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Parametric Modeling and Prognosis of Result Based Career Selection Based on Fuzzy Expert System and Decision Trees

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1. Introduction

1.1 Expert system and its applications

An Expert System is a set of programs that manipulate encoded knowledge to solve problems in a specialized domain that normally requires human expertise. The expert's knowledge is obtained from the specialists or other sources of expertise, such as texts, journal articles and databases

Year	# of expert systems developed
1985	50
1986	86
1987	1100
1988	2200
1992	12000

Table 1. Increase in number of expert systems developed yearly (based on Durkin, 1998)

Area systems	% of Expert
Engineering & manufacturing	35
Business	29
Medicine	11
Environment & Energy	9
Agriculture	5
Telecommunications	4
Government	4
Law	3
Transportation	1

Table 2. Applications of expert systems in various fields.

Human computer interaction and web-based intelligent tutoring concepts come into play while implementing an online educational tool whose target is mostly unskilled or novice users. The users (the students in this context) have to be provided with tools that will be helpful in improving their skills in the targeted area. A successful web based education system should have intelligence to tackle the variation in student skills and backgrounds and it should also be able to adapt its contents according to that variation. These mentioned issues are the main concerns for web-based intelligent tutoring research area. For a robot supported laboratory the skill building is both to learn and to gain experience about the control of the robot involved in the experiment setup and to be successful in carrying out the experimentation that is required for the student in order to gain practical knowledge in the targeted area. In order to adapt the context of the experimentation to the variation in student behaviors, students should be modeled according to their skills and knowledge backgrounds. User modelling is an important aspect of both human computer interaction and web-based intelligent tutoring research areas. AI techniques can be applied to the user modelling for implementation of online experimentation framework to get useful information about the student skill and knowledge level for providing help when necessary and assessing his/her performance.

Examples of the early and famous expert systems

- DENDRAL - Stanford Univ. (1965)
  - Analysis of chemical compunds
  - Rule-based system
- CADACEUS - Univ. of Pittsburgh (1970)
  - Diagnosis of human internal diseases
- MYCYSMA - MIT (1971)
  - Symbolic mathematical analysis

ES are appropriate in domains when/where:

- there are no established theories
- human expertise is scarce or in high demand, but recognized experts exist
- the information is fuzzy, inexact or incomplete
- the domain is highly specific

Human computer interaction field deals with enhancing the ways in which users interact with one or more computational machines through design, evaluation and implementation of interactive computing systems. From the perspective of telerobotics or more specifically online robotic experimentation, human computer interaction field deals with providing interfaces for remote users which enable them to do the necessary manipulation successfully. There is a strong need for an intelligent interface for a framework for remote access of robot supported laboratories through the Internet. The two main reasons for that are:

1. The need for intelligently coaching the student to achieve the goals of the experimentation successfully.
2. The need for evaluating student's performance while carrying out the experiment.

Student evaluation, the first main issue mentioned above, is one of the key issues for a remote experimentation framework. Students who are carrying out the experimentation, online without a human assistant or a teacher, should all be evaluated according to their varying success levels. The interface should possess suitable intelligence to categorize the student according to his or her performance during the course of the experiment and possibly to evaluate whether an increase or decrease in performance is present according to the past performance of the users. Necessary grades can then be given to those students according to the performance category in which they tend to fall.

Students, while doing the experiments online by themselves should be coached just as in the case for a traditional laboratory work where the coach is a human assistant or a teacher. They can be given useful directions and recommendations in the form of messages on the interface. Another aspect of coaching is to adapt the level of the complexity of the experiment to the level of the student. Skilled students can be excluded from some parts of the experiment, where unskilled students or students showing a poor performance can be directed to finish the fundamental parts or repeat the unsuccessful parts of the experiment. This idea coincides with the aim of using adaptive hypermedia for intelligent web-based tutoring tools, where the content of the tutor is changed adaptively to suit the student's individual needs and interests.

There are also other key aspects for a successful interface, which are:

- Having a layout that provides the student with all the necessary information about the objectives and the states of the experiment, and visual displays for aiding the users to see the state of the robot and the experimental setup.
- Providing a security mechanism that prevents unwanted and unauthorized access to protect the system from possible malicious use. Another issue for the robot-supported online experimentation is providing a scenario for the experiment. The experiment should involve a useful scenario that is relevant to the educational context that it is applied to and which must have tasks that have different levels of complexity to be accomplished.

By this way, using an intelligent interface for an online robot-supported experimentation will be justified. The educational contexts to benefit from remote experimentation can be range from mechatronics laboratories to chemistry laboratories. According to the scenario, the students can be directed to complete the levels of the experiment according to their skill level and be coached without the actual presence of a human assistant or a teacher.

In accordance with the issues and the needs stated, the aim of the work given in this thesis is to build a user assessment and coaching framework for an intelligent interface in use during remote access of labs through the Internet involving telerobotics or teleoperation. The lab setup can be assisted by either a robot or any device that is connected to the Internet.

