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# CLASSIFYING STUDENTS BASED ON FUZZY LOGIC TO DEVISE INDIVIDUAL STUDY PLANS

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**Abstract.** E-learning has become a very popular way to involve students in educational paths. Today many different proposals for e-learning paths are available, and the evaluation of different study plans is very important, both from the student's side and from the educational institution perspective, in order to have better and more motivated participants. This article is devoted to the classification of students by the level of knowledge for the adequate selection of an individual study plan.

**Keywords:** students' classification; study plan; information systems; e-learning.

## 1. INTRODUCTION

The problem of differentiating students' level of basic knowledge before they start the educational path is acute in professional education and training. In this type of education students are not homogeneous and the selection of a study plan is a non-trivial task.

The aim of introducing the classification of students in terms of knowledge into the educational process is to create the most favorable conditions for the participants, taking into account characteristics of students, as well as providing individual problem solving approach that will reduce the time of the course and rise the quality of education by teaching according to the level of basic knowledge in the discipline.

There are many advantages of this approach:

a) the acceleration of the development of educational programs,

b) the variation of organization of training with the students

c) the overall quality of the educational process, more suited to participants' needs,

d) the flexibility of the curriculum model, which is developed on the basis of the basic curriculum. This "flexible" part allows teacher to consider the interests, needs and opportunities of the students. This flexibility is, however, hardly implementable in real contexts, especially when the number of students is high and/or the parameters to be acquired and considered are numerous.

E-learning provides a profitable background to implement the classification of students: e-learning learning paths are today very popular because of the many advantages they provide both to educational institutions, to participants and to trainers. Among the many advantages, we can list the possibility of profiling students in advance, collecting information and tests remotely thus simplifying organizational aspects (especially in presence of large numbers of participants), considerably reducing costs and efforts required to implement classification mechanism. Last but not the least, the flexibility of implementation of differentiated learning paths according to the profile of the students is the specific element for this paper: in traditional settings, customizing an educational path for a specific students is substantially not possible, due to costs and management issues. In e-learning, not only this is feasible, but also convenient and useful.

In the next sections we will present the application of a mathematical model for the classification of students in order to assign the training path that is most appropriate to their abilities. This model is based on the application of fuzzy logic and multi-criteria evaluation, in order to take into account the individuality of the subject and its characteristics.

The results that may be obtained from the application of these methods to the selection of students are particularly relevant in cases of international master degrees, where candidates come from countries with very different school systems, and where backgrounds are often not comparable.

## 2. CLASSIFYING STUDENTS

The proposed method is based on the construction of a fuzzy decision tree for classification of new students, as the subjective assessments of students are included as evaluated parameters.

We describe the basic rules of fuzzy logic, which enable the integration of subjective estimates of the parameters in the measure of student knowledge $CV_i$, where $i = 1..N$ is number of the student.

Then rank students on several parameters of estimates included in the index $CV_i$, and compose their overall rating. To do this, the method of multi-criteria assessment of students is used.

Every course present in the e-learning system has been classified in advance, with specific characteristics required in order to have the best match between the ability of the subject and the content of the course. We then construct a students classifier for the chosen course which determines the degree of belonging to the student groups in terms of knowledge. In these situations the use of e-learning platforms distributing learning objects (Los) that have been creating using standards like SCORM, could be of great help in matching metadata contained in the LO with the results of the classification system we are proposing.

### 2.1. Students multi-criteria evaluation

This method provides a composite index which consists of a consolidation of both quantitative and qualitative indicators using the procedures of expert evaluation, ranking, normalization and encoding benchmarks. It can be used to evaluate any set of objects for a variety of indicators (criteria).

The method consists of the following steps:

- Chose optimal number of indicators;
- Ranked indicators in importance according to the preferences of the decision maker;
- Determined weight factors for each indicator. The weight factors for $C_j$ are defined as:

$$C_j = 1 - \frac{R_j - 1}{M}, \tag{1}$$

$j = 1..M$, where $M$ is a number of indicators.

Then the coefficients are normalized:

$$\widetilde{C_j} = \frac{C_j}{\sum_{m=1}^{M} C_m}; \tag{2}$$

- Students are ranked in importance according to the decision maker preferences for each indicator. Students are compared for each indicator, and the results are tabulated;
- Determined weight factors for each student for each indicator and results are normalized.

$$C_{ji} = 1 - \frac{R_{ji} - 1}{K}, \tag{3}$$

$i = 1..K$, $j = 1..M$; $K$ is number of students; $M$ is number of indicators.

$$C_{ji}^{*} = \frac{C_{ji}}{\sum_{k=1}^{K} C_{jk}}, \tag{4}$$

where $C_{ji}^{*}$ is normalized indicators.

