

Fuzzy Logic for Refining the Evaluation of Learners' Performance in Online Engineering Education

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Abstract—Intelligent tutoring systems have been widely used for optimizing the educational process by creating a student-centered learning environment. As a matter of fact, an integral part of intelligent tutoring systems is the evaluation of the learners' performance. In traditional learning, the instructors process the grade of the students, derived from the assessment units, and other factors, such as the difficulty of the exercises or their effort, in order to produce the final students' score in the course. However, in most cases, the evaluation of learners' performance in intelligent tutoring systems takes place by calculating an average grade of students without taking into account the aforementioned factors. In view of the above, this paper presents a novel way for refining the evaluation of students' performance using fuzzy logic. As a testbed for our research, we have designed and implemented an intelligent tutoring system holding social networking characteristics for teaching the engineering course of "Compilers". More specifically, the system is responsible for acquiring information about students such as their grades, the kinds of misconceptions, the level of tests' difficulty as well as their effort including their social interaction, i.e. participation in forums, making comments in posts and posting regarding the educational process. Taking these into consideration, the fuzzy logic model diagnoses the accuracy of students' grades and then the system suggests that the instructor redefines them appropriately. Our system was evaluated using t-test and the results show high accuracy and objectivity in the evaluation of students' performance.

Index Terms—Evaluation of Student Performance, Fuzzy Logic, Intelligent Tutoring Systems, E-learning, Assessment units.

I. INTRODUCTION

Over the last decades, the field of education has flourished by the utilization of online and electronic methods. Hence, educational software can be constructed for assisting students have access to the learning material and assessment units from any place and at any time. However, given that educational software is offered to a heterogeneous group of learners who have different needs and preferences, the need for incorporating personalization is accentuated [1, 2]. As such, the research area of Intelligent Tutoring Systems (ITSs) has arisen [3, 4]. ITSs employ sophisticated techniques in their reasoning and diagnostic mechanisms in

order to create a personalized learning environment for the students, by taking into consideration their learning needs and preferences. Student modeling, which is a core element for constructing ITSs, can hold information about students and can then serve for creating a more qualitative learning experience [5, 6]. Information about students can be their grades, misconceptions, efforts, etc.

When providing education through online methods and ITSs, a very crucial aspect is the evaluation of learners' performance. In traditional classrooms, the instructors calculate the final grade of the students derived from the assessment units and other factors such as the difficulty of the exercises or their effort, in order to produce the final students' grade in a course. However, this has not been widely and thoroughly examined in the field of e-learning and ITSs [7]. To this direction, the evaluation of students' performance could not be calculated in an unsophisticated way by simply delivering the average of a students' grade.

In the related scientific literature, there are several preliminary efforts for evaluating the learners' performance. Among them, there are fuzzy logic techniques [8, 9]. Fuzzy logic techniques can serve as the medium to provide a more optimized evaluation of students performance. More specifically, the performance of students is a constantly changeable characteristic in the educational process and could be affected by several aspects, such as the difficulty of an exercise or the effort of a student.

In view of the above, this paper presents a novel way for refining the evaluation of the learner's performance. On the contrary, in most cases, the final grade of a student is simply the average of his/her overall grades. However, with this rationale, the final grade can be overrated, underrated and rarely fair. To overcome this obstacle, a novel fuzzy logic model is employed. As a testbed for our research, we have developed an intelligent and social tutoring system for teaching the undergraduate course of "Compilers" in a higher educational institute. It is underlined that our system is a fully operating social network, where students can post their personal opinion regarding the educational process, comment on other posts or talk to each other in forums. As such, our system takes into account the final learners' grade, the kinds of misconceptions made in tests, the level of tests' difficulty and the students' effort, and using the fuzzy logic model, it produces suggestions in order the teacher to redefine the final grade for being more accurate and objective. Our system was evaluated using t-test and the results are very promising towards providing a more robust depiction of the students' performance.