The specific goals of the approach are that:

1. The interface should provide the student with "hands on" experimentation by using visual feedback and give the user as much freedom as possible to control the experiment;\
2. The system should evaluate the user performance, adapt the context to the level of acquired knowledge and skill of the user, and thus intelligently coach him/her to successfully do the experiment and get the most out of the experimentation.

The concepts and tools borrowed from fields such as web-based intelligent tutoring, human-computer interaction, user-adapted interaction and Internet telerobotics are necessary for the successful accomplishment of our goals in the education oriented lab access through the Internet.

The main objective of this study is, thus, to develop an intelligent interface that can be used for the Internet access of robot supported laboratory. The main differences from the previously surveyed works that are already present in the literature are that the proposed system learns how to assess based on the user behavior while providing online robotics-enhanced experimentation, and coaches him/her towards the successful achievement of the tasks while evaluating user performances. Thus, the proposed approach is behavior-based task planning of online users by being a combination of concepts borrowed from intelligent tutoring, student modeling and Internet robotics. Some important properties of the system can be stated briefly as follows:

- From the nature of the Internet, the system serves to a diverse number of students each having different knowledge and skill levels. The system is adaptive to these different levels and provides each student with enough assistance for accomplishing the desired experiment and getting the necessary knowledge and experience.
- Assistance provided to the student is in the form of generated messages or mandatory commands such as the repetition of a previously failed step of the experiment.
- Students are assigned experiments having different complexity levels according to their past and present performances.
- The system grades students according to their performances, and stores grades and student profiles in a database.
- The system has an authentication module to ensure security and to recall a previous user from the database.

Fuzzy approach is most suitable for modelling user behaviours from a pattern matching point of view because of its abilities of generalization over the training data set to deal with the fuzzy nature of the user behaviour data. A rule-based system only on its own would require every combination of possible user behaviour data should be explicitly encoded within. Therefore employing a neural network is a feasible solution to the problem of modelling students while doing an online experimentation by using previously defined behaviour stereotypes.

2. Fuzzy expert systems

A fuzzy expert system is an expert system that uses fuzzy logic instead of Boolean logic. In other words, a fuzzy expert system is a collection of membership functions and rules that are used to reason about data. Unlike conventional expert systems, which are mainly symbolic reasoning engines, fuzzy expert systems are oriented toward numerical processing. The rules in a fuzzy expert system are usually of a form similar to the following:

$$\textbf{if x is low and y is high then z} = \textbf{medium}$$

Where x and y are input variables (names for know data values), z is an output variable (a name for a data value to be computed), low is a membership function (fuzzy subset) defined on x, high is a membership function defined on y, and medium is a membership function defined on z. The part of the rule between the "if" and "then" is the rule's premise or antecedent. This is a fuzzy logic expression that describes to what degree the rule is applicable. The part of the rule following the "then" is the rule's conclusion or consequent. This part of the rule assigns a membership function to each of one or more output variables. Most tools for working with fuzzy expert systems allow more than one conclusion per rule. A typical fuzzy expert system has more than one rule. The entire group of rules is collectively known as a rule base or knowledge base.

2.1 The inference process

With the definition of the rules and membership functions in hand, we now need to know how to apply this knowledge to specific values of the input variables to compute the values of the output variables. This process is referred to as inferencing. In a fuzzy expert system, the inference process is a combination of four subprocesses: fuzzification, inference, composition, and defuzzification. The defuzzification subprocess is optional. For the sake of example in the following discussion, assume that the variables x, y, and z all take on values in the interval [0, 10], and that we have the following membership functions and rules defined.

$$\mathrm{Low}(t) = 1 - t / 10$$
$$\mathrm{High}(t) = t / 10$$

Rule 1 : if x is low and y is low then z is high
Rule 2 : if x is low and y is high then z is low
Rule 3 : if x is high and y is low then z is low
Rule 4 : if x is high and y is high then z is high

Notice that instead of assigning a single value to the output variable z, each rule assigns an entire fuzzy subset (low or high). In this example, low (t)+high (t)=1.0 for all t. This is not required, but it is fairly common. The value of t at which low (t) is maximum is the same as the value of t at which high (t) is minimum, and vice-versa. This is also not required, but fairly common. The same membership functions are used for all variables.

A fuzzy rule based expert system contains fuzzy rules in its knowledge base and derives conclusions from the user inputs and fuzzy reasoning process. A fuzzy controller is a knowledge based control scheme in which scaling functions of physical variables are used to cope with uncertainty in process dynamics or the control environment. They must usually predefined membership function and fuzzy inference rules to map numeric data into linguistic variable terms (e.g. very high, young,) and to make fuzzy reasoning work. The linguistic variables are usually defined as fuzzy sets with appropriate membership functions. Recently, many fuzzy systems that automatically derive fuzzy if-then rules from numeric data have been developed. In these systems, prototypes of fuzzy rule bases can then be built quickly without the help of human experts, thus avoiding a development bottleneck. Membership functions still need to be predefined, however, and thus are usually built by human experts or experienced users. The same problem as before then arises: if the experts are not available, then the membership functions cannot be accurately defined, or the fuzzy systems developed may not perform well. A recent methodology was developed to automatically generate membership functions by Hong. et al. this methodology can be applied to a set of data used for a speaker independent voice recognition application.

