Knowledge Representation in Intelligent Tutoring System

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Abstract. This study presents a compilation of techniques for Knowledge Representation (KR) in Intelligent Tutoring System (ITS). Shows pros and cons of each approach in order to use the proper technique according to the needs. Analyses literature related to ITS and KR to find the approaches. Highlights: Fuzzy Cognitive Maps, Bayesian Network, Semantic Networks, Graphs, among other methods. Each approach contributes with elements to model knowledge. We made a comparison of each model with determined factors. Each technique of KR provides his own vision of how the world should look. Besides, it shows what information is necessary to represent and what is important to ignore. Different approaches to intelligent reasoning lead to different goals and definitions of success.

Keywords: Knowledge representation · Intelligent tutoring systems · Fuzzy cognitive maps · Bayesian networks

1 Introduction

For many years technology had been involved in the educational process. This kind of technology called educational technology concerns the study and ethical practice to facilitate learning and improve the performance; made possible through the creation, use, and proper management of resources and technological processes [2]. In particular, we are focused on Intelligent Tutoring Systems (ITS) and other systems that support the teaching through the computer.

An Intelligent Tutoring System is defined as a software system that uses artificial intelligence techniques to interact with students and teach them [8,23] almost in the same way as a teacher does [4]. Carbonell [3] proposed a generalized architecture for ITS, which considers further of user interface, three core modules [4,23]: (1) Tutoring model, (2) domain model, and (3) student model.

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A computer-based education system needs to know what to teach, which is called knowledge domain. When represented in a way that computer understands it. Then is called Knowledge Representation (KR). It is important to consider the KR processes and automates information management through computers. In addition, make inferences that allow decision-making as a human does in order to improve the tutoring task.

Authors such as [20,22] establish that in the human semantic memory exist a hierarchy of concepts with relations to organize the knowledge. Hence, arises the idea of representing knowledge by mean of graphs. Samples of this techniques are Concepts Maps, Bayesian Network, Cognitive Maps, Conceptual Graphs, Knowledge Maps, Semantic Network and Memory Maps. Our study analyzes the mentioned techniques, and develops a comparative schema to define the elements of knowledge considered by those techniques.

The objectives of our work are: to identify the methods used in ITS to represent knowledge, to obtain features given by each approach, to define a taxonomy about the elements that are considered to represent knowledge, to compare different approaches according to the elements identified, and finally, to highlight the use of each technique according to its characteristics.

This paper is organized as follows: Section two describes the elements obtained from each technique. Section three compares each method according to identified factors. Section four analyzes each method, and section five gives an example of the taxonomy elements in a Bayesian Network. Finally, conclusions and references are shown.

2 Features of the Knowledge Representation in ITS

In this section, we summarized the elements that were considered to represent knowledge in an educational environment. Literature review was made to find

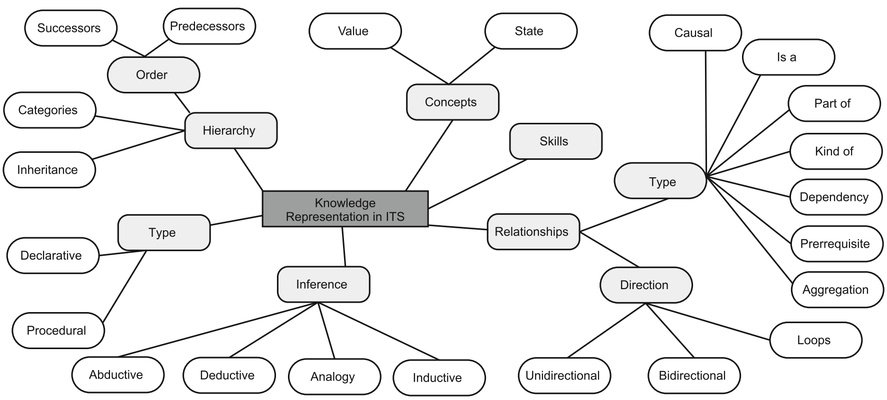

Fig. 1. Elements to KR in ITS

the previous approaches. Articles related to KR and ITS were reviewed. Figure 1 depicts the elements identified. The features of knowledge representation are:

