# Proposal of Fuzzy Logic-based Students´ Learning Assessment Model


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**Abstract.** The cognitive diagnosis is defined as the abstract process of gathering information about the student's learning and transforming that information based on instructional decisions. A model that captures the expert knowledge of experienced professors and is used to design a cognitive diagnostic model based on Fuzzy Logic is presented in this article. Particularly, a diagnosis system with four variables (three input variables and one output variable) and 27 fuzzy rules.



**Keywords:** Student evaluation, Intelligent tutoring systems, Fuzzy inference system, Student model.


## 1 Introduction

The content of the student models in the Intelligent Tutoring Systems (ITSs) varies widely, that is why there is no unanimous agreement on the topics that should be included it. Briefly, the models that "recognize" the plans followed by the student or the corresponding path toward the search for solutions to the problems discussed [1] can be mentioned, whereas other models evaluate the student's performance or his/her ability in problem-solving [2]. As a consequence of this broad and not well defined problem, the design of a new student model implies making careful decisions about the fundamental features that one wishes to model in the student in the context of an Intelligent Tutorial System.

Currently, many researchers state that the main purpose of the Student Model in the context of an ITS is to guide and advise the pedagogical decisions of the system. The design's approach toward intelligent decision making warrants a reactive functionality from the system toward the activity and accomplishments of the student [3-4].

From a theoretical point of view, the student model should include all the aspects of the student's behavior and the knowledge acquired in order to adapt to the students' learning needs [5], however, from a practical point of view, the information in the model is restricted due to the difficulty in acquiring reliable data (the evidence can be quite scarce) about the student.

In student modeling, the student's behavior is extremely relevant. This concept is used to refer to the student's observable response to a specific stimulus in a particular domain, and constitutes the main entry to the student model [6]. From this evidence, the diagnosis module would have to infer the unobservable behavior of the student. Therefore, it can be concluded that the less information there is about the student, the harder it will be to estimate the diagnosis. Another problem related to the information acquired by the system is the high level of uncertainty due to the data's interpretative nature and the assumptions that sometimes need to be taken. Various technologies have been used in order to face the problem of the student model with diverse results (e.g. Bayesian networks [7] or neuronal networks [8]).

The model introduced in this article attempts to obtain appropriate pedagogical decisions taking into consideration the information acquired by the system and traditional specific tests. The results of these tests will be analyzed and will serve as the decisions' support. Particularly, the diagnosis module design will be dealt with. Such module will process the information in order to inform the system properly.

The proposal especially provides the capture of the uncertainty present in the student's behavior as well as the teacher's qualitative knowledge so that the treatment of all that information can be clearly interpreted by fuzzy logic.

The current article is organized in the following way: in section 2 the concept of cognitive diagnosis module is presented; in section 3 the cognitive diagnosis models based on Fuzzy Logic are shown and the proposed model is presented; conclusions will be presented in the last section.

## 2 Cognitive Diagnosis Module

Assessing the student's knowledge is as easy as measuring a person's height ot weight. The measurement is made on special attributes such as mental representations and problem-solving processes which are not externally visible. An approach to research a student's knowledge which is currently being developed is Cognitive Diagnostic Assessment (CDA). The cognitive diagnostic assessment attempts to measure students' specific knowledge structures and processing skills to offer information about their cognitive strengths and weaknesses as well as to improve their learning opportunities.

According to [9-10] the meaning of the term 'cognition' in the context of educational assessment differs from its meaning in cognitive psychology. In the area of educational assessment, observational studies on real scenarios predominate to build profiles of the students' abilities through tests of diverse granularity. In the area of cognitive psychology, random complex experiments carried out in laboratories to investigate perception, memory, etc. in detail stand out.

In the field of education, the achievements in learning are considered as gradual developments of cognitive abilities, that is why the assessment should offer useful information about the change in the organization and structure of knowledge, especially explicit in descriptions of what the students use to be successful in dominating the knowledge they are acquiring.

In cognitive diagnosis models [11, 12, 13], the Item Response Theory (IRT) stands out. In an IRT model it is assumed that there is a latent variable or θ construct which is directly unobservable and which should be estimated for each student from the answers provided by this measurement instrument. Such models are based on the probability of an item being answered according to a student's ability and to other parameters that the item possesses.

