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Reasoning Methodologies for Intelligent e-Learning Systems

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Abstract

Intelligent e-Learning systems (IeLSs) are knowledge-based systems and developed on the basis of the knowledge engineering and artificial intelligence (AI) theories, methodologies and concepts. Many types of IeLSs are in existence today and are applies to different domains and tasks, e.g., healthcare, government, commerce, and education. To a limited degree, AI technology permits the IeLS to accept knowledge from human input, and then use that knowledge through simulated thought and reasoning processes to solve problems. The field of reasoning methodologies is very important for the development of IeLSs software. Recently, these methodologies receive increasing attention within the development of a new generation of e-Learning community. This paper aims in shedding some lights into three of the reasoning methodologies, namely; reasoning with production rules, fuzzy-rules, and case-based reasoning. In addition, the paper addresses the technical problems and challenges in the designing process of the intelligent e-Learning systems. Our analysis shows that the combination of such techniques enabling the design of a robust IeLSs.

Keywords: Production rules, Fuzzy-rules, a Case-based reasoning, intelligent information systems, intelligent e-Learning, Artificial intelligence.

Introduction

The field of artificial intelligence (AI) in education has become the most challenging area in the last several years. It includes the disciplines; cognitive and social psychology, computer science, empirical psychology, software and knowledge engineering [4].The goal of the field is to deliver computer-based systems (or knowledge-based software) which can be used in real teaching, learning and training situations. Using AI concepts and techniques new forms of intelligent e-learning/tutoring software can be created that allow the computer to act as an intelligent learner/ tutor. Such AI-based intelligent system can adjust its tutorial to the student's knowledge, experience, strengths, and weaknesses. It may even be able to carry on a natural language dialogue.

Intelligent e-Learning systems (IeLSs) are knowledge-based systems that imitate the human mind. The developing of these systems is based on many disciplines, e.g., machine learning, knowledge engineering, artificial intelligence, virtual reality, cybernetics, cognitive science, neurosciences, computer science, psychology, mathematics, biology, linguistics and engineering [1,3,5].The main characteristics of these systems are the ability of inference, reasoning, perception, learning, and knowledge-based systems. AI is the backbone of the IeLSs.AI gives IeLS added computing capability, allowing them to exhibit more intelligent behavior. To a limited degree, AI permits IeLS to accept knowledge from human input, and then use that knowledge through simulated thought and reasoning processes to solve problems. The research area in this field covers a variety of reasoning methodologies, e.g.; automated reasoning, case-based reasoning, commonsense reasoning, fuzzy reasoning, geometric reasoning, non-monotonic reasoning, model-based reasoning, probabilistic reasoning, causal reasoning, qualitative reasoning, spatial reasoning and temporal reasoning [6, 10, 13]. In this paper we focus our discussion around three of the reasoning methodologies, namely; reasoning with production rules, fuzzy-rules, and case-based reasoning. It also addresses the technical problems and challenges in the designing process of the intelligent e-Learning systems.

The objective of this paper is two-fold. First, to explore the advantages and disadvantages of some of the AI reasoning techniques which are recently used in developing the intelligent e-learning systems .Second, to investigate the difficulties and challenges in the designing process of such systems. In sections 2, 3, and 4 we provide an overview of reasoning approaches with production, fuzzy rules and cases respectively. In section 5, we provide an overview of technical features of intelligent e-Learning systems. Challenges in the designing process of the intelligent e-Learning systems are discussed in section 6.The paper is concluded in section 7.

Reasoning with Production Rules

Rules are easily manipulated by reasoning systems. Forward chaining can be used to produce new facts (hence the term “production” rules), and backward chaining can deduce whether statements are true or not. Rule-based systems were one of the first large-scale commercial successes of artificial intelligence research. An expert system or knowledge-based system is the common term used to describe a rule-based processing system. It consists of three major elements, a knowledge base (the set of if-then rules and known facts), a working memory or database of derived facts and data, and an inference engine, which contains the reasoning logic used to process the rules and data [4].

Rule-based systems solve problems by taking an input specification and then “chaining” together the appropriate set of rules from the rule base to arrive at a solution. Given the same exact problem situation, the system will go through exactly the same amount of work to come up with the solution. In other words rule-based systems don’t inherently learn. In addition, given a problem that is outside the system’s original scope, the system often can’t render any assistance. Finally, rule-based systems are very time-consuming to build and maintain because rule extraction from experts is labor-intensive and rules are inherently dependent on other rules, making the addition of new knowledge to the system a complex debugging task.