The conventional practice of student performance practices used globally is based on the marks obtained in the courses opted. The marks are averaged for an overall estimation of the show of the students. In an advanced system the cumulative assessment is done in a group for awarding the grades based on the cumulative performance index (CPI) evaluated on the statistical model, agreed upon by the Academic Council of the University.

The attendance is taken as variable A_1 to A_N (Fig. 1.0) in the respective subjects, the overall attendance A_O is calculated on simple averaging function. The evaluated A_O is then taken into account for deciding whether the student will be allowed to appear in the examination or the student will be detained. This is based on simple comparison operator of less than or equal to the specified attendance. Once the student satisfies this condition of minimum attendance required, the student is made to appear in the examination. On the basis of evaluation of the answer sheets individualistic marks B_1 to B_N are derived for subjects 1,2, 3 … N respectively. As in case of attendance, the marks of individual subjects are also averaged to fetch overall marks B_O. On the basis of this B_O the result of the student is formulated and a division based on characterization of marks range is done. Mathematically on the basis of overall attendance the students qualify to appear in the examination based on a crisp rule as

$$x : X \rightarrow \{0, 1\}, \text{ where } f_A(x) = \begin{cases} 1, \text{if } x \in A \\ 0, \text{if } x \notin A \end{cases}$$

Fig. 1.

Where X is the eligibility percentage of overall attendance, if the overall attendance is > 65%, $f_A(x)$ is 1, then the student is allowed to appear in the exam.
In an advanced conventional system a grading system is eviscerated which is based on the cumulative indexing of the students. This is also a linear method reporting the output of performance on the basis of comparative grading in a group.
The conventional system adopted by the academic institutions is well endeavored and is time tested. The intelligence or the cognitive performance derivation is lacking. Moreover the logical weaving of attendance and the marks obtained in a subject is not done, the outcome of this results in a standalone performance rating and is also not amicable for the parents to assimilate.

2.2 Architecture of a fuzzy expert system

Fig. 2 shows the basic architecture of a fuzzy expert system. Individual components are illustrated as follows.

