Overlay Method and Knowledge Evaluation Using Fuzzy Logic

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Abstract. E-learning took place between information and communication technology on one side and education on the other. Authoring shells are kind of e-learning systems capable for generating intelligent tutoring systems. These systems usually models learner's knowledge by using overlay method during tests. In this paper is presented an advanced approach in refining and making flexible mark of learner's knowledge by applying fuzzy system in overlay method.

Introduction

Information and communication technology (ICT) became inseparable part of educational systems that helps teachers during class lectures or replace the same combining numerous methods and way of realizing learning and teaching process. Application of technology and development of educational systems are in support of e-learning paradigm that today comprise not only intelligent e-learning systems, but also other medias like CD-ROM, CAI, video conferencing, satellite distribution of learning materials and virtual knowledge networks. Today, development on e-learning field is aimed into designing Learning Management System (LMS) [1] and Intelligent Tutoring System (ITS) [2]. In a difference of LMS that mainly distribute electronically content on learner's request, ITS implement intelligence in several segments or learning and teaching process realization.

Generally, ITS is a system based on several knowledge representation technologies. Knowledge representation in ITS not only incorporate student's knowledge, but also and domain knowledge that learner uses during knowledge creation in purpose of teaching. Mentioned knowledge kinds and ITS designers designated modular architecture [3] of the system containing:

- Expert module – for designing domain knowledge,
- Teacher module – for designing teaching content,
- Learner module – for storing information of users progress on a chosen domain knowledge and
- Communication module – that interconnects all modules and system users.

Learner module provides main learning and teaching functions and comprises testing of the learner's knowledge following by generating mark and recommendations for the further work. In this paper is described one of the methods for testing and evaluating learner's knowledge that is implemented in Tutor-Expert system (TEx-Sys) [4]. TEx-Sys is defined as intelligent hypermedial authoring shell that means it is an instance of intelligent authoring shells (IAS) and servers as ITS generator. Domain knowledge representation in TEx-Sys system is based on semantic network with frames technology [5].

TEx-Sys implements two methods of knowledge evaluation. Quiz method [6] dynamically generates questions and answers over a set of nodes and links in semantic network with frames laying as a base for domain knowledge. The other is overlay method that uses domain knowledge as a source for generating problem knowledge. Given knowledge in generated problem, learner tries to expand to the original domain knowledge. Results of difference analysis between mentioned knowledge provides input for calculating mark of the test. Knowledge overlay technique looks at the differences between learner and teacher, enabling wrong knowledge assumptions as well as misconceptions. In that purpose three knowledge bases are compared:

- {Expert} knowledge base containing expert's knowledge in chosen domain,
- {Problem} knowledge base having generated test set of nodes and links,
- {Solution} knowledge base containing solution to the problem.

These knowledge bases are realized using semantic network with framework technique [7]. When learner runs testing module he is offered by three types of tests:

- Test 1: All links are removed from chosen domain knowledge. Learner has to input missing links
- Test 2: Fragment of knowledge is generated with having not less than 30% and not more than 70% of original nodes in chosen domain knowledge. Learner has to fulfill missing nodes and their connections.
- Test 3: Fragment of knowledge is generated with having not less than 50% of the nodes and some of nodes are wrongly connected. Learner has to find wrongly connected nodes and fulfill missing nodes.

Choosing type of test takes {Expert} knowledge base and by removing nodes, removing and/or wrongly connecting nodes generates {Problem} base. By solving this base learner can remove nodes, add missing nodes and add new nodes that are not in {Expert} knowledge base. With links are following treatments: adding new connections, removing correct connection, removing wrong connection, adding correct connection, adding wrong connection and adding missing connection. These actions over nodes and connections define their status. Overlaying nodes and connections in {Expert}, {Problem} and {Solution} knowledge bases completes reconstruction of tracing learner's way in creating solution.

System TEx-Sys has elaborated qualitative criterions of evaluation based on numeric and descriptive qualifications and in connection with knowledge representation technique and chosen elements of semantic network in formalism for designing knowledge base. Separated quantification of nodes and links in semantic network defines criterions for nodes and links scores. These criterions are very strict and not flexible in generating students mark. By determining weighting factor for elements of semantic network we try to make some elements more important than the other. The other step in making flexible knowledge mark uses fuzzy system. In following is described such a procedure.

