FUZZY LOGIC APPLICATIONS TO STUDENTS’ EVALUATION IN INTELLIGENT LEARNING SYSTEMS

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Abstract. Intelligent Learning Systems (ILS) require more general evaluations directed to many different qualitative and quantitative purposes. The paper states the minimum evaluation objectives in today’s ILS implemented on sophisticated multi-agent architectures. The paper also describes part of an ILS containing several fuzzy techniques to perform students’ evaluations related to different purposes. The methods and techniques have been used in TUTOR3 and in other previous ITS. The results show that the techniques are valuable not only to get a deeper understanding of the learning process, but also to enhance collaborative learning of groups of students in different environments.

Keywords: Student Evaluation, Fuzzy Logic, Intelligent Learning Systems, Intelligent Tutoring Systems.

1. Introduction

1.1 The students’ evaluation problem

The problem of the students’ evaluation has always been a question of major concern in Academic Institutions due to its inherent difficulties. These difficulties are associated to the understanding of the students’ learning process. Learning is a mental process of change and its assessment is known as evaluation.

The main features of evaluation are:
1) Its purpose, and the way it serves to that purpose. Due to the fact that there is no way of reflecting in an absolute way the human changes produced by learning, evaluation has always to be designed for specific purposes. The evaluation objectives can be varied and
very different; the levels of accomplishment of those objectives can be assessed qualitative or quantitatively.

As an example, the purpose of the evaluation in traditional education and regular exams has been only to check the knowledge and abilities acquired by the student and establish a linear ordering of the students related to the overall knowledge gained by the students during the course.

2) Its design, including in the first place the learning effects to be measured and how are they going to be measured.

3) Its implementation, trying to avoid the presence of spurious variables and external effects that could influence the student's mental state or his reactions that have to be measured in the evaluation process. In that line of thinking, traditional student's evaluations, conceived as exams, provide stress concentrations on the students which could sensibly alter the results of the evaluation process.

In recent years there has been some attempts to improve classical evaluation procedures by including fuzzy logic techniques. Biswas [2] presented a fuzzy evaluation method for the application of fuzzy sets in students' answerscripts evaluation. In the same paper he generalizes his proposal by adopting a fuzzy matrix-valued marking. However, this approach has several drawbacks: because he uses a matching function $S$ to measure the degrees of similarity between the standard fuzzy sets and the fuzzy marks, it takes a considerable amount of time to perform the matching operations. Besides, two different fuzzy marks may be translated into the same awarded grade and this seems not very fair.

Chen and Lee [4] have also presented two fuzzy methods overcoming Biswas's drawbacks. However, when we are dealing with Intelligent Tutoring Systems or Intelligent Learning Systems we have to face more complex evaluation objectives, as we will see later on, and the above mentioned methods are not appropriate.

De Arriaga et al. [6] have proposed two fuzzy evaluation methods to initially assess and update permanently the student learning style, which is an important feature of the student behavior model. In the first method the student learning style is represented by a discrete fuzzy set, defining the possibilities of each basic learning style for that particular student; in the second method a fuzzy set is built to describe for each student and each basic type of learning a fuzzy set. Both methods use the student answers during the learning process to update those fuzzy sets.

### 1.2 The evolution of Intelligent Learning Systems (ILS)

During the last years the analysis and design of Intelligent Tutoring Systems (ITS) has suffered important changes caused by new impacts of Artificial Intelligence and Information and Communication Technologies in general. The incorporation of Multi-Agent Architectures in the beginnings of the 90’s improved a great deal the ITS capabilities allowing the cooperation of optics, models and ideas from Cognitive Psychology and other disciplines for the development of virtual laboratories.

On the other hand, in the field of educational sciences, new approaches to learning, known as student centered education [5],[7],[8], have set up new methods and techniques for education based on active, collaborative and cooperative learning environments. The incorporation of those approaches to ITS has produced a new generation of intelligent systems, called ILS, in which the emphasis is put on learning more than on teaching. The tutorial functions in ILS are focussed on coaching, motivating, giving advice and evaluating the student behavior.

Among the many contributions to the subject, we would like to cite the work by Vassileva et al. [13] who have built a distributed and collaborative multi-agent help environment where it is possible to get human resources according to request. Canut, Gouraderes and Sanchis [3] use a novel agent model with mobility, autonomy and intelligence for its ITS design. El Alami, de Arriaga and Ugena [9] presented also a specific intelligent agent composed by
state and control modules, three layers (reactive, tactic and strategic) for the specific knowledge needed by the agent to execute its task, planning and learning capabilities, as well as communication and collaborative functionalities including natural language understanding. Laureano and de Arriaga [11], [12] have proposed a reactive multi-agent architecture without a detailed student model and planning capabilities, useful for coaching purposes.

2. Evaluation objectives in ILS

The student overall behavior, represented by his answers, solutions to the problems and decision making, is the only input to the system for its guidance and functioning. In consequence, the student’ evaluation has to be used for the most important decisions of the system, which obviously depend on the capabilities of the system.