This paper is structured as follows. In section 2, a literature review is presented. Section 3 describes the domain knowledge of the system. In section 4, the

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characteristics based on which the evaluation of students' performance implemented are analyzed. Section 5 introduces the developed fuzzy logic model for refining the evaluation of students' performance. Finally, the last section continues with some conclusions deduced from the study and future work for extending this study.

II. RELATED WORK

Several studies focus on the evaluation of student performance using fuzzy logic, providing a cognitive diagnosis beyond classical methods adhered to constant mathematical calculation. These studies mainly developed a fuzzy logic model to estimate the student performance considering the marks he/she achieved in course [8, 10, 11, 12] (Table I). However, other studies combine student characteristics [9, 13, 14, 15, 16, 17], like his/her effort, progression, attendance etc, with assessment ones [15, 17], such as complexity, difficulty, and importance of test questions, in order to analyze student learning outcomes (Table I).

Regarding the fuzzy logic settings (Table II), the most widely used membership function is triangular, and trapezoidal is followed. As fuzzy inference, the researchers mainly apply the Mamdani method, whereas as defuzzification they preferred centriod and center of gravity. Table I illustrates the comparative analysis of works in the field of student performance evaluation using fuzzy logic.

In view of the above and after a thorough investigation in the related scientific literature, we came up with the result that in our approach, we use different students' characteristics than the ones presented in the literature, as well as a novel fuzzy logic approach for refining the evaluation of learners' performance.

TABLE I: A LITERATURE REVIEW IN THE FIELD OF FUZZY BASED STUDENT PERFORMANCE EVALUATION: FUZZY INPUT AND OUTPUT

Reference	Input	Output
[10]	1. Semester 1 student mark 2. Semester 2 student mark	Academic performance
[15]	1. Accuracy rate of student for questions 2. Complexity of questions	Student effort
	1. Student effort 2. Importance of questions	Adjustment grade
[16]	1. Student interest and effort 2. Student progression 3. Student's mark in relation to mean group mark 4. Trimester mark in relation to 4 grade	Recommendation regarding student's final mark
[9]	1. Student's attendance 2. Internal assessment 3. Term examination	Student overall performance
[11]	1. Student exam 1 score 2. Student exam 2 score	Student performance result
[13]	1. Hardworking 2. Knowledge depth 3. Technical knowledge	Student grade
[17]	1. Exam average grades 2. Difficulty of exam questions	Exam level
	1. Student grade 2. Exam level	Student level
[14]	1. Marks progression 2. Level of test approval	Student level of knowledge

	3. Final mark in reference to course's average	
[8]	1. Lab exam 2. Theory exam 3. Project exam	Student performance
[12]	1. Exam paper 1 2. Exam paper 2	Student performance

TABLE II: A LITERATURE REVIEW IN THE FIELD OF FUZZY BASED STUDENT PERFORMANCE EVALUATION: FUZZY SETTINGS

Reference	Membership Function	Fuzzy inference	Defuzzification
[10]	Triangular, trapezoidal	Mamdani	Centriod
[15]	Triangular	Mamdani	Center of Gravity
	Triangular	Mamdani	Center of Gravity
[16]	n/m	n/m	Center of Gravity
[9]	Trapezoidal	Mamdani	n/m
[11]	Triangular	Mamdani	Centriod
[13]	Bell shaped	Mamdani	Centriod
[17]	Trapezoidal	Mamdani	Weighted average
	Trapezoidal	Mamdani	Weighted average
[14]	n/m	n/m	Center of Gravity
[8]	Triangular	Mamdani	Centriod
[12]	Triangular	Mamdani	Centriod

III. DOMAIN KNOWLEDGE

The presented system is a Social Networking Learning (SN-Learning [18, 19]) educational platform which has been used in the tutoring of an undergraduate course in a higher educational institute. As a SN-Learning system, it has a social character being shown by a forum in order the students and instructors to communicate, posting items pertaining to the educational material and assessments, as well as commenting to other students' and instructors' posts.