- **Concepts:**
  The concept is an elemental piece of knowledge. According to the domain expert, it cannot be divided into smaller parts. Whereby, a concept is considered the primary unit of knowledge [13].
  The related work with computer assisted education that we analyzed is based on two essential aspects: First, the quantitative aspect, defined as the value or weight of knowledge possession [15]. It refers to a numeric value assigned to the node that represents the concept. Second, the qualitative aspect, defined as a state that refers to a discrete value where the knowledge possession can be [15].
- **Skills:** A skill is a cognitive process that interacts with one or more concepts, usually through an application. It has a particular purpose and produces an internal or external result [13,17].
- **Relationships:** Relationships are known as links. The relationships goal is to know how the concepts are related [1,6,13–15,17,24].
  Relationships can be of three types according to the link direction: (1) Unidirectional: A relation of a concept A to a concept B [10,14,18,21]; (2) Bidirectional: A relation of a concept A to a concept B and vice versa [18,21]; (3) Loops: A relation with a concept itself maybe through other concepts. [18,25].
- **Inference:** It is also called reasoning. The inference refers to obtain deductions or conclusions based on knowledge already established [5]. The main types of inference are [18]:
  - Abductive: It consists in finding the state of the world (configuration) that is the most probable given the evidence [11].
  - Deductive: It refers to predicting an effect given cause. Thus, we can get responses about the consequences of a given cause, but we cannot answer why results are produced [25]. Beginning from the general to the particular [6].
  - Analogy and inductive: They are important but they are not used in ITS. So, we do not give attention to this kind of inference.
- **Type of Knowledge:** There are two types of knowledge [10,13,26]: (1) Procedural Knowledge focuses on tasks that must be performed to reach a particular objective or goal. It is knowledge about "how to do something"; (2) Declarative knowledge refers to the representation of objects and events, knowledge about facts and relationships. It is the knowledge about "that something is true or false". All declarative knowledge are explicit knowledge.
  Declarative knowledge is applied in educational institutions. It is easy to represent and structure, so it is the kind of knowledge that is taught by computer-aided systems.
- **Hierarchical Structure:** Information for this kind of techniques is organized through a hierarchical structure to form superclasses and subclasses and to share properties [16].

Based on the hierarchical structure, some elements are derived, which are considered by different authors as important because they establish a structure in order to maintain the contents [1,15,17]. These elements are:

- Successors y predecessors: Successors concepts are knowledge elements that are considered after the current [15]. This means the current concept is the basis for learning the next idea. The predecessors concepts are considered as previous elements needed to understand the current. It is relevant prior knowledge acquired because establishes the basis for the next one [12,15,17].
- Categories: The categorization is a process through which the object is located within a class or category, involving attribution of meaning [20].
- Inheritance: It is a reasoning system that deduces properties of a concept based on the concepts properties higher in the hierarchy [27].

3 Comparison Between Knowledge Representation Approaches

This section exposes a comparative analysis of the different methods through tables, and analyzes the elements defined in the previous section. Tables referenced below consider the same symbology. The first column shows the name of the approaches discussed, while remaining columns show the elements of knowledge that are being evaluated. The x expresses those elements considered in the articles studied, while c corresponds to those elements not found in the study. However the approach could support it, if required.

Concepts and Attributes: In contrast to other techniques such as ontologies, the analyzed approaches shown in Table 1 only consider concept attributes concerning the quantifiable value or qualitative state. Regarding the first, techniques such as Bayesian Networks, Fuzzy Cognitive Maps or Maps of Knowledge consider the quantitative aspect to define a degree or probability of knowledge possession. Second, the state attribute, considers a discrete aspect about the knowledge possession, this means, knowledge can be classified in states such as excellent, very good, good, regular, undesirable, or just approved or not approved.

These attributes add extra value to the knowledge representation considering the domain uncertainty. A Bayesian Network considers the quantitative aspect to model the knowledge domain; however, the analyzed studies did not contemplate the qualitative aspect that could be easily represented. The Bayesian Causal Maps did not consider neither the quantitative value nor qualitative state, according to the analyzed articles. At last, Fuzzy Cognitive Maps and Knowledge Maps consider both quantitative and qualitative aspects.

Relationships: The Relationships contemplated in each approach vary considerably according to the author's need. Table 1 shows eight different types. The column that indicates the relation shows those structure that can define their own relations. Methods such as Concepts Maps, Conceptual Graphs, Semantic

Table 1. Relationships comparative

		attributes			Kind of relation								Relationships direction		
Approach	Concepts	Value	State	Relationships	Causal	Is a	Part of	Kind of	Dependency	Prerrequisite	Aggregation	Define relation	Unidirectional	Bidirectional	Loops
Concepts Maps	x			x					x		x	c	c		
Bayesian Network	x	x	c	x	x					x			x		
Bayesian Causal Maps	x	c	c	x	x				x		x		c		x
Fuzzy Cognitive Maps	x	x	x	x	x					x			x		
Graphs	x			x			x		x			c	c		
Knowledge Maps	x	x	x	x			x						x		
Semantic Networks	x			x			x	x			x	c	x	c	c
Memory Maps	x			x								x	x		

network, and Memory Maps show great flexibility to represent the knowledge domain because they can describe their relation.