Thus, to calculate the weights used the relations of order between objects. However, the use of ordinal information may result in the loss of useful information. If necessary to take into account the quantitative information weight factors are calculated as (if large values are more preferable):

$$C_{ji}^{*} = \frac{W_{ji}}{\sum_{k=1}^{K} W_{jk}} \tag{5}$$

if small values are more preferable than as follows:

$$C_{ji}^{*} = \frac{1/W_{ji}}{\sum_{k=1}^{K} 1/W_{jk}}. \tag{6}$$

In this case, step 4 (ranking sites for each indicator) is omitted.

- Generalized index values calculated for each student.

$$\overline{W_i} = \sum_{j=1}^{M} \widetilde{C_j} \times C_{ji}^{*}. \tag{7}$$

### 2.2. Fuzzy Decision Trees

Classification using fuzzy decision trees can handle the situation, which is not just about belonging to some class, attribute, but regards the grade of membership. An object can have properties of both factors in some way so you don't lose this knowledge using fuzzy decision trees.

The main idea of this approach is a combination of decision trees and fuzzy logic.

A distinctive feature of decision trees is that each example is definitely belongs to a particular node. In the fuzzy case it is not [5]. For each of the attributes necessary to allocate some of its linguistic values and to determine the degree of membership of examples to them. Instead of the number of examples of a particular node, fuzzy decision tree groups the degree of membership. Ratio is the ratio of examples $D_j \in S^N$ of the node $N$ for the target value of i is calculated as:

$$P_i^N = \sum_{S^N} \min\left(\mu_N(D_j), \mu_i(D_j)\right), \tag{8}$$

where $\mu_N(D_j)$ is grade of membership of example *Dj* to the node *N*; $\mu_i(D_j)$ is grade of membership of an example relatively to the target value *i*; $S^N$ is set of all examples of node *N*. Then find the ratio

$$P^N = \sum_i P_i^N \quad (9)$$

indicating the general characteristics of the examples of the node *N*. Standard decision tree algorithm determines the ratio of the number of examples belonging to a particular attribute to the total number of examples. For fuzzy decision trees is used the ratio $\frac{P_i^N}{P^N}$ to calculate which the degree of membership is used.

Expression

$$E(S^N) = -\sum_i \frac{P_i^N}{P^N} \cdot \log_2 \frac{P_i^N}{P^N} \quad (10)$$

gives an estimate of the average amount of information to determine the class of the object from the set $P^N$.

In the next step of the construction of a fuzzy decision tree, the algorithm calculates the entropy of the partition on the attribute A with values $a_j$:

$$E(S^N, A) = \sum_j \frac{P^{Mj}}{P^N} E(S^{N|j}) \quad (11)$$

where the node $N|j$ is a child node for *N*.

Algorithm selects the attribute $A^x$ with the maximum information gain:

$$G(S^N, A): G(S^N, A) = E(S^N) - E(S^N, A). \quad (12)$$

Node *N* is divided into several sub-nodes $N|j$. Grade of membership of an example $D_k$ node $N|j$ is calculated incrementally from the node *N* as

$$\mu_{N|j}(e_k) = \min\left(\mu_{N|j}(D_k), \mu_{N|j}(D_k, a_j)\right), \quad (13)$$

where $\mu_i(D_k, a_j)$ shows the degree of membership of $D_k$ to the attribute $a_j$. Sub node $N|j$ is deleted if all the examples in it have zero grade of membership. The algorithm is repeated until all the examples will be classified or all attributes for partition will be used.

Belonging to the target class for the new record is calculated as:

$$\delta_j = \frac{\sum_l \sum_k P_k^l \cdot \mu_l(D_j) \cdot x_k}{\sum_l (\mu_l(D_j) \cdot \sum_k P_k^l)}. \quad (14)$$

Where $P_k^l$ is a leaf examples ratio of tree *l* for the value of the target class *k*; $\mu_l(D_j)$ is a degree of membership to a node of *l*, $\chi k$ is a value of the target class *k* membership to a positive outcome of the classification.

## 3. CONCLUSION

The article provides an overview of methods that can be used to assess the level of the knowledge and classification of students. The method of classification of students allows to assess the degree of membership of a new student to the particular group.

To account the subjective and inaccurate information about students selected, an approach based on fuzzy set theory, which allows to assess the degree of membership of the student to the particular class.

One of the objectives of this work was to evaluate the level of the knowledge of the student for the teacher, based on which he can be classified in one group or the other, according to which in the future will be based educational program and developed an individual study plan used through an e-learning platform. In this way, the monitoring and tracking capabilities of e-learning platforms will be able to provide feedback about the initial profile and path chosen for the student, and the final results that will be measured at the end of the e-learning activities

Note, however, that if you want a more detailed classification, it is necessary to build additional decision trees (forests) [5].

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