The domain knowledge of the system concerns concepts of the engineering education, and more specifically, the course of "Compilers" of an undergraduate program in a University. The course is separated into three parts (Table III). Parts A and B include three chapters each, while Part C includes four chapters. Regarding the assessment process, the system delivers an exam for each one of the three parts; the grades of these exams are taken into consideration for calculating the final grade of the student.

TABLE III: DOMAIN KNOWLEDGE FOR THE COMPILERS COURSE

Part	Chapters
	Introduction to Compilers
Part A	Formal Languages and Formal Grammar Finite State Machines
	Scanning and Lexical Analysis
Part B	Parsing and Syntax Analysis Syntax Directed Translation and Semantic Analysis
	Runtime Environment
Part C	Code Generation Code Optimization Compiler Verification and Validation

IV. EVALUATION OF LEARNERS' PERFORMANCE

The learners' characteristics that are used in the fuzzy logic model and have been reported as important in the related scientific literature are the following [20]:

- Final learners' grade: The grade of the students in the tests is an important characteristic for identifying their knowledge levels. The final grade concerns the average of all the grades that a student has achieved in all the tests. However, in some cases, the grades can be affected by external factors (such as stress, boredom, etc.) and cannot be the sole identifier for the students' knowledge acquaintances.
- Kind of misconceptions: The kinds of misconceptions that a student makes in tests play an important role for identifying his/her knowledge level. The system can reason between several misconceptions of students, such as syntax, semantic and logical misconceptions (Table IV). Logical misconceptions can arise from students' misunderstanding of the learning material causing the program to product illogical output. They can involve larger sections of code and the general flow of the code. However, logical misconceptions cannot cause the program not to work, and thus, they cannot be detected easily. Syntax misconceptions are more easily identifiable, since they occur in cases of a wrong sequence in computer programming of the field of compilers. In general, they are usually of short length, even involving a single-digit mistake. Examples of syntax misconceptions can be missing semicolons at a line's end, and an extra or a missing bracket at end of a function. Semantic misconceptions are improper uses of program statements. The difference between logical and semantic misconceptions is that logical mistakes produce wrong data while semantic ones produce nothing meaningful at all. The higher-weighted misconception is the logical one indicating a serious knowledge gap, whereas the lower-weighted misconception is the syntax one.

TABLE IV: KINDS OF MISCONCEPTIONS

Misconceptions	Explanation	Case
Syntax	Lack of knowledge	Typos where parentheses or single characters are input incorrectly.
Semantic	Error in meaning/context	Wrong word in the wrong place in a human language sentence. A computer language example would be confusing a metric with an imperial input value.
Logical	Error in program flow	Use of a wrong conditional operator or null reference errors are good examples.

- Level of tests' difficulty: This characteristic is very important since it can tailor the assessment process to the specific knowledge capabilities of the students. Indeed, students with a high knowledge level can better meet the advanced difficulty level of an exercises, while students with poor knowledge acquaintances can better cope with exercises of an intermediate difficulty. Hence, this characteristic is related to the difficulty

level of the all the questions which the student has attempted to solve. It needs to be noted that each question has a level of difficulty between 0 (easiest question) and 1 (most difficult question). The system adjusts the question items of tests according to students' profile, meanwhile students have the option to define themselves the level of test's difficulty they want to examine.

- Students' effort: The student's effort is a very important characteristic that is taken into consideration by instructors when deciding the final grade of a student. Indeed, the effort of a student can be a significant determinant for grading both in traditional and online learning. The student effort involves several sub characteristics concerning students, such as their grades in all the tests of each part (Table III), the number of their attempts in participating in exams (how many times the student has tried a test until achieving success), as well as their social interaction, namely participation in forums, making comments in posts and posting regarding the educational process. It needs to be noted that in terms of interaction, the instructors have determined when a student will be regarded as active based on his/her activity or passive.

