Pedagogical Protocols Selection Automatic Assistance

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Abstract. The preliminary results presented in this paper corresponds to a research project oriented to the search of the relationship between the predilection of students concerning learning style and the pedagogical protocols used by the human tutors (professors during the first courses of the Computer Engineering undergraduate Program) by using intelligent systems tools.

1 Introduction

In the tutor module of an intelligent tutoring system, the main sub module contains the pedagogical protocols, which are made up of two basic components: the profile analyzer and the database of pedagogical protocols available in the system. The system has a database of pedagogical protocols [Salgueiro et al., 2005]. Its use will be subordinated to the availability of the contents in the knowledge module, although the lesson always can be generated for some of the available protocols. In order to collect data about the way in which each student learns lists of learning styles will be used as well as tools for data collection. Beginning with the provided information by each student [Felder, 1988; Figueroa, 2003], his or her learning style will be determined. Afterwards, in a second step, the learning style will be linked to the pedagogical protocol. The Felder [1988] list is a validated tool that allows obtaining solid data from students. After giving a questionnaire to the students, we will try to get data records on different sets by using the intelligent systems based tools (such as SOM and TDIDT) in order to obtain a relationship between the preferences of the students and pedagogical protocols. From a statistically significant sample of students for which the lists of complete learning styles had been taken, we will try to see if the learning styles can be grouped according to the education techniques or pedagogical protocols. This will allow correlating the preference of the student with the most suitable pedagogical protocol in the system. As the selection of the pedagogical protocol is one of the elements to determine, it is desired to group the students in families with common characteristics. Therefore the research presented is oriented towards the search of the relationship between the predilection of students concerning learning style and the pedagogical protocols used by the human tutors (professors).

2 The Problem

During the first courses of the computer engineering undergraduate program at the University of Buenos Aires, the number of human tutors in Programming Area is usually not enough: the students/tutors ratio is very high and there is a great heterogeneity in the acquired knowledge and background of students. The main idea behind this paper is to describe a system that could emulate a human tutor in the process of helping a student to select a course according to his learning preferences. Thus, the tutor will be able to provide student with a high level of flexibility for the selection of the most adequate tutorial type. This could be a feasible solution to the stated problem.

3 Proposed Solution

The proposed solution can be achieved using the Self Organizing Maps (SOM) neural networks (also known with the name Kohonen [2001] maps) that make a "determined clustering" or grouping action according to common characteristic of the original set of individuals. Once obtained the resulting groups of SOM network an induction algorithm will be used to find the rules that characterize each one of these groups. In this case the algorithms to be used will belong to the family of Top-Down Induction Trees (TDIT) algorithms. Although several algorithms exist that make these functions, a very complete one is Quinlan´s C4.5 [Quinlan, 1993], an extension of algorithm ID3 (Induction Decision Trees) also proposed by Quinlan [Quinlan, 1987]. Its objective is to generate a decision tree and the inference rules that characterize this tree. In this particular case, the C4.5 will take as input the data of the students already clustered by SOM and the output will be the rules describing each cluster.

Once obtaining the smallest amount of rules by pruning the tree to avoid over fitting, we move to another stage of the analysis in which, by means of an inference process, we found the relation between the SOM clusters and the pedagogical protocols available. In order to carry out the inference, additional data concerning to the performance of students with different protocols of education in the courses under study were used. The scheme of the solution can be seen as follows: we start from a student population for which we have their preferences concerning learning styles through the lists of Felder, we form groups of students by using SOM, a table is generated using the previously classified students, using all the attributes that describe them and the cluster predicted by SOM, then a TDIDT algorithm is used to generate the rules that best describe each cluster, relating a particular cluster not only with all its attributes, as in the table of classified students, but also with a set of rules.

In the inference of the pedagogic protocol stage we try to relate the groups generated by SOM to the pedagogical protocols by training a Back propagation type neural network. In order to find the relationship between the learning style and the pedagogical protocol that best fits each group, the basic protocols described by Perkins [Perkins, 1995] in Theory One were used: [a] The *didactic or skillful instruction*: It satisfies a need that arises within the framework of the instruction in order to expand the repertoire of student knowledge [b] *The training*: It satisfies the need to make sure the student will have an effective practice, [c] *Socratic education*: This type of instruction is applied to provide educational aid to the student to include/understand certain concepts by himself and to give him the opportunity to investigate and learn how to do it, all by himself.