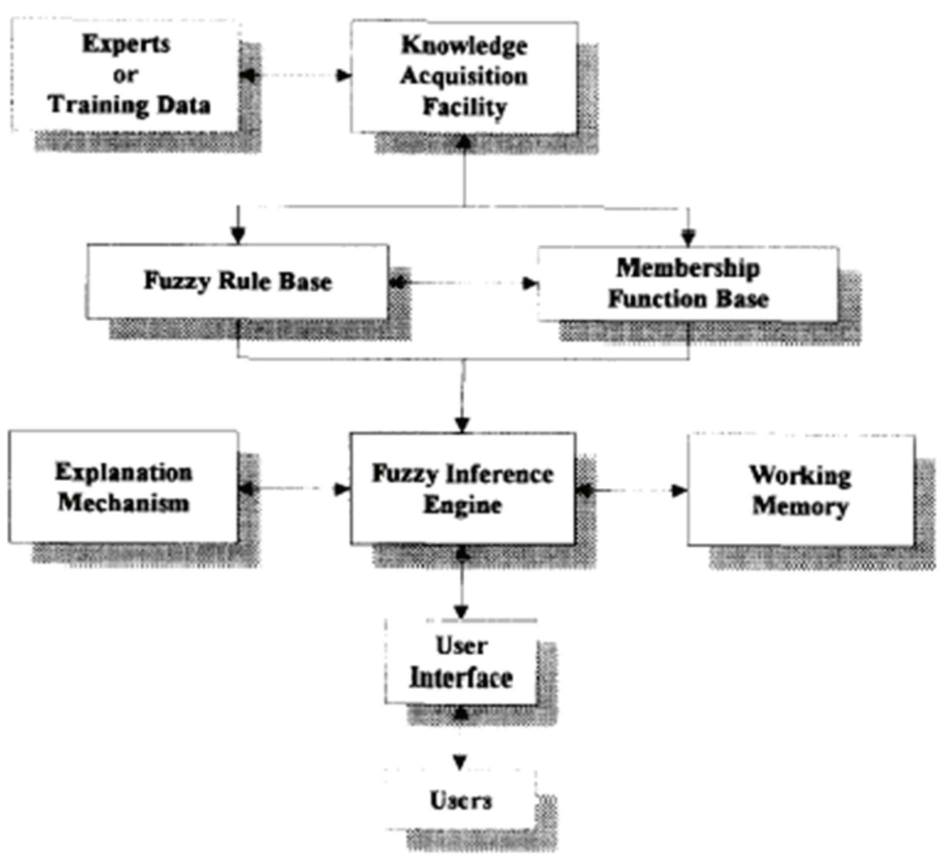

Fig. 2. Architecture of a fuzzy expert system

User interface: For communication between users and the fuzzy expert system. The interface should be as friendly as possible.
Membership function base: A mechanism that presents the membership functions of different linguistic terms.
Fuzzy rule base: A mechanism for storing fuzzy rules as expert knowledge.
Fuzzy inference engine: A program that executes the inference cycle of fuzzy matching, fuzzy conflict resolution, and fuzzy rule firing according to given facts.
Explanation mechanism: A mechanism that explains the inference process to users.
Working memory: A storage facility that saves user inputs and temporary results.
Knowledge-acquisition facility: An effective knowledge-acquisition tool for conventional interviewing or automatically acquiring the expert's knowledge, or an effective machine-learning approach to deriving rules and membership functions automatically from training instances, or both. Here the membership functions are stored in a knowledge base (instead of being put in the interface) since by our method, decision rules and membership functions are acquired by a learning method. When users input, facts through the user interface, the fuzzy inference engine automatically reasons using the fuzzy rules and the membership functions, and sends fuzzy or crisp results through the user interface to the users as outputs. In the next section, we propose a general learning method as a knowledge-acquisition facility for automatically deriving membership functions and fuzzy rules from a given set of training instances. Based on the membership functions and the fuzzy rules derived, a corresponding fuzzy inference procedure to process user inputs is developed.

2.3 Data-driven fuzzy rule based approach

Reasoning based on fuzzy approaches has been successfully applied for the inference of multiple attributes containing imprecise data; in particular, fuzzy rule-based systems (FRBS) which provide intuitive methods of reasoning have enjoyed much success in solving real-world problems. Recent developments in this area also show the availability of FRBS which allow interpretation of the inference in the form of linguistic statements whilst having high accuracy rates. The use of linguistic rule models such as "If assignment is very poor and exam is average then the final result is poor" helps capturing the natural way in which humans make judgements and decisions. Furthermore, historical data that is readily available in certain application domains can be used to build fuzzy models which integrate information from data with expert opinions. It is also important that the designed fuzzy models are interpretable by, and explainable to, the user . This section describes a newly proposed data-driven fuzzy rule induction method that achieves such objectives, and shows how the method can be applied to the classification of student performance. Description of Neuro-Fuzzy Classification (NEFCLASS) algorithm, which will be used later for comparison, is also given briefly in this section.

2.4 Inducting primitive machine intelligence in performance analysis and reporting by linear logic

The present scenario of performance evaluation is on the basis of a linear model where the result of the process is in terms of the division or the grades obtained by the student. The system is not capable of deriving cognitive inherence based on the attendance and the marks obtained. It is left to the student, parent and the employer to derive the performance on the division or the grades.

3. The logical engine

Several approaches using fuzzy techniques have been proposed to provide a practical method for evaluating student academic performance. However, these approaches are largely based on expert opinions and are difficult to explore and utilize valuable information embedded in collected data. This paper proposes a new method for evaluating student academic performance based on data-driven fuzzy rule induction. A suitable fuzzy inference mechanism and associated Rule Induction Algorithm is given. The new method has been applied to perform *Criterion-Referenced Evaluation (CRE)* and comparisons are made with typical existing methods, revealing significant advantages of the present work. The new method has also been applied to perform *Norm- Referenced Evaluation (NRE)*, demonstrating its potential as an extended method of evaluation that can produce new and informative scores based on information gathered from data. The need of the hour is to device a proposition where, an intelligent system sits inside the conventional system and deduce decisions based on the attendance and the marks obtained. Two sets are formulated Set A is for attendance and Set B is for marks obtained in the examination by the student.

$$\mu_A(x): \mathrm{X} \rightarrow \{0, 1\}, \text{ where}$$

$$\mu_A(x) = 1 \text{ if x is totally in A; } (\text{Eligible})$$

$$\mu_A(x) = 0 \text{ if x is not in A; } (\text{Not Eligible})$$

$$0 < \mu_A(x) < 1 \text{ if x is partly in A.}$$

3.1 The knowledge acquisition facility

A new learning method for automatically deriving fuzzy rules and membership functions from a given set of training instances is proposed here as the knowledge acquisition facility.

3.1.1 Notation and definitions

In a training instance, both input and desired output are known. For a m-dimensional input space, the ith training example can then be described as

$$\left(\mathbf{x_{i1}}, \mathbf{x_{i2}}, \cdots, \mathbf{x_{im}}; \mathbf{y_i}\right),$$

where x_{ir} (1 < *r* < *m)* is the r^{th} attribute value of the i^{th} training example and y_i is the output value of the i^{th} training example.

For example, assume an insurance company decides *insurance fees* according to two attributes: *age a*nd *property.* If the insurance company evaluates and decides the insurance fee for a person of age 20 possessing property worth $30000 should be $1000, then the example is represented as (age = 20, property = $30 000, insurance fee = $1000).