Weighting Factor in Semantic Network with Frames

Elements of semantic network with frames are nodes, links, properties and property values in frames. Actions of adding, updating or deleting some element of semantic network with frames will imply on overall count of points for that element. For example, if correct node is added into semantic network with frames, then overall count of points for nodes is increased by weight factor of that node. Then score for nodes will be the scale between sum-total score for nodes and sum-total maximal score for nodes which is equal to sum of all nodes' weight factor in domain knowledge.

Weight Factor for Nodes

Problem of defining weight factor for elements of semantic network with frames will be explained on nodes example. Semantic network is abstracted by directional graphs where the node is vertex and the link between two nodes is arc. Directional graph G is ordered triplet (V, E, I) where V is set of vertices, E set of edges, and I set incidences containing triplets (v_i, e, v_j) where v_j is tail of edge e and v_i is its head. Vertex v_j is a child in relation to v_i, i.e. vertex v_i is a parent to v_j via edge e. Weight factor of vertices are determined by their position in directed graph. Generally looking, parent vertices have larger weight factor then their child vertices. On figure 1 vertices v_1 and v_2 have larger weight factor then v_5 and v_6 because they do not have parents, relative to v_5 and v_6 having no child. Vertices v_3 and v_4 have children and parents, thus having larger weight factor then v_5 and v_6 and smaller weight factor then v_1 and v_2. Though, vertex v_3 is "weightier" then v_4 because he is parent of v_4.

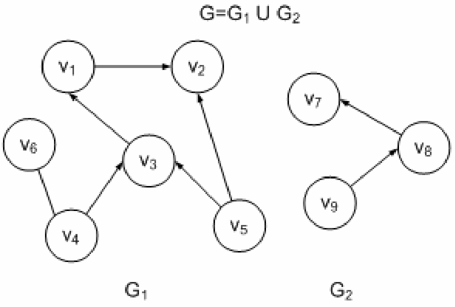
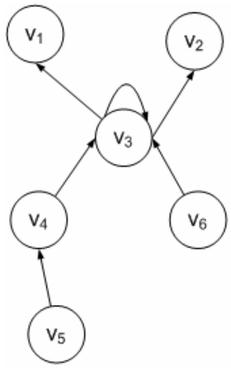


Fig. 1. Subgraphs of directed graph

Directed graph on figure 1 contains two sub-graphs G_1=(V_1, E, I_1) and G_2=(V_2, E, I_2) containing disjunctive sets I_1 and I_2 whose union is incidence set of graph G. Same assumption goes to the sets V_1 and V_2, relatively $V_1 \cap V_2 = \varnothing$ and $V_1 \cup V_2 = V$.

Weight factor of directed graphs vertex is determined by overall count of parents in mediated and intermediated relation to all other vertices in directed graph. In case of two vertices having equal count of parents in relation to all other vertices, than the one with more mediated or intermediated children is having larger weight factor.

Determination of weight factor for graph G vertices starts with implementation of incidence matrix. (i, j) element of the incidence matrix M(G) for directed graph G is determined by counting number of connections between vertexes v_j and v_i. For each incidence matrix M(G) is defined matrix M'(G) whose elements are equal to elements of M(G) except diagonal elements which are set to zero.



$$M(G)=\begin{bmatrix}0&0&1&0&0&0\\0&0&1&0&0&0\\0&0&1&1&0&1\\0&0&0&0&1&0\\0&0&0&0&0&0\\0&0&0&0&0&0\end{bmatrix}$$

Fig. 2. Example of incidence matrix

For vertex v_i in directed graph G on base of M'(G) matrix can be attached pair (p_i, c_i) where p_i is number of parents, and c_i number of children for vertex v_i. Now it is natural to define function f^m which will calculate number of children for vertex v_i by summating elements in i row of matrix $M'(G)^m$, and summating elements of i-th column of matrix $M'(G)^m$.

$$\begin{aligned}&f^m : V \to N_0 \times N_0\\&f^m(v_i) = (p_i^m, c_i^m)\\&p^m{}_i = \sum_{k=1}^{n} a_{k,i}, c_i^m = \sum_{k=1}^{n} a_{i,k}\\&M'(G)^m = \left[a_{i,j}\right]\\&n = |V|\end{aligned} \tag{1}$$

By the function (1) diagonal elements of M(G) matrix are not summated because these elements tells that vertex is simultaneously parent and child of itself. This function gives us for each vertex overall number of parents and children in immediate connection with other elements of directed graph *G*.