Based on the aforementioned characteristics, our system performs refining of the evaluation of students' performance (Fig. 1). More specifically, the system estimates if a grade is overrated, fair or underrated and correspondingly provides responsive actions for a more accurate and objective grading.

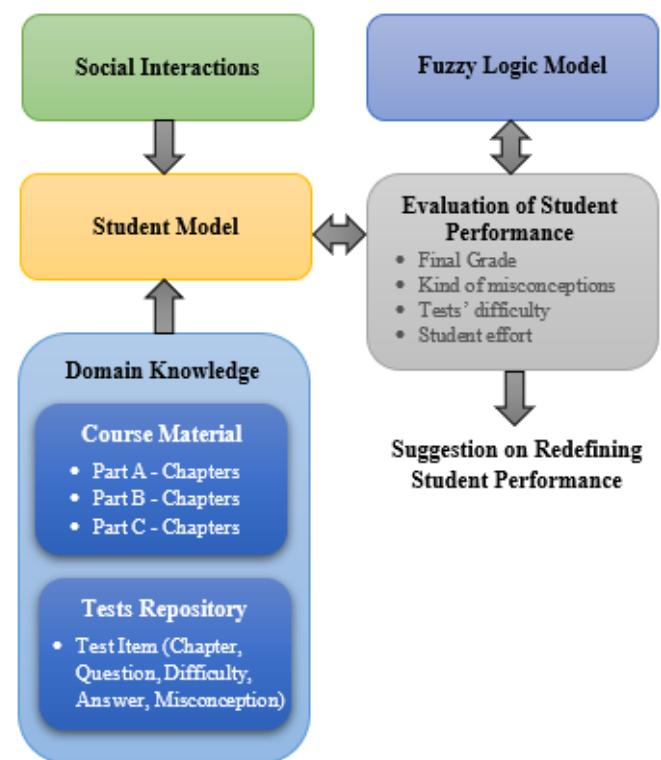


Fig. 1. System logical architecture

V. DESCRIPTION OF DEVELOPED FUZZY LOGIC MODEL

The fuzzy logic model comprises of three major components (Fig. 2):

1. Fuzzifier: It gets the values for input variables as they are resulted from student's records, and converts them to a fuzzy input set using membership functions.
2. Inference Mechanism: It gets the fuzzy input set and produces the fuzzy output value using IF-THEN type fuzzy rules.
3. Defuzzifier: It converts the fuzzy output value to crisp one using membership functions.

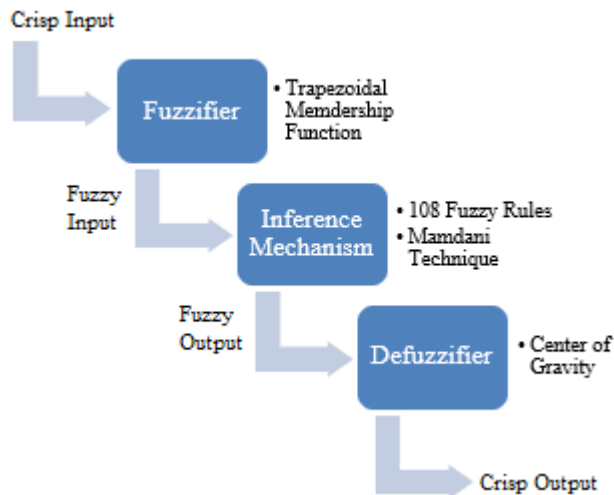


Fig. 2. Fuzzy Logic Model

A. Fuzzifier

The input variables of the fuzzy model are four, namely final learner's grade, kind of misconceptions, level of tests' difficulty and student effort. All the input values are in numeric format and are transformed into fuzzy ones using trapezoidal membership functions. Table V illustrates the fuzzy input set variables, their linguistic expressions and their intervals.