Relationships direction can be of three types such as unidirectional, bidirectional, and loops. Each approach can handle at least the unidirectional relation; these relations are the most used. A Semantic Network is the unique capable of handle connections in both directions and loops. Bayesian Causal Maps have the ability to control loops, an aspect that a simple Bayesian Network cannot do by definition.

Inference and type of knowledge: Table 2 shows information about the type of inference of each approach, and the type of knowledge that can represent. The kind of knowledge is related to the quantitative information that can be stored in the domain representation. So, Bayesian Networks, Bayesian Causal Maps and Fuzzy Cognitive Maps use the previous advantage by nature of their theories. These theories have the possibility of the abductive and deductive inference. Memory Maps are able to perform deductive inference though it was not required in the analyzed studies. Regarding to kind of knowledge, all approaches are focused in representing the declarative knowledge since this is the type of knowledge that represent the ITS.

Hierarchical Structure: All the approaches use concepts and relations; therefore, they have a similar graphic representation based in a hierarchical structure: (1) Concepts are derived from this representation such as successors and predecessors to keep an order in the learning of concepts; (2) hierarchy is used to organize knowledge in a tree structure; (3) categorization is used to group concepts with similarity; finally, (4) inheritance is used to acquire properties from the parents. All elements can be represented in the approaches, explicitly or implicitly. It depends on what the authors want to represent. Memory Maps represents explicitly each factor considered in this study (Table 2).

4 Approaches Analysis

According to Davis [5], knowledge representation approaches are a substitution of the reality, the only entirely accurate representation of an object is the object itself. All other representations are inaccurate; they inevitably contain simplifying assumptions. Each representation approach provides its own vision of how the world should be; furthermore, they define which aspects are important to represent and which to ignore. Different conceptions of intelligent reasoning nature lead to different goals and different definitions of success. A language designed to express facts declaratively is not necessarily useful to express the imperative information characteristic of a reasoning strategy.

Taking into account the previous paragraphs, the best approach to represent knowledge is given by the problem to be solved and the objectives. So, each method has advantages and disadvantages to model knowledge domains. Nevertheless, the techniques analyzed share the ability to represent knowledge through concepts and relations, forming a hierarchical structure with advantages entailed.

Concepts Maps and Conceptual Graphs have, among other advantages, the capacity to represent the type of relation between concepts as the author wants. This fact has not been as well studied as the first two; however its foundation promises great scope.

Semantic Networks can be seen as ontologies having a great capacity of knowledge representation. Ontologies have a high flexibility to represent information due to their great expressiveness to model the world. This kind of semantic network has the Web Ontology Language (OWL) standard, created by the World Wide Web Consortium (W3C). Among all the techniques mentioned in this paper, ontologies are considered the best technique when there is not need to model uncertainty. Its main disadvantage is not take the quantitative aspects of the world.

Table 2. Inference, knowledge, and structure comparative

	Inference				Knowledge		Hierarchical Structure				
Approach	Abductive	Deductive	Analogy	Inductive	Declarative	Procedural	Successors	Predecessors	Hierarchy	Category	Inheritance
Concepts Maps		c			c		c	x	c	x	c
Bayesian Network	x	x			c		c	c	c	x	c
Bayesian Causal Maps	x	x			c		c	x	c	c	c
Fuzzy Cognitive Maps	x	x			c		c	c	x	c	c
Graphs		c			c		c	c	c	c	c
Knowledge Maps		c			c		x	x	x	c	c
Semantic Networks		c			c		c	c	x	c	x
Memory Maps		c			x		x	x	x	x	x

Knowledge Maps argue good principles, even considering weights on concepts to model knowledge. However, they are not among the commonly used techniques to represent knowledge. Authors of this approach do not argue the practical use of the weights or the type of inference we can make with them.

Bayesian Networks are a technique of approximate reasoning to model the world without much semantic expressiveness, which is the main disadvantage. They were developed to resolve domains that manage uncertainty. Besides, another advantage is the abductive and deductive inference that can be achieved with its representation. Bayesian Causal Maps have arisen to give greater semantic flexibility to the original Bayesian Networks [25]. One of the major contributions of Bayesian Causal Maps are the handle of loops; not considered by the Bayesian Networks in their theory.

Finally, Fuzzy Cognitive Maps merge advantages of both, Cognitive Maps and Fuzzy Logic. This method, same as Bayesian Networks, allows to model domains with uncertainty through causal relationships. Besides, Fuzzy Logic includes abductive and deductive inference capacity. In contrast to Bayesian Causal Maps, it has been quite used in literature for different areas [7].

Table 3 displays the most significant advantage for each approach, and its main disadvantage. Even though, some techniques are emerging, they have a promising future. Other methods are well established in the literature; however, there are missing elements to represent certain domains.