Forward chaining is a data-driven reasoning process where a set of rules is used to drive new facts from an initial set of data. It does not use the resolution algorithm used in predicate logic. The forward-chaining algorithm generates new data by the simple and straightforward application or firing of the rules. As a differencing procedure, forward chaining is very fast. Forward chaining is also used in real-time monitoring and diagnostic systems where quick identification and response to problems are required.

Backward chaining is often called goal-directed differencing, because a particular consequence or goal clause is evaluated first, and then we go backward through the rules. Unlike forward chaining, which uses-rules to produce new information, backward chaining uses rules to answer questions about whether a goal clause is true or not. Backward chaining is more focused than forward chaining, because it only processes rules that are relevant to the question. It is similar to how resolution is used in predicate logic. However, it does not use contradiction. It simply traverses the rule base trying to prove that clauses are true in a systematic manner. Backward chaining is used for advisory systems, where users ask questions and get asked leading questions to find an answer. A famous early expert system, Mycin, used backward chaining to perform diagnoses of bacterial infections in medical patients. One advantage of backward chaining is that, because the differencing is directed, information can be requested from the user when it is needed. Some reasoning systems also provide a trace capability which allows the user to ask the inference engine why it asking for some piece of information, or why it came to some conclusion.

Reasoning with Fuzzy Rules

In the rich history of rule-based reasoning in AI, the inference engines almost without exception were based on Boolean or binary logic. However, in the same way that neural networks have enriched the AI landscape by providing an alternative to symbol processing techniques, fuzzy logic has provided an alternative to Boolean logic-based systems [13]. Unlike Boolean logic, which has only two states, true or false, fuzzy logic deals with truth values which range continuously from 0 to 1. Thus something could be half true 0.5 or very likely true 0.9 or probably not true 0.1. The use of fuzzy logic in reasoning systems impacts not only the inference engine but the knowledge representation itself [13]. For, instead of making arbitrary distinctions between variables and states, as is required with Boolean logic systems, fuzzy logic allows one to express knowledge in a rule format that is close to a natural language expression. For example, we could say If temperature is hot and humidity is sticky then fan speed is high .

Example 1 (Fuzzy Rules):

IF	**the interest-rate outlook is down,**
THEN	**do not buy money-market funds**

Example 2 (Rules-of-Thumb):

An apple a day keeps the doctor away.

A stitch in time saves nine

Example 3 (Fuzzy Rules):

IF	**you're old,**
THEN	**you have owned several homes.**

Example 4 (Rules with certainty factors):

IF	**The patient is sneezing,**
AND	**Has a runny nose,**
AND	**Has watery eyes,**
THEN	**The patient has a cold, CF = 0.5**

Example 5 (Sea Creature Rule):

IF	**The creature has a backbone**
AND	**The creature has a vertical fin**
AND	**The creature breathes through gills**
THEN	**The creature is a fish**

The PROLOG code of Sea Creature Rule

Figure 1: Some Examples

The difference between this fuzzy rule and the Boolean-logic rules we used in our forward- and backward-chaining examples is that the clauses “temperature is hot” and “humidity is sticky” are not strictly true or false. Clauses in fuzzy rules are real-valued functions called membership functions that map the fuzzy set “hot” onto the domain of the fuzzy variable “temperature” and produce a truth-value that ranges from 0.0 to 1.0 (a continuous output value, much like neural networks).

Reasoning with fuzzy rule systems is a forward-chaining procedure. The initial numeric data values are fuzzified, that is, turned into fuzzy values using the membership functions. Instead of a match and conflict resolution phase where we select a triggered rule to fire, in fuzzy systems, all rules are evaluated, because all fuzzy rules can be true to some degree (ranging from 0.0 to 1.0). The antecedent clause truth values are combined using fuzzy logic operators (a fuzzy conjunction or and operation takes the minimum value of the two fuzzy clauses). Next, the fuzzy sets specified in the consequent clauses of all rules are combined, using the rule truth values as scaling factors. The result is a single fuzzy set, which is then defuzzified to return a crisp output value

Reasoning with Cases

The case is a list of features that lead to a particular outcome. (e.g. The information on a patient history and the associated diagnosis). The complex case is a connected set of subcases that form the problem solving task’s structure (e.g. the design of an airplane). Determining the appropriate case features is the main knowledge engineering task in case-based AI software. This task involves defining the terminology of the domain and gathering representative cases of problem solving by the expert representation of cased can be in any of several forms (predicate, frames).