By appliance of function (1) we have following results in (2):

$$\begin{aligned}
f^1(v_1) &= (0,1) \\
f^1(v_2) &= (0,1) \\
f^1(v_3) &= (2,2) \\
f^1(v_4) &= (1,1) \\
f^1(v_5) &= (1,0) \\
f^1(v_6) &= (1,0)
\end{aligned} \tag{2}$$

If $M'(G)^2$ is calculated, then each vertex of directed graph will have number of parents and children in intermediate connection looked by second level of incidence. For example, vertexes v_1 and v_2 have children v_4 and v_6, while v_3 has v_5 as intermediate child. Other vertexes do not have intermediate children. Function f^2 will for each vertex attach ordered pair by matrix $M'(G)^2$.

$$M'(G)^2 = \begin{bmatrix} 0 & 0 & 0 & 1 & 0 & 1 \\ 0 & 0 & 0 & 1 & 0 & 1 \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix} \qquad \begin{aligned}
f^2(v_1) &= (0,2) \\
f^2(v_2) &= (0,2) \\
f^2(v_3) &= (0,1) \\
f^2(v_4) &= (2,0) \\
f^2(v_5) &= (1,0) \\
f^2(v_6) &= (2,0)
\end{aligned}$$

Fig. 3. Second level of incidence in graph G

After getting null-matrix as result of powering *M'*(*G*) matrix, we can define function *F* which will for each vertex v_i attach ordered triplet (p_i, c_i, r_i) where p_i and c_i are total number of parents and children for v_i, while r_i is number of round connections (cycles) for v_i.

$$\begin{aligned}
&F(v_i) = \left(\sum_{k=1}^{m-1} p_i^{\,k}, \sum_{k=1}^{m-1} c_i^{\,k}, r_i\right) \\
&m = \min\left\{n \in N : M'(G)^n = \left[0\right]\right\} \\
&c_i = a_{i,i}, M(G) = \left[\, a_{i,j} \,\right]
\end{aligned} \tag{3}$$

If we put in order results of function f_i for each vertex in directed graph *G* we will have table 1.

Table 1. Vertices and results of function f_i

	f1	f2	f3	F
v1	(0,1)	(0,2)	(0,1)	(0,4,0)
v2	(0,1)	(0,2)	(0,1)	(0,4,0)
v3	(2,2)	(0,1)	(0,0)	(2,3,1)
v4	(1,1)	(2,0)	(0,0)	(3,1,0)
v5	(1,0)	(1,0)	(2,0)	(4,0,0)
v6	(1,0)	(2,0)	(0,0)	(3,0,0)

More important are those vertices having less number of parents. If two vertices have same number of parents than more important would be the one having greater number of children. In case of two vertices having equal number of parents and equal number of children, than more important one would have greater number of cycles. By this principle, vertices v_1 and v_2 are the most important and have the same weight factor. Next important vertex is v_3. Vertices v_4 and v_6 have equal number of parents, but v_4 is more important because having one child. If we sort ascending results of *F* function for each vertex than we will have sequence:

$$(4,0,0)\ ,\ (3,0,0)\ ,\ (3,1,0)\ ,\ (2,3,1),\ (0,4,0) \qquad (\mathbf{4})$$

This sequence has 5 elements and by dividing index of the element with overall number of elements in sequence, we will calculate weight factor for each element in sequence. The least weight factor has v_5 while v_1 and v_2 have weight factor equal to 1, which is also maximal value for the weight factor.