3.1.2 The algorithm

The learning activity is shown in Fig. 3

A set of training instances is collected from the environment. Our task here is to generate automatically reasonable membership functions and appropriate decision rules from these training data, so that they can represent important features of the data set. The proposed learning algorithm can be divided into five main steps:

Step 1. cluster and fuzzify the output data;

Step 2. construct initial membership functions for input attributes;
Step 3. construct the initial decision table;
Step 4. simplify the initial decision table;
Step 5. rebuild membership functions in the simplification process;
Step 6. derive decision rules from the decision table.

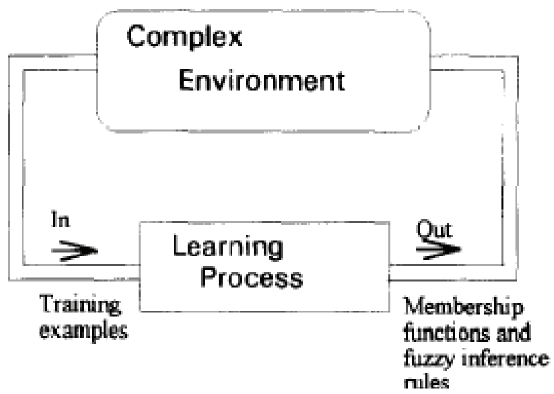

Fig. 3. Learning activity.

3.2 Weighted Subset Hood-Based Algorithm (WSBA)

Simplicity in generating fuzzy rules and the ability to produce high classification accuracy are the main objectives in the development of WSBA. To achieve these objectives, fuzzy subset hood measures and weighted linguistic fuzzy modelling are employed.

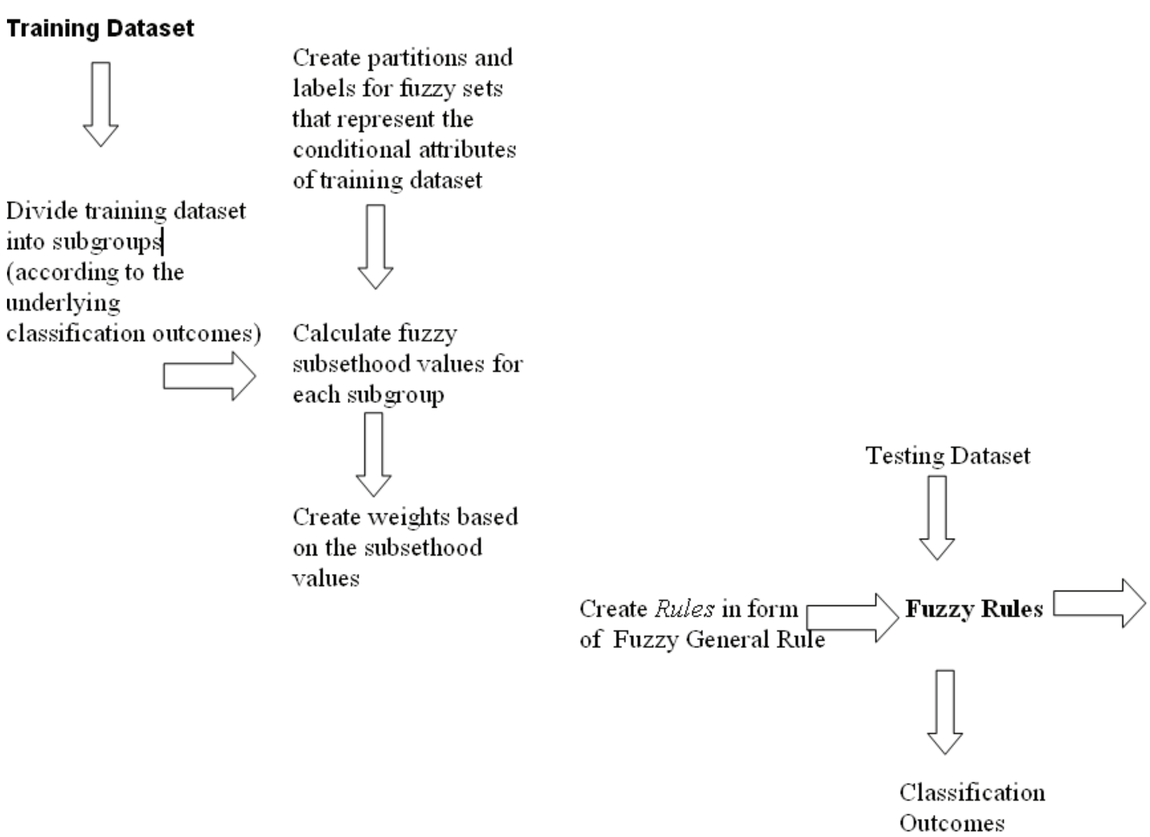

Fig. 4. Structure of WSBA Approach

This method does not require any threshold value and generates a fixed number of rules according to the number of classes of interest (i.e. one rule will be created for each class). In the process of generating fuzzy rules, linguistic terms that have a weight greater than zero will automatically be promoted to become part of the antecedents of the resulting fuzzy rules. Any linguistic term that has a weight equal to 0 will of course be removed from the fuzzy rule. This will make the rules simpler than the original default rules. In running WSBA for classification tasks, the concluding classification will be that of the rule whose overall weight is the highest amongst all. The structure of WSBA approach is shown in Figure 4. Example applications of WSBA can be found in.