On the other hand, when one wishes to consider and manipulate the uncertainty associated with subjective assessment, the models used can be those based on Fuzzy Logic [14, 15, 16]. One of the main characteristics of Fuzzy Logic is the obtaining of descriptions of properties through values that smoothly and constantly changes, associating the semantic partitions of these values to linguistic labels [17]. For instance, the competence fuzzy measurement in a specific area, in the context of a list of agreed measurement criteria (e.g. Very competent, competent, barely competent), it is to determine how well a specific value associated with these criteria reflects the semantic concept of competence. Regarding the student's behavior description, fuzzy Logic can be used to provide a linguistic description of the cognitive characteristics based on the teachers' opinions and to manipulate the uncertainty associated with subjective assessment. Furthermore, the teachers' qualitative reasoning is presented in a way that can be easily interpreted by the designers of the Intelligent Tutoring Systems. Jameson [18] presents excellent reading material about the management of uncertainty in the student model.

The information in the diagnosis module depends on the nature of the system. This information can vary from the answers to the questions in a questionnaire to student problem resolution. Moreover, the student's academic history can be a component of the diagnosis.

The diagnosis module's output is hard to define. As a primary objective, a diagnostic model tries to reflect the student's knowledge state with precision and could return a student's profile.

The term profile derives from psychology and is defined as the set of different measures of a person or group of persons, each one of them expressed in the same unit of measurement. A user's profile, in general, can be defined as a collection of personal information. The information is stored without its interpretation. These properties are stored after they are assigned values. These values can be final or can change throughout time.

If we deal with the cognitive profile [19] of a student, the information refers to the set of abilities and learning strategies the student uses. These profiles represent cognitive abilities, intellectual competences, intentions, learning styles, preferences and interactions with the system. Similarly, [20] it considers a state of knowledge that comprises the level of knowledge, errors and student's misunderstandings.

## 3 Student Diagnosis based-on Fuzzy Logic

Many researchers have worked in the application of the Fuzzy Logic theory in educational areas, especially in student's assessment. In [21] a high school student's assessment method based on fuzzy sets is presented. In [22] the authors present a teaching assessment method. In [23] a fuzzy graded assessment system to translate numeric grades into letters is presented. Meanwhile, Biswas [24] presents two methods for the assessment of students' written answers using fuzzy sets. In [25] fuzzy structure model is built for a grades' system from different exams grades in order to obtain an individual grade for each student. In [26] two methods for written answers assessment using fuzzy sets is presented thus improving on Biswas' method. In [27] an approach based on fuzzy sets to evaluate the learning results from peer and teacher assessments. In [28] a grading system that takes difficulty, importance and complexity of the questions into account in order to evaluate the students' written answers. The method uses membership functions.

In [29] a fuzzy system to evaluate the student's achievement taking importance, difficulty and complexity of questions into account based on Mandani's fuzzy inference and the center of gravity defuzzification method is presented. However, this method is not sensitive enough to reflect the students' achievements. One can try to eliminate such difficulty by [30] through the automatic generation of weights for the following attributes: accuracy rate, time rate, difficulty, complexity, cost of the response and importance of fuzzy rules, respectively, through fuzzy reasoning.

### 3.1 Definition of a diagnosis model

The diagnosis model consists of the following 6-uple:

*Diagnosis = <Subject, T, Test, CF, Behavior, Interpreter>*

*Subject:* it is the area of knowledge that one wishes to evaluate and on which the students ‘cognitive profile will be estimated.

*T*: set of topics included in the topic that one wishes to evaluate; $T=\{t_i \,/\, t_i \in Subject \wedge t_i=(name_i, objective_i)\}$

*Test:* set of tests. These tests are of a varied nature, from traditional test grades to results based on computer tests.

*CF: cognitive features of the student;* in this case the level of knowledge is considered, but motivation is planned to be added later on.

The *Behavior* is a set that saves the test results and is defined taking into account for each topic $t_i$ , a set of *m* tests $t_{ij}$, the result of the evaluation $e_{ij}$ and the date of the evaluation $d_{uj}$:

$Behavior\ (Test\_files\ (\ (t_1,\ tests_1(t_{11},t_{12},\ \ldots,t_{1m}),\ eval_1(e_{11},e_{12},\ldots e_{1,m}),\ date_1(d_{11},d_{12},\ldots,d_{1m})),\ (t_2,\ tests_2\ (t_{21},t_{22},\ldots,t2_m),\ eval_2(e_{21},e_{22},\ldots e_{2m}),\ date_2(d_{21},d_{22},\ldots,d_{2m})),\ldots,\ (t_n,\ tests_n\ (t_{n1},t_{n2},\ \ldots,t_{nm}),\ eval_n(e_{n1},e_{n2},\ldots e_{nm}),\ date_n(d_{n1},d_{n2},\ldots,d_{nm})))$

Finally, *Interpreter* is the function that maps the evidence of the student's behavior in his or her cognitive profile. Such function is based on a fuzzy Logic system. These systems have a direct relationship among fuzzy concepts (such as fuzzy sets, linguistic variables, etc) and fuzzy logic. In figure 2 a Fuzzy Logic (LD) basic system is shown:

