Proceedings of the World Congress on Engineering and Computer Science 2008
WCECS 2008, October 22 - 24, 2008, San Francisco, USA

Multi-Criteria Learners Classification for Selecting an Appropriate Teaching Method

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***Abstract*—Most important teacher's duty is making learners interested. But E-Learning systems are not regarding enough to this reality. In the other words, they represent content in a same way to different learners. For more effectiveness, system should be able to adapt its tutoring method with different learners. Thus, system should select proper method from existing teaching methods. We have a restricted number of teaching methods in our system. Therefore, each teaching method must be selected for a class of learners. So, each learner, based on his/her characteristics should be placed in a correct class. System should tutor to each class with a suitable teaching method. This method should be designed by a psychologist team and a professional teacher. System should be able to estimate learner's classes by a little or no mistake. Then, it should be able to adapt teaching method with different classes. In the other words, system should behave with different classes of learners in different ways, according to their common characteristics. In this paper we will propose a method for classification of learners. In our proposed method, classification is down based on three metrics: Learner's Rate of Doing Exercises, Emotional Affectability and Environmental Affectability. Using these three metrics we will analyze how the system could classify learners and how it could select an appropriate teaching method for each class. We have assigned a numeric value to each class. With our proposed method, system can estimate classes of learners with a good probability.**

***Index Terms*—E-Learning, Learners Classification, Learner Model.**

I. Introduction

E-learning systems and educational hypermedia systems are generally consist of three parts: learning content, learner model, and adaptation model [1], [2], [3], [4], [5]. These systems are attempting to adapt educational content to individual learners using information that is stored in learner model [1], [6], [7], [8], [9], [10], [11]. But they don't consider enough to representing method of this content. In the other words, their focus is on selecting an appropriate content to each learner [1], [6], [8], [9], [10], [11], but they should consider to selecting an appropriate teaching method. It means that an effective e-learning system must represent the same content for different learners differently. Although, there are some researches in the context of learners classification [12], but they are not consider to important differences of learners such as learning ability and emotional affectability for classifying them.

Different learners are differently affected by emotional and environmental motivators. In the other words, their cognition ability is differently changeable by amending their emotional states or their environmental conditions. Furthermore, learning ability in individual learners in the same conditions is not alike. We propose that e-learning system should select different teaching method for different learners regarding to their characteristics. Characteristics that we are focused on them are: learning rate, emotional affectability, and environmental affectability.

System can use a restricted number of teaching methods. Thus, it is essential for e-learning system to classify the learners. Each class of learners should be related to one teaching method. Classification is done based on three metrics that have been mentioned above.

The structure of this paper is as follow: after introduction in the second section different classes of learners will be investigated. In the third section our proposed methods for detecting classes of learners will be explained. Selecting an appropriate method for representing content to each class will be discussed in the section four. Finally in the section five evaluation results of our proposed method will be represented.

II. Different Classes of Learners

We can classify learners in different classes for teaching them according to their common characteristics. Learners are different in learning rate, emotional and environmental affectability. We can utilize these differences for more effective representation of educational content. Each of these three metrics is in the three levels: high, medium, and low (Table 1).

Table 1: Learners Classes

	High	Medium	Low
Learning Rate		*	*
Emotional Affectability	*		*
Environmental Affectability	*		*

According to table 1 we can distinguish 27 classes of learners. We can assign a numeric value (between 0 and 26) to each class. This class number must be saved in the learner model.

Manuscript received July 18, 2008. Multi-Criteria Learners Classification for Selecting an Appropriate Teaching Method.

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III. Learner Class Number Computation Method

System utilizes implicit parameters and asking some questions for class number detection. We will explain our proposed method in the four next subsections.

A. Learner Class Computation According to Learning Rate

For learners classification based on learning rate we have focused on number of mistakes and time of doing exercises. Our proposed system maintains probability of doing mistake in each exercise in the meta-data of it. Also, predicted time of doing each exercise should be stored in the meta-data of each exercise. This probability and time are recommended by teacher of the course. We have utilized (1) for computing learner's rate class.

$$\triangle V = V - V_p = \frac{N - N_F}{T} - \frac{1 - \overline{F}_{ps}}{\overline{T}_{ps}} \quad (1)$$

That $\triangle V$ is difference between learner's rate and predicted rate. V_p is the predicted rate and V is learner's rate. N is the number of exercises in this session, N_F is the number of mistakes in this session, T is time of this session, $\overline{F}_{ps}$ is average of predicted mistake probability for exercises of this session, and $\overline{T}_{ps}$ is mean of predicted time to doing exercises in this session. If $\triangle V > \alpha$, $\alpha > 0$, learner's rate is high. If $\alpha \leq \triangle V \leq \beta$, learner's rate is normal and if $V > \beta$, he/she belongs to low rate learners class. The values of α and β are determined by teacher of course regarding to educational content. This result is perfectly valid when we encounter with a session in which $\sum CE_s \geq \tau$. The value of τ is determined by psychology and agronomy experts. Increasing the number of sessions will lead to more precise result.