4 The Experiments

Two courses (A and B) will be taken belonging to the area of Programming. The only fundamental difference between both of them was centered in the form of education, that is to say, in the pedagogical protocol used in the classes. From this frame of reference, two courses were evaluated according to the control variables raised by García [1995]. The variables raised for the reference courses are the following ones: [a] Similar contents of the courses, [b] Similar schedules, [c] Similar bibliography used for references, [c] Random entrance of the students, without preference defined to some course, [d] Similar previous formation of the assistants and instructors in charge of practical works, [e] Similar didactic tools and [f] Way in which the class is dictated, where each one of the tutors presents the classes based on the pedagogical protocol that turns out more natural to carry out to him.

The possible options are defined in Theory One and that are analyzed in this investigation, independently of the needs or preferences of individualized students. Two more particular hypotheses arise from this main one: (a) The composition of styles of learning (needs and preferences of students) of each student determine the style of education (or pedagogical protocol) (b) Those students for whom the education style does not agree with their preference, show difficulties in the approval of the taught subjects. From the second hypothesis it is given off that for the approved students, the protocol preferred by most of them will have to be the one that agrees with the one used in class by the tutor, whereas for the failed ones, the protocol must be inverted for most of them.

In order to validate this affirmation a network of Back propagation type was trained with the following characteristics: [1] the approved students of the course with professor who dictates in Socratic style and the most of the failed ones of the course with professor who dictates in skillful way and the network is trained considering as output the Socratic protocol, [2] the approved students of the course with professor who dictates in skillful style plus the failed ones of the course with professor who dictates in Socratic way and the network is trained considering the output exit as skillful protocol. In order to suppress the "data noise" the training is carried out in the previously indicated way due to the fact that the groups that are outside the analysis contribute to increase the data noise (those students that approved with any protocol which will be considered “indifferent” and those that failed by lack of study or other reasons) and hope that the error of the tool is minor than the percentage of elements that are outside the analysis.

Therefore, each generated cluster will be analyzed in the following way: [a] approved students: [a1] majority class is related the correct protocol selection, [a2] minority class is related to the indifferent selection; and [b] failed students: [b1] majority class is related to inverted protocol selection, [b2] minority class is related to lack of study. Now we look to relate the forms of education and the learning styles. Following the hypothesis: failed students who do not belong to the main cluster predicted by SOM must have a different preference concerning a pedagogical protocol (inverted in this case) from the one the professor used when they attended the classes. Obtained information may be used by a sub module gives a ranking of best suitable pedagogical protocol, in descendent order with respect to the preference for the selected student.

The fundamental steps for the experimental design are described in Table 1 where it starts with the data capture from the students (to lists of learning styles) and it is used them like entrance for the training of a neural network of SOM type to generate the different groups. Soon the rules identify what describes these groups by means of the TDIDT algorithms.

Table 1. Steps for the experimental design

Step	Input	Action	Output
1	Data recollection from students	Use Felder tool on students	Result of the Felder tool.
2	Felder tool result	SOM Training	Students Clusters
3	Cluster + Felder tool results.	Use C4.5 algorithm	Rules describing each generated cluster and the corresponding decision tree.
4	Academic performance	Academic data grid	Academic grid
5	Result of the Felder tool + Academic grid + Clusters	Analysis of the cluster and determination of reprobated students.	Reprobated Student List for each cluster.
6	Result of the Felder tool.	Back propagation training	Determination of the training error and the data out of analysis. Find the relation between learning style and pedagogic protocol.

If the amount of clusters is very high, it may occur that it does not exists a correlation between so many pedagogical protocols and clusters, since it is started from the hypothesis that 3 pedagogical protocols exist (the proposed by Theory One). The number of clusters which is expected to get will be annotated between two and three. The results obtained from SOM were two clusters of data with all the attributes: Cluster 1 with 6 (5%) and Cluster 2 with 114 (95%). The result is within the awaited amount of clusters and therefore the experimental data, they agree in the amount of clusters generated. As all the data are categorical, the generated rules will not have any range for them (for example: the continuous data). In order to find the attributes with greater gain of information, it is required to use the first N passages of the TDIDT Algorithm. In this case, the first nine were taken and the rules appear in Table 2.