Table 3. Main advantages and disadvantages of the approaches

Approach	Advantage	Disadvantage
Concepts maps	Definition of relations	Need for more efficient inference
Bayesian network	Abductive and deductive inference	Limited semantic representation
Bayesian causal maps	Abductive and deductive inference	New approach and little used
Fuzzy cognitive maps	Abductive and deductive inference	Limited availability of support tools
Graphs	Definition of relations	Need for more efficient inference
Knowledge maps	Quantitative and qualitative aspects to represent the domain	Need for more efficient inference
Semantic networks	High semantic expressivity	No handling uncertainty
Memory maps	Adequate semantic expressivity	New approach and little used

5 Representing a Bayesian Network with the Taxonomy

In order to show how to represent knowledge with a Bayesian Network, in this section we present an example of a specific domain in the field of Software Engineering. The Figure 2 displays a first chapter of the Personal Software Process (PSP) book [9], a course being taught to freshmen in computer engineering. A Bayesian Network was generated to express structured knowledge of PSP. The network includes variables (concepts), relation, and probabilistic values [19]. The network represents several aspects of the taxonomy:

1. Successors and predecessors: In relationship *Measure*-*Quality*, the variable *Measure* is a predecessor to *Quality* and *Quality* is a successor of *Measure*.
2. Categories and inheritance: In relation *Improvement_process* and *Measure* with *Quality*, the variable *Quality* is a category of *Improvement_process* and *Measure*. *Quality* includes and takes attributes from *Improvement_process* and *Measure* (inheritance).
3. Declarative knowledge: It is Knowledge easy to represent and structure. The knowledge represented by ITS.
4. Abductive and deductive inference: The algorithms of Bayesian Networks, combined with probabilistic values, give the possibility to do inference. For instance, does the student know the concept Quality? Taking into account that he/she knows the concept Measure. Does the student knows the concept Measure? Taking into account that he/she knows the concept Quality.
5. The direction of relationship: The relation is *unidirectional*, the arrow starts in a variable and finishes in other always with one direction.
6. Type of relationship: The relationship is *Causal*, this kind of relation gives the possibility of inference. A cause has an effect and an effect has a cause.
7. Attributes of concept value and state: The numeric values are represented by *Value* and the *State* is represented by two variables, present and absent. Present means knowledge possession and absent means the opposite.

With this representation we can manage the content of a course inside an ITS, furthermore, we can make inferences about if the student has or not a knowledge.

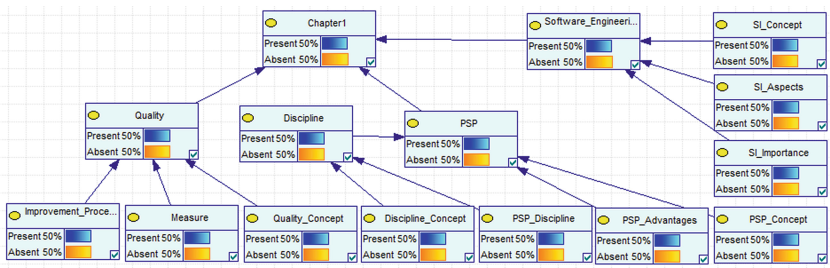

Fig. 2. Knowledge representation about PSP topic

6 Conclusions

This study collected approaches to represent knowledge in computer-aided teaching systems. All approaches are based on concepts with their relations to form a hierarchical structure. Each approach faces a particular problem according to the domain, showing its advantages and disadvantages to confront that problem.

Techniques such as Concepts Maps, Conceptual Graphs, Memory Maps, and Semantic Networks are useful when semantic expressiveness is needed to model a domain, and not to deal with advanced reasoning. Ontologies stand out as Semantic Networks because they have a standard controlled by W3C. Besides, these are an important part of the development of the Semantic Web. Ontologies allow to show high semantic expressiveness to represent the domain accurately and use of ontological reasoning.

Bayesian Network, Bayesian Causal Maps, Fuzzy Cognitive Maps, and Knowledge Maps represent the best choice when do not wish to express the domain in great detail. Instead, prefers high degree of reasoning to make inferences that allow controlling uncertainty and other quantitative aspects.

For future work, a simple algorithm can make recommendations with the information obtained in this study, to adapt the user needs to represent knowledge. This can be done through the taxonomy, using the leaf nodes of the hierarchy. The taxonomy can be converted in a network, where all nodes converge in a central node. Central node gives us probabilities about what is the approach (KR) that we need to use.

Besides, it is necessary to find other knowledge representation techniques that allow to extend the options of recommendation. Finally, we will develop an ontology of the knowledge representation in ITS.

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