B. Learner Class Computation According to Emotional Affectability

For detecting that how much learner is effectible in contrast to his/her emotions, system must estimate learner's current emotional state at first. For detecting emotions some researchers have utilized facial or vocal recognition [13], [14], [15], [16]. Some others have utilized some special sensors for movement recognition [16], [17]. Also, there are some researches about recognizing emotions by the other means. In this work, we request the learner to determine his/her emotional states at the start of the session, 10 minutes later and 20 minutes later. We have assigned a numeric value for each emotional state. Positive emotional state has positive value and negative one has negative value. After each request sum of values is computed and after the session, average of this value is computed as overall emotional state.

As it mentioned in previous section, mean time of doing exercises and number of mistakes is computed for each session. System should find two sessions that learner's emotional state value of them has most difference. Then system can use (2) for detecting class of learner based on his/her emotional affectability.

$$EF = \frac{\sum_{i=1}^{3} CN_{1i}}{\sum_{i=1}^{3} CN_{2i}} \times \frac{\overline{T}_1 - \overline{T}_{ps1}}{\overline{T}_2 - \overline{T}_{ps2}} \times \frac{\overline{F}_1 - \overline{F}_{ps1}}{\overline{F}_2 - \overline{F}_{ps2}} \quad (2)$$

That EF is learner's Emotional Factor. $\sum_{i=1}^{3} CN_{1i}$ is overall emotional value for session by most overall emotional value. $\sum_{i=1}^{3} CN_{2i}$ is overall emotional value for session by least overall emotional value. $\overline{T}_1$ and $\overline{T}_2$ are average times of doing exercises by learner, $\overline{T}_{ps1}$ and $\overline{T}_{ps2}$ are average of predicted time, $\overline{F}_1$ and $\overline{F}_2$ are average of mistakes for learner, $\overline{F}_{ps1}$ and $\overline{F}_{ps2}$ are average of predicted mistake probability related to sessions 1 and 2.
If $EF \geq \delta,\ 3/4 \leq \delta \leq 1$, learner's affectability is low, if $\lambda \leq EF < \delta,\ 1/2 \leq \lambda < 3/4$, learner's affectability is medium, and if $EF < \lambda$, he/she belongs to high effectible class. Determining exact values for δ and λ depends on educational content and is done by the teacher and a psychologist team.

It should be mentioned that comparison is between two sessions by most difference on overall emotional values and least difference on overall environmental values. It can lead to more exact result.

C. Learners Class Computation According to Environmental Affectability

For detecting that how much learner is effectible in contrast to environmental changes, system should ask learner some questions about his/her environment. These questions are:

- Is temperature appropriate?
- Is your chair comfortable?
- Is your desk comfortable?
- Is the lightness of room enough for study?

And so on. For each question, system request learner to select a number between 1 and 3. Number 1 implies that he/she is not comfortable, number 2 implies that he is comfortable but he is not satisfied completely, and number 3 implies that he/she is wholly satisfied. Sum of these numbers for each session illustrate satisfaction degree of learner. We estimate learner's environmental affectability by means of (3).

ISBN: 978-988-98671-0-2

$$\mathrm{ENF} = \frac{\sum_{i=1}^{4} \mathrm{ES}_{1i}}{\sum_{i=1}^{4} \mathrm{ES}_{2i}} \times \frac{\overline{T}_1 - \overline{T}_{ps1}}{\overline{T}_2 - \overline{T}_{ps2}} \times \frac{\overline{F}_1 - \overline{F}_{ps1}}{\overline{F}_2 - \overline{F}_{ps2}} \qquad (3)$$

That ENF is the Environmental Factor. $\sum_{i=1}^{4} \mathrm{ES}_{1i}$ is the satisfaction degree for session by most satisfaction degree. $\sum_{i=1}^{4} \mathrm{ES}_{2i}$ is the satisfaction degree for session by least satisfaction degree. $\overline{T}_1$ and $\overline{T}_2$ are average times of doing exercises by learner, $\overline{T}_{ps1}$ and $\overline{T}_{ps2}$ are average of predicted time, $\overline{F}_1$ and $\overline{F}_2$ are average of mistakes for learner, $\overline{F}_{ps1}$ and $\overline{F}_{ps2}$ are average of predicted mistake probability related to sessions 1 and 2. If $\mathrm{ENF} \geq \theta$, $3/4 \leq \theta \leq 1$, he/she belongs to class by low affectability. If $\sigma \leq \mathrm{ENF} < \theta$, $1/2 \leq \sigma < 3/4$, system will detect that his/her affectability is medium. If $\mathrm{ENF} < \sigma$, the learner belongs to high effectible class. θ and σ are determined by an agronomist and the teacher of the course according to Pedagogical content.