TABLE V: FUZZY INPUT SET

Variable	Linguistic Term	Symbol	Interval
Final grade (FG)	Failed	FLD	(0, 0, 30, 35)
	Below average	BAVG	(30, 35, 45, 50)
	Good	GD	(45, 50, 70, 80)
	Excellent	EXL	(70, 80, 100, 100)
Misconceptions (MCN)	Syntax	SNT	(0, 0, 0.3, 0.4)
	Semantic	SMC	(0.3, 0.4, 0.6, 0.8)
	Logical	LGC	(0.6, 0.8, 1, 1)
Tests' difficulty (TD)	Easy	ES	(0, 0, 0.3, 0.4)
	Intermediate	IMD	(0.3, 0.4, 0.6, 0.8)
	Difficult	DFC	(0.6, 0.8, 1, 1)
Student effort (SE)	Low	LW	(0, 0, 0.3, 0.4)
	Moderate	MDT	(0.3, 0.4, 0.6, 0.8)
	High	HI	(0.6, 0.8, 1, 1)

As an example of a fuzzy variable representation, Fig. 3 shows the equations of the trapezoidal membership function for each linguistic expression of student effort variable, whereas Fig. 4 illustrates its scheme. It should be noted that in fuzzy logic, the fuzzification of a crisp value can result in multiple fuzzy values with different weight. For instance,

the value 0.33 for student effort belongs to low with weight 0.7 and to moderate with weight 0.3.

$$\mu_{LW}(x) = \begin{cases} 1, & x \leq 0.3 \\ \frac{0.4 - x}{0.1}, & 0.3 \leq x \leq 0.4 \\ 0, & x \geq 0.4 \end{cases}$$

$$\mu_{MDT}(x) = \begin{cases} 0, & x \leq 0.3 \text{ or } x \geq 0.8 \\ \frac{x - 0.3}{0.1}, & 0.3 \leq x \leq 0.4 \\ 1, & 0.4 \leq x \leq 0.6 \\ \frac{0.8 - x}{0.2}, & 0.6 \leq x \leq 0.8 \\ 0, & x \geq 0.8 \end{cases}$$

$$\mu_{HI}(x) = \begin{cases} 0, & x \leq 0.6 \\ \frac{x - 0.6}{0.2}, & 0.6 \leq x \leq 0.8 \\ 1, & x \geq 0.8 \end{cases}$$

Fig. 3. Equations of Student Effort Membership Functions

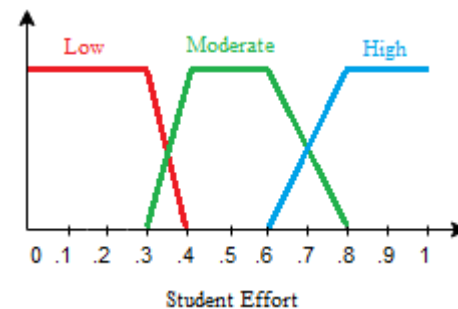


Fig. 4. Scheme of Student Effort Membership Functions

Regarding the output of the fuzzy model, it returns the evaluation of student's performance according to fuzzy input set and the fuzzy rules. Table VI illustrates the fuzzy output set variable, along with its linguistic expressions and their intervals.

TABLE VI: FUZZY OUTPUT SET

Variable	Linguistic Term	Symbol	Interval
Evaluation of Performance (EP)	Underrated	UR	(0, 0, 0.3, 0.4)
	Fair	FR	(0.3, 0.4, 0.6, 0.8)
	Overrated	OR	(0.6, 0.8, 1, 1)

B. Inference Mechanism

This is the core part of the fuzzy model where the fuzzy output is produced by applying fuzzy rules according to fuzzy input. Thus, a set of 108 simple IF-THEN type fuzzy rules was conducted. The inference engine employs Mamdani method, in order to determine the output in case of several active rules.