3.3 Neuro-Fuzzy Classification (NEFCLASS)

Neuro-Fuzzy Classification (NEFCLASS) is an FRBS which combines a neural network learning approach with a fuzzy rule-based inference method . NEFCLASS can be encoded as a three-layer feedforward neural network. The first layer represents the fuzzy input variables, the second layer represents the fuzzy rulesets and the third layer represents the output variables. The functional units in this network implement t-norms and t-conorms, replacing the activation functions that are commonly used in conventional neural networks. NEFCLASS is a data-driven FRBS that has the ability to create fuzzy membership functions and fuzzy rules automatically from training instances. Prior knowledge in the form of fuzzy rules can also be added to the rule base and used alongside new rules created using the training dataset.

Fuzzy rules are generated based on overlapping rectangular clusters that are created by the grid representing fuzzy sets for the conditional attributes. Clusters that cover areas where training data is located are added to the emerging rule-base. The system allows the user to choose the maximum number of rules, otherwise the number of rules are restricted to that of just the best performing ones. The firing strength of each rule is used to reach the conclusion on the decision class of new observations.

The number of partitions and the shape of membership functions of the conditional attributes are user-defined. The rule learning process can be started, for example, using a fixed number of equally distributed triangular membership functions. A simple heuristic method is used for the optimization of membership functions. The optimization process results in changes to the membership function's shape by making the supports of the fuzzy set larger or smaller. Constraints can be employed in the optimization process to make sure that the fuzzy sets overlap each other.

NEFCLASS has undergone through several refinements over the years. For example, to enhance the interpretability of the induced fuzzy rules, NEFCLASS offers additional features such as rule pruning and variable pruning. The system has also been tested not only for classification of benchmark datasets but also for real world problems such as presented in.

3.4 Experimental results

The experiments presented in this section served as examples to illustrate the potential of WSBA for the evaluation of student performance. Note that a wide range of assessment methods are available and have been used (see for example), depending on the purpose to conduct the assessment. In this paper, only CRE and NRE are considered for the implementation. The objective of the experiment involving CRE is to provide evidence that the proposed algorithm will produce results similar to the original grades obtained using statistical methods, if an ideal and representative training data is available.

The objective of the experiment involving NRE is to show that WSBA is able to produce grades that can be used to provide additional information on the achievement of the students. In conducting these experiments, the following aspects have been taken into account:

In data-driven rule based systems, decision classes of the training instances are typically those given by experts. In students' performance evaluation, such decisions are normally given by experts based on an aggregation of numerical crisp scores. This method is used to obtain the decision class for the training data.

The small training data (SAP50A and SAP50B) is used as an example and in the form of numerical crisp scores, which is the most popular way to measure student performance. Note that the fuzzy approach allows the possibility of utilizing data in the form of fuzzy values such as those proposed in or in terms of linguistic labels that represent the fuzzy sets. In such cases, the decision class for the training data is determined by fuzzy values (see for example).

To avoid confusion, 'original score/grade' in this section will refer to the score and grade obtained from the use of the standard statistical mean and 'new score/grade' will refer to the score or grade obtained from existing fuzzy approaches, including WSBA and NEFCLASS. Note that both datasets used include only numerical scores, to facilitate comparison with other approaches. This need not be the case in general, the scores of individual assessment components may be given in fuzzy terms (as often the case for coursework grading for instances).

3.5 Criterion Referenced Evaluation (CRE)

NEFCLASS is used for further comparison, employing a fuzzy rule-based approach. The dataset used for the purpose of training WSBA and NEFCLASS models is a set of student performance records (labeled SAP50A). It consists of 50 instances, involving three conditional attributes: assignment, test and final exam, and five possible classification outcomes: Unsatisfactory (E), Satisfactory (D), Average (C), Good (B) and Excellent (A). Note that the term 'Average' describing students' performance used in this paper is not referring to the statistical average. For the sake of simplicity, only five linguistic labels similar to the classification outcomes are used to represent student achievements. The fuzzy partitions and labels are based on expert opinions representing the students' performance. The primary assumption is that the partitions chosen by experts are those best possible to represent the training data (SAP50A).

Clearly, better fuzzification, if available will help improve the experimental results reported below. Note that the given definition of the fuzzy sets is obtained solely on the basis of the normal distribution of the crisp marks given. This ensures their comparison with other approaches.

The classification of the grades in this experiment is based on an interval that refers to the level of performance given by experts. To facilitate a fair comparison, the same dataset consisting of 15 instances and having the same features as the training dataset is used for all of the methods. For instance:

Marks	Grade	Level of achievement
0-25	E	Unsatisfactory
26-45	D	Satisfactory
46-55	C	Average
56-75	B	Good
76-100	A	Excellent

It can be seen that the conventional fuzzy approaches produce different scores from the original (that is obtained by statistical mean). Thus, it is expected that when the new scores are translated into new grades, some of them may be different from the original grades. In particular, the results returned by the method of Biswas (1995), give rise to unexpected new scores such as case 10 where the original score of 61.67 (grade B) was downgraded to 35 (grade D). This is due to the approximation that is used in creating mid-grade points, and partly due to the use of fuzzy input values. Note that the use of mid-grade points has also resulted in a minimum score of 12.5 and a maximum score of 87.5, narrower than the original range.