The Intelligent Tutorial System requires minor amount of information to select the pedagogical protocol of the student and with easier access information (it is simpler to know the answers of some key questions in the list that the answers to the entire questionnaire). Training this way it is managed to suppress the "noise" that contributes the

Table 2. Resulting rules to cross the tree generated by the C4.5 Algorithm

Rule	Antecedent	Consequent
Rule 1	**If** “Normally they consider me: Extrovert”	**Then** Cluster 2
Rule 2	**If** “Normally they don’t consider me Reserved neither Extroverted”	**Then** Cluster 1
Rule 3	**If** “I Remember easily: Something that I have thought much”	**Then** Cluster 2
Rule 4	**If** “I don’t remember easily something that I have thought much or something that I did”	**Then** Cluster 1
Rule 5	**If** “I learn: To a normal rate, methodically. If I make an effort , it profit”.	**Then** Cluster 2
Rule 6	**If** “I do not learn to a normal rate, not methodically neither disordered”	**Then** Cluster 1
Rule 7	**If** “When I think about what I did yesterday, most of the times I think about: Images”	**Then** Cluster 2
Rule 8	**If** “When I think about what I did yesterday, most of the times I think about: Words”	**Then** Cluster 2
Rule 9	**If** “When I think about what I did yesterday, most of the times I don’t think about words neither images”	**Then** Cluster 1

groups that are outside the analysis. In Table 3 the results of the students discriminated by courses can be seen, counting total students, students failed classified as belonging to the cluster in opposition to the one of the majority and the percentage that relates the failed and approved students that in addition are bad classified.

For this experience the network of the Backpropagation type trained and a ranking (scale) of pedagogical protocols most adapted for a particular situation was obtained, in order to give flexibility to the module that stores the contents.

Table 3. Summary of percentage obtained for the analysis of students, by courses

Observed Characteristic	Course A	Course B
Total of Students (For this study)	47	53
Students who reprobated the partial evaluation and were in a course with different pedagogical protocol	30	0
Students who approved the partial evaluation were in a course with different pedagogical protocol (inverted)	10	33
Approved students (no mattering about the protocol)	7	20
Reprobated students respect to the approved ones, within the subgroup badly classified	75%	0%

For the training of the Back propagation network 67% of the data (qualifications) were used randomly whereas 33% of the remaining data were used to validate the generated model. After more than 100 training of 1000 cycles each one, where it was carried out in order to diminish the error in the resulting network, it was reached the conclusion that the optimal values for the parameters of the network are those that are seen on Table 3.

Table 4. Neural Net Training Results

Characteristic	Value
% Error (Training group)	3.75%
% Error (Validation group)	2.00%
Network characteristics	
Input neuron	13
First hidden layer neurons	20
Second hidden layer neurons	20
Output neurons	2

This training is valid since the error of the tool (3,75% for the set of training and 2,00 % for the validation set) is minor than the error of the elements that were outside the analysis, which represents the students who did not approve because lack of study, although the pedagogical protocol agreed with the preference of the student (who is 25%). Therefore it is possible to conclude that: [a] course B is related to cluster 1: since the errors induced by elements of cluster 2 within the course are in a 75% or in other words, the network classifies to 75% of the students failed in the course and [b] course A is related to cluster 2: since another possible allocation in this case does not exist and in addition the percentage error of classification and reprobation is of 0%. The obtained results agree with the affirmations of Perkins, where the Back propagation network predicts that most of the failed students must have received classes using another pedagogical protocol. Socratic protocol is related with Cluster 2 and Magistral protocol is related with Cluster 1.

5 Preliminary Conclusions

The preliminary research described in this paper tend to provide to the field of the Intelligent Tutorial Systems a tool, to facilitate the automatic selection of the suitable pedagogical protocol, according to the student preferences.

When validating the model against the real data, as much for the data triangulation as the training of the neural networks that support the model, it was found that the data adapted very satisfactorily to the preliminary test conditions became not only a theoretical tool, but also a validated instrument to help the selection of the best course pedagogical protocol according to student strengths.

Next research step will focus on verifying experimentally the expectation that right selection of the pedagogical protocol will imply the improvement of the student population engineering undergraduate program course performance.

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