An example of the developed fuzzy rules is the following:

1. **IF** FG=FLD **AND** MCN=SMC **AND** TD=IMD **AND** SE=HI **THEN** EP=UR
2. **IF** FG=BAVG **AND** MCN=SNT **AND** TD=IMD **AND** SE=HI **THEN** EP=UR
3. **IF** FG=GD **AND** MCN=SMC **AND** TD=IMD **AND**

- SE=HI THEN EP=UR
4. IF FG=EXL AND MCN=SNT AND TD=DFC AND SE=HI THEN EP=UR
 5. IF FG=FLD AND MCN=LGC AND TD=IMD AND SE=MDT THEN EP=FR
 6. IF FG=BAVG AND MCN=LGC AND TD=ES AND SE=MDT THEN EP=FR
 7. IF FG=GD AND MCN=SMC AND TD=IMD AND SE=HI THEN EP=FR
 8. IF FG=EXL AND MCN=SMC AND TD=DFC AND SE=MDT THEN EP=FR
 9. IF FG=BAVC AND MCN=LGC AND TD=ES AND SE=LW THEN EP=OR
 10. IF FG=GD AND MCN=SMT AND TD=ES AND SE=LW THEN EP=OR
 11. IF FG=EXL AND MCN=SMT AND TD=ES AND SE=LW THEN EP=OR
 12. IF FG=EXL AND MCN=LGC AND TD=IMD AND SE=LW THEN EP=OR

The facts based on which the fuzzy rules were designed can be explained through the following examples: if a student gets a good final grade, this grade can be diagnosed as underrated when s/he made semantic misconceptions on difficult-level tests and s/he was very active in the SN-Learning platform (rule 3); whereas, the final grade can be fair when the semantic misconceptions are occurred in intermediate-level tests and his/her effort is still high (rule 7); or, it can be characterized as overrated when the semantic misconceptions are occurred in easy-level tests and his/her participation in the learning process is low (rule 10). Therefore, depending on the diagnosis of the fuzzy model about student performance, the teacher can adjust the final grade of student in the course.

C. Defuzzifier

In this stage, an inverse process of fuzzifier is performed in order to transform the fuzzy output produced by inference mechanism into a crisp output. The defuzzification technique used in this model is the Center of Gravity (COG).

D. Examples of operation

Table VII illustrates three examples of operation, as they are emerged from platform's log files. As it is observed, Student A's final grade resulted from the average of the lesson's assessments was redefined and altered from 45% to 55%. This was occurred because according to the platform's suggestions, the teacher decided to increase student's final grade in order the grade to be more representative to student's performance during the course. In particular, platform's suggestions were based on the output of the fuzzy logic model. As such, depending on the fuzzy input set, the rules that have below average or good final grade, and syntax or semantic misconceptions, and intermediate tests' difficult and high student effort, are activated and combined (like rule 2 and 3) resulting to the diagnosis of underrated grade. Regarding Student B and C, following the same process, the fuzzy logic model diagnosed an underrated and overrated final grade, respectively, and the teacher decided to increase the score of Student B to 78% (from 72%), whereas to decrease the score of Student C to 85% (from

89%).

TABLE VII: EXAMPLES OF OPERATION

Stud.	Final Grade	Miscon cep.	Tests' Diff.	Stud. Effort	Eval. Perf.	Teach. React.
A	Crisp	45	0.34	0.44	0.82	0.26
	Fuzzy	BAVG, GD	SNT, SMC	IMD	HI	UR
B	Crisp	72	0.31	0.67	0.89	0.25
	Fuzzy	GD, EXL	SNT, SMC	IMD, DFC	HI	UR
C	Crisp	89	0.62	0.36	0.27	0.83
	Fuzzy	EXL	SMC, LGC	ES, IMD	LW	OR