The idea of case-based reasoning is becoming popular in developing knowledge-based systems because it automates applications that are based on precedent or that contain incomplete causal models [6]. In rule-based systems an incomplete mode or an environment which does not take into account all variables could result in either an answer built on incomplete data or simply no answer at all. Case-based methodology attempt to get around this shortcoming by inputting and analyzing problem data.

Patient: 65-years old female not working, with nausea and vomiting.

Medical History: cancer head of pancreas

Physical Exam: tender hepatomegaly liver, large amount of inflammatory about 3 liters, multiple liver pyogenic abscesses and large pancreatic head mass.

Figure 2: Example of a “ liver cancer case” description”

Research reveals that students learn best when they are presented with examples (cases) of problem-solving knowledge and are then required applying the knowledge to real situations. The case-base of examples and exercises capture realistic problem-solving situations and presents them to the students as virtual simulations, each example/exercise includes:

i) A multi-media description of the problem, which may evolve over time,

ii) A description of the correct actions to take including order-independent, optional, and alternative steps;

iii) A multi-media explanation of why these steps are correct;
iv) The list of methods to determine whether students correctly executed the steps;
v) The list of principles that must be learned to take the correct action.

Table (1) shows a comparison between case-based and rule-based reasoning methodologies .From this table, it can be seen that, case-based reasoning methodology directly addresses the problems found in rule-based approach.

Argument	Case-based	Rule-based
Knowledge source	Experience	Knowledge engineer.
The basic unit of knowledge.	Case	Rule
Knowledge acquisition.	By assimilating new cases either first hand or through reports from others.	By adding new rules through knowledge engineer.(knowledge acquisition bottleneck).
Remembering	Can remember its own experience	Can't remember its experience
Learning	Can learn from his/her mistakes	Can't learn
Reasoning	Can reason by analogy	Can't reason by analogy.

Table (1) A Comparison between CBR and Rule Based

Technical Features of Intelligent e-Learning Systems

Based on the previous discussion, one can concluded that, intelligent e-Learning system is a knowledge-based system (not data-base system) .This system permits the knowledge and experience of one or more experts to be captured and stored in a computer. This knowledge can then be used by anyone requiring it in a specific domain and task. The main stage in developing IeLS for any specific task is to build a “knowledge base” in that domain of interest. The knowledge of that domain must be collected, codified, organized and arranged in a systematic order. The process of collecting and organizing the knowledge is called knowledge engineering. It is the most difficult and time-consuming stage of any IeLS development process. Although a variety of knowledge representation techniques [8] (e.g. logic, lists, trees, semantic networks, frames, scripts ,ontology , production rules and cases) have been developed over the years, these techniques share two common characteristics. First, they can be programmed with certain computer languages and tools. Second, they are designed so that the facts and other knowledge contained within them can be manipulated by an “inference system”, the other major part of an IeLS. The inference system uses search and pattern matching techniques on the knowledge base to answer questions, draw conclusions, or otherwise perform an intelligent function.

An intelligent e-Learning system consists of three major components: a knowledge base, an inference engine, and a user interface. The knowledge base contains all the facts, ideas, relationships, and interactions of a narrow domain. The inference engine analyzes the knowledge and draws conclusions from it. The user interface software permits new knowledge to be entered into the knowledge base and implements communication with the user. The purpose of the system is not to replace the experts, but simply to make their knowledge and experience more widely available. Typically there are more problems to solve than there are experts available to handle them.The system permits others to increase their productivity, improve the quality of their decisions, or simply to solve problems when as expert is not available.

(a) Rule-based e-learning systems

The general structure of the rule-based e-Learning system (RBeLS) is composed of three main software components, namely; the knowledge base, inference mechanism and user interface. The knowledge base and inference engine are analogous to the knowledge stored in memory and the reasoning capabilities of the human experts that the system is emulating. The inference engine contains a set of formal logic relationships which may or may not resemble the way that real human expert reach conclusions. The knowledge base is structured in a if-then organization. The rules have to be defined in a limited number of formal ways. Typically they may be a set of some hundreds of if-then (or if A and B but not C then D) types of relationships that describe all the domain specific knowledge used by the human expert. The most difficult and time consuming part of the developing a RBeLS is the extraction of knowledge form the head of an acknowledged expert (or a group of experts) and then transforming it into a form acceptable to the system’s knowledge based structure.