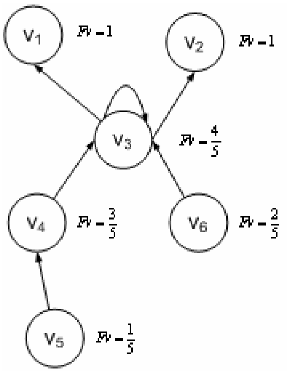


Fig. 4. Weight factors for vertices in graph *G*

After determination of weight factor for vertices in directed graph, weight factor for edge is calculated as average of weight factors for vertices on that edge. Figure 5 shows that edges having tail in v_3 will have weight factor $\frac{7}{10}$ and $\frac{3}{5}$.

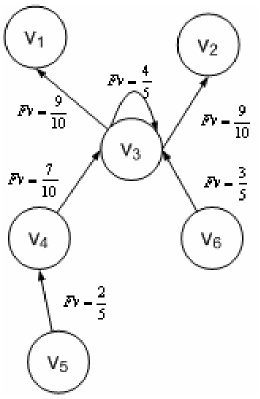


Fig. 5. Weight factor for edges in graph G

Weight factor of properties in frame of generic node will depend on weight factor of node. For example, if the weight factor of generic node is *k* and that node has a frame with *m* properties, than weight factor for each property in this node's frame will be $\frac{k}{m}$. On the same principle is calculated the weight factor for property values in frames of individual nodes.

Obviously there is bijection between graph's vertices and nodes in semantic network, as well as graph's edges and node's connections. This bijection translate weight factor of vertices and edges into weight factor of nodes and connections.

Fuzzy-Logic Appliance in Knowledge Evaluation

Student's knowledge evaluation can be generally described using fuzzy system [8] having uncertain input vector and certain output scalar as a presentation of student knowledge mark.

Input variable in fuzzy system for determining mark of the knowledge is 4-dimensional uncertain vector. Every element of this vector represents achieved scores for specific semantic network with frames element. Conversion from uncertain to certain is practiced by membership functions. Membership degrees are going to be calculated using center to maximum method. Output value of the fuzzy system is knowledge evaluation mark.

Score for semantic network with frames elements will be proportion of weight factor in solution base with sum of weight factor for nodes in expert and problem bases. We will define weight functions *V*(*base*, *element*) where base parameter can be task, solution or expert, while element parameter can be node, link, property or property value. Weight function for specific base and specific semantic network with frames element is a sum of all weight factors for specific kind of element. For example, *V*(*task*, *node*) is sum of weight factor of all nodes in task base.

Table 2. Certain vector determination by using importance function

		Knowledge bases			**Score**	**Certain Vector**
		Task	Solution	Expert		
Element	Node	3.4	4.1	6.2	**0.87**	(0.87, 0.55, 0.75, 0.90)
	Link	4.4	5.2	8.7	**0.55**	
	Property	2.9	4.4	4.9	**0.75**	
	Property Value	3.2	5.1	5.3	**0.90**	

It is naturally to define function *Score*(*element*) as ratio of difference *V*(*solution*, *element*) – *V*(*problem*, *element*) with difference *V*(*expert*, *element*) – *V*(*problem*, *element*). In table 2 is given example for determining certain vector by weighting elements of semantic network with frames in expert, problem and solution knowledge bases. In case to facilitate difference between importances for expert and problem knowledge bases for a given element of semantic node with framework, than score for that element is not taken in certain vector, thus vector's dimension is decreased.

Each dimension of certain vector has defined membership function. Determination of these functions is intuitive and is based on experience. Usually, scores for nodes and links are more important than other elements. On figure 6 are given membership functions for all elements of semantic network with frames.