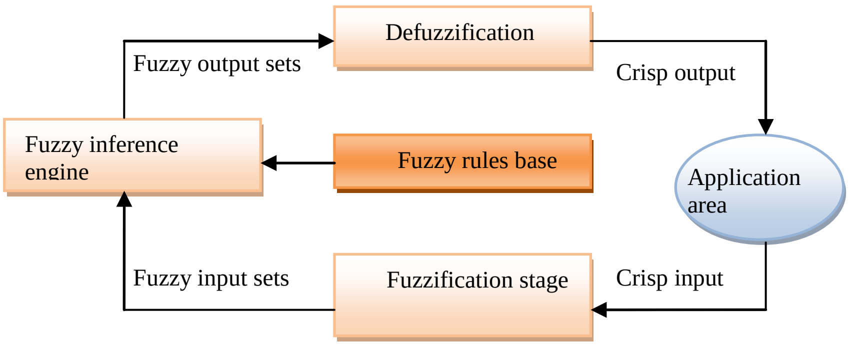


**Fig. 1.** Basic fuzzy logic system: fuzzification process is where the crisp data of application area is transformed into a fuzzy set; defuzzification process refers to the translation of fuzzy sets into crisp output; fuzzy inference involves in defuzzification of the conditions of the rules to the conclusion of the rules.

Crisp data of a specific area of application is selected and the fuzzifier turns them into a fuzzy set. A fuzzy set A on an object universe X is defined through its affiliation function, defined by the interval [0,1], i.e., the function $\mu_A$: X → [0,1]. $\mu_A$ (x) indicates the degree of affiliation of each element x to the fuzzy set A.

A base of fuzzy rules consists of fuzzy If-then rules. For instance, the rule:

*If (very satisfactory level of approval) and (final grade in reference to the course's average above average) and (growing marks progression) Then (high level of knowledge)*

Such rule has four linguistic variables: *level of approval, final grade in reference to the course's average, marks progression* and *level of knowledge* and they take linguistic values *very satisfactory, above average, growing* and *high*. These values are fuzzy sets (also known as linguistic terms).

The engine of fuzzy inference: after the crisp values are defuzzified in their respective linguistic values, the engine of inference accesses the base of rules to derive linguistic values for the output and intermediate linguistic variables.

Finally, the defuzzifier turns the output into crisp values.

Returning to the Interpreter function, the input information is the measurable evidence of the student's behavior and it will be used to estimate certain students' cognitive characteristics which are not evident.

The experienced teachers define a subjective description of the student's answers through linguistic variables $E_1, E_2, \ldots, E_n$ about measurable evidence (for instance, test grades). Each variable can take on different linguistic values. The set $T(E_i)=\{V_{i1},V_{i2},\ldots V_{im}\}$ is the set of terms of $E_i$.

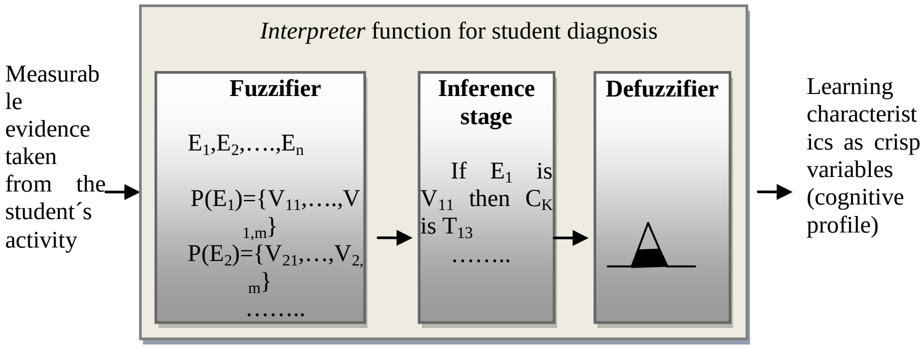


**Fig. 2**. Schematic of the diagnostic model

The fuzzy inference represents the teachers' reasoning when they qualitatively categorize the students according to their cognitive skills. The qualitative description of the students' characteristics is represented with linguistic variables $C_k$. Each of them can take on different linguistic values: $T(C_k)=\{T_{k1},T_{k2},\ldots,T_{kL}\}$.

The defuzzification represents the teachers final decision when it classifies the students in one of the values $T_{k1},T_{k2},\ldots,T_{kL}$. In order to achieve crisp values one can resort to diverse methods such as the gravity center procedure.

### 3.2 Specifying a Diagnosis Model

The proposed model in previous paragraphs has specialized in a concrete diagnosis case. The model estimates the level of knowledge reached by the student at the moment he or she finishes the course (figure 3). That is to say, it tries to capture an indicator that integrates the academic achievement reached based on information generated by our university courses. The acquired information is analyzed by the system based on midterms, finals and specific computing tests' grades.