Using Chen and Lee's method, all of the new scores are higher than the original. This is due to the use of maximum values of the degree of satisfaction created for each level of achievement. As for the results produced by Law's method, it is expected that the new scores will be different because the expected value for each grade has been predefined in advance according to the percentage of students who will receive a certain grade. Thus, results produced by this method may not reflect the students' true performance and they will be different if the expert evaluator changes the setting for the percentage.

By using the data-driven fuzzy rule-based approaches, fuzzy membership values obtained from fuzzy rules can be used to determine the new grade. Thus, it can be observed that the use of membership values in describing a student result has several advantages.

First, these membership values can be interpreted as how strong the student's performance belongs to a specific grade. This can be very useful in differentiating smoothly student performances over boundary cases, giving a second opinion in deciding on borderline performances.

Second, with the use of fuzzy values, further analysis of estimated performance can be carried out directly, without the need for fuzzification.

Third, the success of those methods in performing CRE will allow them to be used for NRE. This also provides the possibility that student performance evaluation can be carried out properly using fuzzy values and linguistic terms (Good, Excellent, etc.) rather than the traditional numerical crisp values.

4. Design of non-linear decision vector

The innovation in the present work is to create a logical mechanism which binds the attendance in the class room and the marks obtained in the examination by the student and to infer the decisions weaved on the sets A and B. This juxtapose will endeavor the performance of the student at the said instance and will also delineate the seed for prognostic modeling of futuristic performance of the students.

Mathematically, lowest memberships will be figured out by the intersection of two sets as

$$\mu A \cap B(x) = min\,[\mu A(x), \mu B(x)] = \mu A(x) \cap \mu B(x),$$

where $x \in X$
The highest memberships will be drawn out by the union of two sets as

$$\mu A \cup B(x) = max\,[\mu A(x), \mu B(x)] = \mu A(x) \cup \mu B(x),$$

where $x \in X$
Graphically it can be represented as

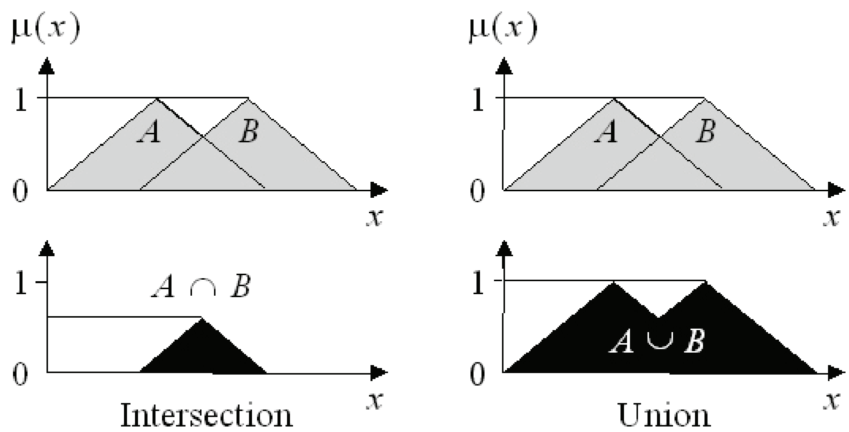

Fig. 5. Non-linear membership degree

The decisions DES41 and DES42 are derivative of the non-linear vector running simultaneously on the set A and set B for attendance and marks respectively. These high end decisions DES4x are being used for the suggestions to be included in the report of the student. These not only make this Communiqué system absolutely unique but also enthrall direction for probabilistic performance modeling of the student.
Mathematically the non-linear (dependent) vector is designed on the Sugeno Fuzzy inference and is as

$$\begin{array}{ll} IF & x \text{ is } A \\ AND & y \text{ is } B \\ THEN & z \text{ is } f(x,y) \end{array}$$

where *x*, *y* and *z* are linguistic variables; *A* and *B* are fuzzy sets on universe of discourses X and *Y*, respectively; and *f*(*x*, *y*) is a mathematical function. The zero order fuzzy model is applied where z is made constant as k.

5. Variables deduction

In the decision support system, the linear and non linear decisions are inferred through the decision vectors devised on the marks obtained and attendance of the student. So the different linguistic variables have been undertaken for the performance analysis and are deduced as follows:

1. The linguistic variables undertaken for the performance reporting of a student at the initial stage are DES1 and DES11 derived from the logical decision agent. These two variables are used for the Gender Confirmation of the student. If the sex of the student

in the student_master table is found to be "M" then the DES1 is set to "son" and the corresponding linguistic variable DES11 is set to "him". In the similar manner if the entry corresponding sex comes out to be false then DES1 is set to "daughter" and the variable DES11 set to "her". Both of these variables are embedded in the report while giving suggestions to the parents regarding their ward.