RBeLS solves problems by taking an input specification and then “chaining” together the appropriate set of rules from the rule base to arrive at a solution. Given the same exact problem situation, the system will go through exactly the same amount of work to come up with the solution. In other words RBeLSs don’t inherently learn. In addition, given a problem that is outside the result-based system's original scope, the system often can't render any assistance. Finally, RBeLSs are very time-consuming to build and maintain because rule extraction from experts is labor-intensive and rules are inherently dependent on other rules, making the addition of new knowledge to the system a complex debugging task.

(b) Case-based e-learning systems

The methodology of case-based reasoning is becoming popular in developing case-based e-Learning systems (CBReLSs) because it automates applications that are based on precedent or that contain incomplete causal models [2, 11.12]. In a RBeLS an incomplete mode or an environment which does not take into account all variables could result in either an answer built on incomplete data or simply no answer at all. Case-based methodologies attempt to get around this shortcoming by inputting and analyzing problem data, then retrieving a similar case from the case memory library, and finally displaying a solution based on examination of these previous cases.

The CBReLS uses an extensive case-based of exercises and examples to teach students. The CBReLSs solve new problems by adapting solutions that were used for previous and similar problems. The methodology of CBReLSs can be summarized in the following steps:

1. The system will search its case-memory for an existing case that matches the input problem specification.
2. If we are lucky (our luck increases as we add new cases to the system), we will find a case that exactly matches the input problem and goes directly to a solution.
3. If we are not luck, we will retrieve a case that is similar to our input situation but not entirely
   appropriate to provide as a completed solution.
4. The system must find and modify small portions of the retrieved case that do not meet the input specification. This process is called "case-adaptation".
5. The result of case adaptation process is (a) completed solution, and (b) generates a new case that can be automatically added to the system's case-memory for future use.

Challenges

The development of intellectual e-Learning systems is a very difficult and complex process that raises a lot of technological and research challenges that have to be addressed in an interdisciplinary way. The IeLSs face the following difficulties and challenges

1-The knowledge-acquisition difficulties: Valuable knowledge is a major resource and it often lies with only a few experts. It is important to capture that knowledge so others can use it. Experts die, retire, get sick, move on to other fields, and otherwise become unavailable. Thus the knowledge is lost. Books can capture some knowledge, but they leave the problem of application up to the reader. Expert systems provide a direct means of applying expertise. Case-Based reasoning addresses this problem, where it is easier to articulate, examine, and evaluate cases than rules.

2- Maintenance difficulties: Intelligent e-Learning system is complex to build and complex to maintain. CBR addresses this problem too ,where maintaining case-based eLearning system is easier than rule-based e-Learning system since adding new knowledge can be as simple as adding a new case.

3- Performance Experience: Productivity of IeLSs development is determined by the efficiency of their knowledge representation techniques and reasoning methodologies. A case-based e-Learning system can remember its own performance, and can modify its behavior to avoid repeating prior mistakes. By reasoning from analogy with past cases, a CBR system should be able to construct solutions to novel problems.

Conclusions and Future Work

The field of reasoning is very important for the development of IeLSs software. The research area in this field covers a variety of reasoning methodologies. In fact these methodologies receive increasing attention within the development of a new generation of e-Learning community. This paper aims in shedding some lights into three of the reasoning methodologies, namely; reasoning with production rules, fuzzy-rules, and case-based reasoning. The combination of such techniques enabling the design of a robust IeLSs. In addition, the paper addresses the technical problems and challenges in the designing of the IeLSs. The case-based reasoning methodology addresses the problems found in rule-based approach.

On the other side, the convergence of artificial intelligence, machine learning, educational technology and web science is enabling the creation of web-based intelligent e-learning systems. Such systems will provide a unique opportunity to distribute learning/education /training across multiple sites while dramatically reducing travel related costs. So, future work is planned for developing IeLSs include the distributed artificial intelligence methodology. Through this methodology, the IeLS is presented as an open information system.

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