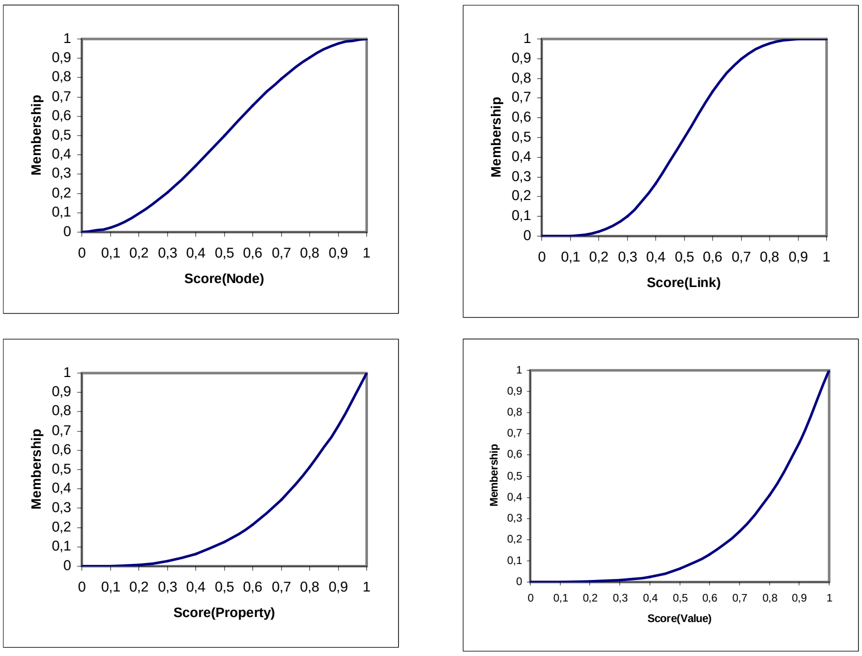


Fig. 6. Membership function for each element of semantic network with frames

If we look on membership function results for scores of semantic network with frames exampled in table 2, then we would get uncertain values as shown in a table 3.

Table 3. Uncertain values example determined by membership functions

	Node	Link	Property	Value
Score	0.87	0.55	0.75	0.90
Membership	0.96	0.61	0.42	0.67

By fuzzy reasoning uncertain membership function's values for semantic network with frames element scores are numbers between 0 and 1. Simple rule for determining that uncertain number is absolute value of membership function's values. Graphically result is displayed as a weight of geometric figure whose vertices are defined by coordinates of certain and uncertain value of membership function, as on figure 7.

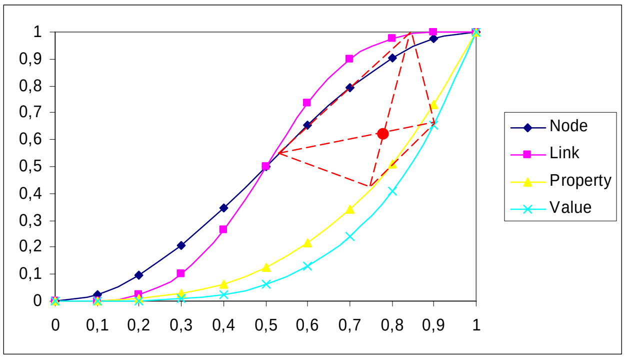


Fig. 7. Method for determining uncertain mark

Output and certain vector of this fuzzy system is mark of learner's knowledge. It is important to define function that for each uncertain number trace concrete number. Similar as membership function, this function is also based on experience. Example of this function is given in figure 8.

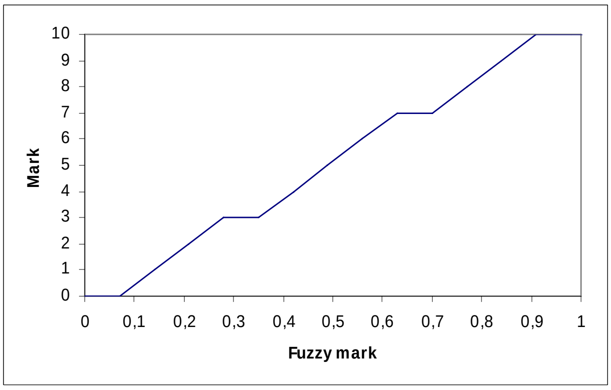


Fig. 8. Determining knowledge mark as function of uncertain mark

Conclusion

Intelligent Tutoring Systems can have different methods for knowledge evaluations. Fuzzy system is one of ordinary choice because of its functionality similar to human process of reasoning. Knowledge mark, as result of approximately human consideration is hardly to explain on precise and procedural way. Fuzzy systems give acceptable and flexible reasoning methods, but sacrifice precision and correctness. One of the main problems during development of fuzzy systems is comprehensible presentation of fuzzy rules and membership functions. Often is necessary to synchronize fuzzy rules with membership function resulting in satisfying results.

One of the solutions is employment of machine learning methods that would improve fuzzy rules and membership functions.

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