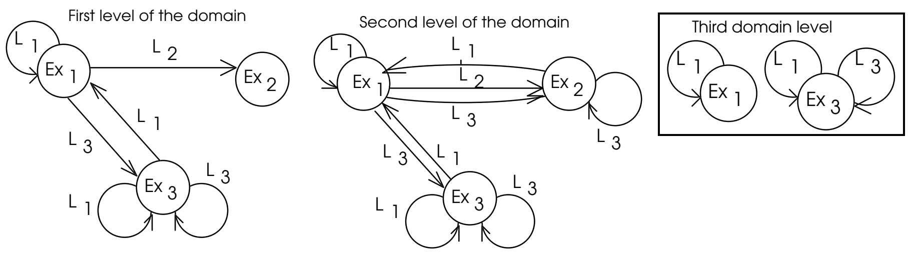

Fig. 14. Horisontal ordering for domain levels 1, 2, and 3 in the example

6 Conclusion

In this paper, we have presented matrix-based way to process knowledge acquired from multiple knowledge sources. The basic representation of knowledge behind is semantic network presentation with objects and their relations. Concepts are used to define semantics of relationship and they are interpreted in a very broad way. Concept includes the name of relation, all necessary attributes of the relation and certain values of the attributes. We discussed about three problems.

First, how to derive the most supported (common) knowledge from knowledge sources. Knowledge obtained from different sources can include different and even conflicting pieces of knowledge. We introduced a method of calculating the amount of support to relations between any two pairs of objects and its use to select the most supported relations. It is necessary to note that most supported knowledge is not always the best one and sometimes cannot be used as correct knowledge. We accept most supported knowledge in applications which use democratic voting-based principle of acquiring knowledge from multiple experts.

Second, we discussed the problem of ordering the experts into categories of competence. We introduced a method which uses amount of support to locate each expert into one competence category with respect to each possible relation and object.

Third, we discussed the problem of deriving vertical structure in the case when there exist statements given by experts concerning also experts' relations with domain objects and each other. We show how experts can be grouped into a multiple structure and can be classified into competence categories at each level.

There are some restrictions in the methods used to describe experts' opinions. In this paper, we have not discussed the problem of semantics from the individual interpretation point of view. Further research is also needed to generalize the results to the cases where ignorance is allowed to have different levels, and support is allowed to be partly (for example from very weak to very weighty).

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