The model developed uses 3 input linguistic variables: marks progression, level of test approval and final grade in reference to the average to estimate the *level of knowledge* output linguistic variable. A brief description of each of them follows:

*Marks progression*. The evolution of marks throughout the academic term is considered to be important. An important growth in the marks indicates an improvement in learning, whereas a sustained decrease implies the opposite. Those cases which can be considered insignificant (in the sense that they ascend or descend monotonously) and which do not impact on the calculation of the level of knowledge.

This variable is calculated based on each student's registered test marks considering their chronology. Their terms (fuzzy sets) are: growing, stable, and decreasing.

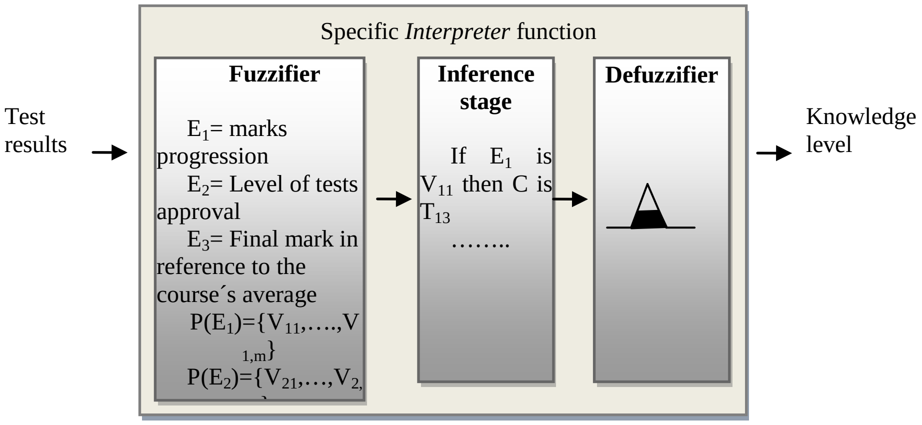


**Fig. 3**. Particular schematic of the diagnostic model

*Level of test approval*. It is the most relevant information to decide each student's level of knowledge. The results of the tests (including exams) are stored in the system. The variable takes the terms not satisfactory, satisfactory and very satisfactory.

*Final mark in reference to the course's average*. Each student's individual performance is compared through their Level of Approval mark with respect to the average performance of all the other students in the course. Those marks far from the average are considered relevant. Those marks close to the average do not influence in the level of knowledge. The following terms are determined: below average, around average and above average.

Finally, the output variable level of knowledge takes on the following terms *low, medium* and *high* indicating the category reached by the student according to the information analyzed in the progression of marks, the level of tests approval and the final grade in reference to the course's average. The estimated level provides a guide to the evaluator, assisting him or her in his or her decision making.

In order to infer the values of the *level of knowledge,* the Level of tests approval which is the input variable that will fundamentally guide the categorization has been considered and the other two variables (*marks progression* and *final grade in reference to the course's average*) will also contribute but to a lesser extent. The experts involved in the development have proposed 27 rules in natural language, two of them are shown below:

Rule 1. *If (level of tests approval* is *very satisfactory)* and *(final mark in reference* *to the course's average* is *above average)* and *(marks progression* is *growing) Then (level of knowledge* is *high)*

Rule 2. *If (level of tests approval* is *satisfactory)* and *(final mark in reference to the course's average* is *around average)* and *(marks progression* is *stable) Then (level of knowledge* is *medium)*

The diagnosis system was used during the years 2010 and part of 2011 in the courses Numerical Analysis (150 students a year) and Computation (350 students a year). A group of students from each course whose final mark was difficult to decide on were identified (approximately 21% per year). During 2010 the system coincided with the teachers' assessment in 87% of the cases and after the correction of some rules, in 2011 they coincided in 89% of the cases.

## 4 Conclusion

In this article a diagnosis model based on fuzzy logic has been presented. One of the main advantages of this model is that it allows for a representation of interpretable knowledge since it is based on rules when the reasoning is well defined as well as when the reasoning is intuitive, as a result of experience. The qualitative and quantitative criteria in student assessment proposed by the teachers can be easily improved (linguistic variables as well as fuzzy rules) adding a high degree of flexibility. For instance, in the specific developed model it has been concluded that four out of the 27 rules can be discarded following the experienced teachers' opinion.

As a future line of research new evidence will be added to the diagnosis model, such as the date of the tests, level of difficulty of the topics. Furthermore, new linguistic variables will be incorporated, such as level of interest and motivation.

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