2. The degree of membership to attendance set A will formulate the linguistic variables DES21 and DES22. The DES21 is derived from the nested block of logical decision agent based on the membership in the set. The attendance of the student can be excellent, good, moderate or non-confirming depending on the regularity of the student. DES22 is the extended decision for suggesting the actions/ modifications to be undertaken by the student and the parent with respect to the overall attendance. While formulating the suggestion regarding attendance the decision variables DES1 and DES11 are also embedded wherever required.
3. On the basis of degree of membership to the marks obtained set B, DES31 and DES32 are formulated. Depending upon the marks obtained by the student, the membership assigns PASS or FAIL status to the student. Set B constitutes the pass students. DES31 determines whether the performance of the student is excellent, good, fair or non confirming. Variable DES32 is used for the suggestion based on the academic performance. It comprises of the individualistic decision based on the linear logical decision agents for attendance and marks obtained. While formulating the suggestion regarding marks DES1, DES11, SUBSHORT, DES21 and DES22 are embedded as per the prerequisite.
4. DES41 and DES42 are the decisions derived from the non linear vector running simultaneously on the set A and set B for attendance and marks respectively. These decisions are embedded for the suggestions regarding career selection given to the parents and are implanted at the end of the student's report.

6. Conclusion

This paper has presented examples of how a fuzzy rule-based approach can be used for aggregation of student academic performance and helps him in his career selection. It has been shown that the proposed approach has several advantages compared to existing fuzzy techniques for the evaluation of student academic performance.

In CRE, the use of fuzzy membership values to determine the decision is very helpful for the user to understand why the new grade was awarded. In CRE, the proposed method has the potential to be developed further for use as an extended method of evaluation by providing new grades that refer to achievements of other groups. The membership values produced by this method are also more meaningful compared to the values produced by statistical standardized-score.

However, it is worth noting that the newly proposed fuzzy approach is not to replace the traditional method of evaluation; instead it is meant to help strengthen the system that is commonly in use, by providing additional information for decision making by the user.

In this paper, WSBA is proposed to be employed for this purpose because of the simplicity of the method. It has been shown that although WSBA employs a simple approach, the proposed method is able to provide classification similar to that produced by more sophisticated algorithm such as NEFCLASS. Of course, more complex fuzzy rule-based methods such as those based on Evolutionary Computation, Fuzzy Clustering and Neural Networks may also be used. However, the simpler approach has an advantage in terms of transparency and understandability of the methods and its results. The proposed method also provides room for other improvements.

In particular, interpretability of learned fuzzy rules has always been regarded as a very important factor in FRBS but has not been sufficiently addressed in this paper. Thus, further research should include this very important issue. As an approximate modellling approach, WSBA has the advantage in producing fuzzy systems of high classification accuracy, but the use of crisp weights to modify fuzzy terms is rather unnatural and may lead to confusion regarding the semantics of the resulting systems. However, the structure of WSBA rulesets enables the system model to be adapted with fuzzy quantifiers , making the model more interpretable whilst maintaining its accuracy.
Also, the creation of fuzzy partitions to be used for WSBA are currently based on expert opinion and partly from statistical information on the training data. The fuzzification is not in any way optimized. Further research should include the use of methods that generate better fuzzy partition automatically from data.The proposed method also provides room for other improvements. In particular, interpretability of learned fuzzy rules has always been regarded as a very important factor in FRBS but has not been sufficiently addressed in this paper.
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Thus, The proposed approach can significantly reduce the time and effort needed for the performance evaluation of large number of students and help build intelligent communiqué system. Based on membership functions and fuzzy rules derived, a corresponding fuzzy inference procedure to process the inputs is developed. Embedding the decision support system fuzzy logic and decision trees , we found that our model gives a rational result, few rules and high performance.

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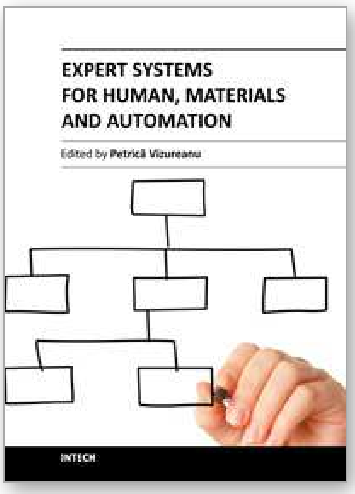

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The ability to create intelligent machines has intrigued humans since ancient times, and today with the advent of the computer and 50 years of research into AI programming techniques, the dream of smart machines is becoming a reality. The concept of human-computer interfaces has been undergoing changes over the years. In carrying out the most important tasks is the lack of formalized application methods, mathematical models and advanced computer support. The evolution of biological systems to adapt to their environment has fascinated and challenged scientists to increase their level of understanding of the functional characteristics of such systems. This book has 19 chapters and explain that the expert systems are products of the artificial intelligence, branch of computer science that seeks to develop intelligent programs for human, materials and automation.

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