In general, the most important evaluation objectives are:

1)-in relationship to the student model:
- Obtain and update the student learning style. According to Honey and Alonso [1] there are four basic learning styles: theoretical, reflexive, pragmatic and active. The four of them are adequate for specific purposes although each student uses one of the four learning styles more often because he feels more comfortable with it. This objective attempts to initially obtain the student learning style not only to personalize the learning process according to his mentality, but also to improve the use of the remainder learning styles. The evaluation has to give information of the changes introduced into the learning style.
- Update the history of the student learning process. Often the student history has been structured into components, as, for example: number of student learning sessions, hours frequency of the sessions, sessions duration, number of errors and type of error for each session, number of exercises and types in each session, etc.
- Update the student conceptual graph. The student model includes a conceptual graph of the learning domain, detailing the graph nodes (concepts, properties, procedures, etc…) acquired and mastered by the student as well as the remainder nodes not yet acquired.
- Obtain regularly the student cognitive components of the ability to be learnt, as they are acquired by the student. BCTA (Behavioral-Cognitive Task Analysis) is a methodology based on the knowledge elicitation techniques [10], that allows the decomposition of the ability to be learnt or the problem to be solved, into its cognitive components considering three levels of execution of the ability: familiarization, normal execution and expert execution. The obtained cognitive components can be classified into: facts, declarative knowledge (concepts, relationships, properties), procedures, strategies and mental models. By following some of the steps of this methodology, the system is able to obtain the student cognitive components acquired.
- Obtain the strategies followed by the student in the solution of the problems, inferred from the student solution path. The evaluation has to have suitable models for that inference.
- Update the potential basic conceptual learning abilities acquired by the student and present in the student model. First, we have to consider which of those basic conceptual learning abilities are relevant to the task or ability to be learnt. Usually the basic conceptual abilities, such as: geometrical reasoning, arithmetic reasoning, spatial vision, linguistic reasoning, analogue reasoning,…are too elementary to be considered as cognitive components in previous objectives included above.

2)-in relationship to the expert module or to the agents in charge of the different aspects of the human expert domain:
- Determination of the student errors as difference between the expert and student behaviors and the elementary analysis of those errors and their shallow reasons.
- Determination of the domain graph nodes related to the errors, and the cognitive components which have not been acquired through learning.
- Determination, using also the student history, of the profound causes of error inferring which are the graph nodes to start with in the remedial tactics.

3)- in relationship to the tutor module or to the agents in charge of the different tutorial functions:
- The arbitration or control of the different agents wishing to act at the same moment along the learning process.
- The suitable intervention of the agent in charge of the functions of General Dydactics. This agent monitors the general learning aspects and situations of the student mental state such as: motivation, interest, tiredness, fatigue, etc. This agent can even suggest the interruption or closing of the learning session when some negative aspects are present.
- The intervention of the tutors in charge of the domain micro-worlds to possibly notify the errors to the student and propose different remedial actions. In the case when the student is advancing quite well along the learning process without significant errors, the tutors could propose pro-actions in order to improve or accelerate the learning process.
- The determination of the final or global student’ evaluation and the linear ordering of the group of students.

4)- in relationship to the interface:
- The personalization of the whole interface or part of it (some of its windows) in order to adapt the interchange of information between the student and the system to the student learning style and the particular student mental state.

3. TUTOR3: A CONCRETE EXAMPLE OF ILS

TUTOR is a long-term effort devoted to study several problems arising in actual implementations of ILS when they include detailed cognitive modelling of the human expert and the student. The actual version TUTOR3 includes so far several fuzzy evaluation techniques for different purposes, that are:
- initial determination and permanent updating of the student’s learning style;
- permanent determination of the student cognitive components of the ability to be learnt;
- overall student’s evaluation (final) and linear order of the students group.

3.1 Methodology and fuzzy logic techniques

a) evaluation of the learning style. Several procedures have been designed to deal with this problem; probably the most interesting from the point of view of the obtained results is the following leading to the construction of a fuzzy set for each student and for each basic learning style according to the steps:
- The initial questionnaire for the initial student’s learning style (and also the following ones used for control or evaluation purposes) is treated previously, before using it, in order to adjoin a fuzzy set to each item in the questionnaire. This fuzzy set qualifies the item in terms of the basic learning styles; so, for example, item 1.12 could be described as:

\[ F(1.12) = 0.75/\text{theoretic.} + 0.9/\text{reflexive} + 0.3/\text{pragmatic} + 0.2/\text{active} \]

meaning that the intensity level of the basic learning styles (theoretical, reflexive, pragmatic and active) needed to solve or answer correctly item 1.12 is, respectively, \((0.75, 0.9, 0.3, 0.2)\).