VI. EXPERIMENTAL RESULTS AND DISCUSSION

Evaluation is considered as a core phase in the development of software. Concerning e-learning software, evaluation plays a crucial role in order to assess the acceptance of it by both students and instructors. Towards a qualitative evaluation, the t-test was employed. Our system employing fuzzy logic was compared to a conventional assessment tool. The conventional version of our system produces a final grade for the students which is the average, and has the same user interface to our fuzzy logic-based system. Both systems were used by 40 undergraduate students who participate at the course "Compilers" in a higher educational institute. More specifically, 20 students used our system employing fuzzy logic, whereas the other 20 students used the conventional version delivering an average final grade. The students used the two systems during an academic semester. After the interaction, the evaluators asked the following question to the 40 students and 10 faculty members of computer science in the university: "Rate the accuracy of the final grade". In view of the above, 20 students gave answers for our system employing fuzzy logic and 20 students gave answers for the conventional assessment tool. Correspondingly, 5 faculty members were asked to evaluate the grades delivered by our system (with fuzzy logic), whereas the other 5 faculty members were asked to evaluate the grades of the conventional version. The question followed a ranking between 0 (lower grade) and 5 (higher grade).

Having set the alpha value at 0.05 and considering the p-value results, we can infer that there is a statistically significant difference between the means of the two trials regarding the aforementioned question. This fact implies that our system employing fuzzy logic outperforms its conventional version (assessment tool delivering average final grading) in terms of the accuracy and objectivity of the students' final grading.

The results, shown in Table VIII and IX, were expected, given that our system employing fuzzy logic takes into consideration the final learners' grade, the kinds of misconceptions, the level of questions' difficulty and the students' effort in order to produce a more accurate and objective final grade. On the other hand, the conventional version of our system which delivers a final grade as an average of the grades in the parts of the course lacks sophisticated techniques in order to refine the evaluation of the learners' performance.

TABLE VIII: QUESTION TO STUDENTS

t-Test: Two-Sample Assuming Equal Variances		
	Variable 1	Variable 2
Mean	2,7	4,25
Variance	2,221053	0,723684
Observations	20	20
Pooled Variance	1,472368	
Hypothesized Mean Difference	0	
df	38	
t Stat	-4,03946	
P(T<=t) one-tail	0,000126	
t Critical one-tail	1,685954	
P(T<=t) two-tail	0,000251	
t Critical two-tail	2,024394	

TABLE IX: QUESTION TO FACULTY MEMBERS

t-Test: Two-Sample Assuming Equal Variances		
	Variable 1	Variable 2
Mean	1,4	4,8
Variance	0,8	0,2
Observations	5	5
Pooled Variance	0,5	
Hypothesized Mean Difference	0	
df	8	
t Stat	-7,60263	
P(T<=t) one-tail	3,14E-05	
t Critical one-tail	1,859548	
P(T<=t) two-tail	6,29E-05	
t Critical two-tail	2,306004	

VII. CONCLUSIONS AND FUTURE WORK

This paper presents a novel way for refining the evaluation of learners' performance in an intelligent tutoring system holding social characteristics for teaching the engineering course of "Compilers". The refinement of the evaluation process employs fuzzy logic and takes as an input several students' characteristics, such as grades of the students, the kinds of misconceptions that they make in tests, the level of questions' difficulty, as well as their effort, including their social interaction (participation in forums, making comments in posts and posting regarding the educational process). The novelty of our approach lies in the selection of students' characteristics which can affect their final grade both in traditional and online learning.

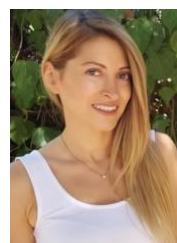
Our system was evaluated using t-test and the results are very encouraging for the refinement of the evaluation of students' performance. Indeed, students and instructors attested that our proposed approached can improve the accuracy and objectivity of the final grading.

Future steps include the combination of machine learning and fuzzy logic to further improve our model as well as the incorporation of other students' characteristics, such as their learning style.

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