- The student’s answers are also expressed in the same way, obtaining also a fuzzy set \(R(1.12)\) associated to each item response. So, if the student answer is completely correct, as in the case of guessing the right answer to a multiple choice question,
R(1.12) will be identical to F(1.12). If the student has to construct the answer, that answer has to be estimated in terms of the basic learning styles or, what is easier, it is estimated in terms of the regular linguistic terms: excellent, very good, good,... These linguistic terms have been previously converted into fuzzy sets, according to the nature of the item. In this case the real estimation of the student’s answer will be the fuzzy composition of two fuzzy sets: the set associated to the item and the set associated to the linguistic term. That is to say, in our example:

\[ R(1.12) = F(1.12) \ast \text{GOOD} \]

where * means the fuzzy composition of those two fuzzy sets; GOOD is the fuzzy set associated to this linguistic term.

-After estimating all the student’s responses, now we can build for this student (John) the fuzzy sets: Theoretic(John), Reflexive(John), Pragmatic(John) and Active(John), defined on the universal set \( \{0, 0.1, 0.2, \ldots, 0.9, 1\} \) as follows:

\[ \text{Theoretic}(\text{John}) = t_1/0.1 + t_2/0.2 + t_3/0.3 + \ldots + t_{10}/1 \]

The values \( t_1, t_2, t_3, \ldots, t_{10} \) are obtained only from the terms \( tx/\text{theoretic} \) existing in \( F(\text{item}) \) and \( R(\text{item}) \). The procedure will be explained by means of an example:

Suppose we want to obtain \( t_3 \) (the pertaining level of 0.3 in \( \text{Theoretic}(\text{John}) \)); we will look for all items \( F(X) \) containing the term 0.3/\text{theoretic}. For each item of those founded we will attribute to \( t_3 \) one point (1.0) when the answer is fully correct; if not, we will attribute to \( t_3 \) only a fraction of a point (according to the estimation \( R(\text{item}) \) of the student’s answer). The sum of the points attributed to \( t_3 \), divided by the number of times that 0.3 has appears in the fuzzy sets of all the items in the questionnaire is the final value for \( t_3 \).

b) Determination of the student’s cognitive components of the ability to be learnt, by means of BCTA (Behavioural-Cognitive Task Analysis) methodology [10]. After that we will follow the following steps:

-According to this decomposition, all the questions, problems and projects proposed students during the learning process and controls, are characterised by means of a fuzzy sets \( C \) on the universe of the cognitive components in a similar as we did in a) with the sets \( F(\text{item}) \).

-The student answers and solutions are also estimated, in a direct way by analysing the cognitive components of the answer, or indirectly, by using linguistic terms (excellent, very good, good...) which also have fuzzy sets associated to them. In this last case, the composition of \( C \) and the fuzzy set of the appropriate linguistic term provides the fuzzy estimation of the student’s answer in terms of the cognitive components of the ability to be learnt.

-The acquired cognitive components are estimated by fuzzy union of the estimation of the student’s response. That way we get a cognitive fuzzy graph detailing the student learning level for each cognitive component.

-A very important point of this procedure is the obtainment of the student mental models, which according to the literature are very different from those of the human expert. The student mental models are used, outside the evaluation process to try to show to the student, by means of practical questions and problems, that they are insufficient and no adequate for reasoning within the learning domain.

c) The overall student grade is obtained by two different procedures: by defuzzification of the graph using any of the standard techniques to obtain a crisp value; and by converting the fuzzy graph into an ordinary fuzzy set that can be translated linguistically to the usual qualitative levels: good, very good, bad... and so on, in order to provide standard final students’ evaluations.
4. Discussion of the obtained results

The evaluation methods above described have been implemented as part of TUTOR3. The evaluations have been used in the following contexts:
- to check if the information provided guarantees the proper functioning and arbitration of the agents in charge of the domain micro-worlds and of the General Dydactics;
- to check if the fuzzy techniques used in the evaluations give plausible results according to traditional academic experience;
- to check if student cognitive fuzzy graph conveys enough information to trigger and establish suitable tutorial tactics by the agents in charge of those tasks.

The results in all cases have been promising.

Besides, these evaluation methods have been included in MEDIC, a project for decision making learning. MEDIC uses a simulation environment to reproduce virtually a Medical Center, allowing collaborative decisions made by a team of students representing the Departments Head and General Manager. Each member of the group has also to evaluate the actions taken by the remainder members (peer-review). The system is now capable of finding the junior managers mental models; the differences of those mental models with those of the expert triggers tutorial actions to gradually reduce the found differences.

5. Conclusions and future works

The results so far obtained in TUTOR3 and MEDIC show that the described evaluation procedures allow the assessment of the cognitive components of the learning task. The use of the human expert mental models, reduces the time of the junior managers to become expert managers quite significantly (25% at least).

The obtainment of the particular learning styles for each group member allows the personalization of the interface. TUTOR3 will evolve in the near future to include all kind the evaluations according to the objectives mentioned in this paper.

References