D. Computation of $\sum \mathrm{CE}_s$ for each Session

We have defined $\sum \mathrm{CE}_s$ for each session as (4). It is a metric of satisfaction degree for learner from environmental and emotional aspects.

$$\sum \mathrm{CE}_s = \sum_{i=1}^{3} \mathrm{CN}_i + \sum_{i=1}^{4} \mathrm{ES}_i \qquad (4)$$

As it mentioned in session III-A increasing in the number of sessions will lead to more precise result in the case of rate of doing exercises. Because in this situation, probability of occurring a session by higher $\sum \mathrm{CE}_s$ will be increased. For detecting class of learner's rate, most desirable session is the highest one in $\sum \mathrm{CE}_s$ value. When system detects a session by higher $\sum \mathrm{CE}_s$ value than previous sessions, it should update learner's rate class. It will cause to more precise reasoning.

IV. Designing a Teaching Method for Each Class

In [18] it has suggested that system induces learner emotions to a suitable state. But for a learner by a little affectability it could be useless. In this case more regarding to emotional states of learner may be damage the learning process. We propose that system behave by different classes of learners differently. We have represented a method for dividing learners in 27 classes by means of 3 metrics: learning rate, emotional affectability and environmental affectability. We have focused on detecting classes of learners. Designing of teaching methods is out of our discussion. For designing of teaching methods according to each class we recommend that a psychologist team assist the development team.

Using our proposed method we can estimate learner's class by a high preciseness. Interacting with learners according to their classes will lead to more satisfaction and thus it can cause to more effective learning process.

V. Evaluation Results of Our Proposed Model

As it mentioned above, our purpose is detecting of learner's class. We have assigned a numeric value between 0 and 26 to each class. In fact, each class number is a triple for example (High, Low, Medium). If we consider High as 2, Medium as 1, and Low as 0 then previous triple will be $(2,0,1)$. We can represent it as 201 in ternary, and it is 19 in decimal. In the other words, the classes are illustrated by triples $(0,0,0)$, $(0,0,1)$, …, $(2,2,2)$ that are correspondent by 0, 1, …, 26. It means that if classes of learners are approximately same in characteristics, their decimal values are near as well. We have simulated our recommended system. We have tested it on 20 students by pre-determined classes. Then we have simulated their reactions by the system. At the first session, class of each learner is set to (1, 1, 1) or 13 in decimal. By increasing number of sessions, previous values will be substituted by the more reasonable obtained results. Fig. 1 has illustrated simulation results.

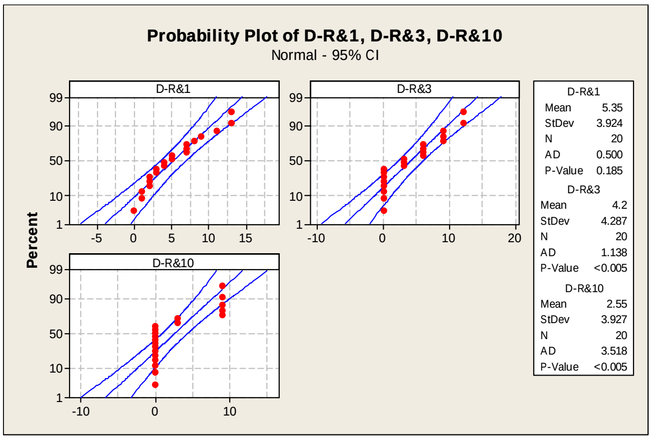

Fig. 1: Difference between real class and detected class when Environmental affectability is the most valuable figure.

In this test, α, β, δ, λ, θ, and σ are in order $1/2$, $3/4$, $3/4$, $1/2$, $3/4$ and $1/2$. Most valuable digit is environmental affectability and least one is rate class number. Diagram D-R&1 shows difference between real class and detected class at first. Diagram D-R&3 shows this difference after three sessions. Diagram D-R&10 is after 10 sessions. If we reverse the value of digits, the evaluation result is as Fig. 2.

In the second situation, obtained results are more precise. For more precise results we should study a large number of learners to discover that how much their rate of doing exercises are variable by occurring emotional and environmental changes. It can lead to more precise values for δ, λ, θ, and σ. Furthermore these values could be variable for different contents.

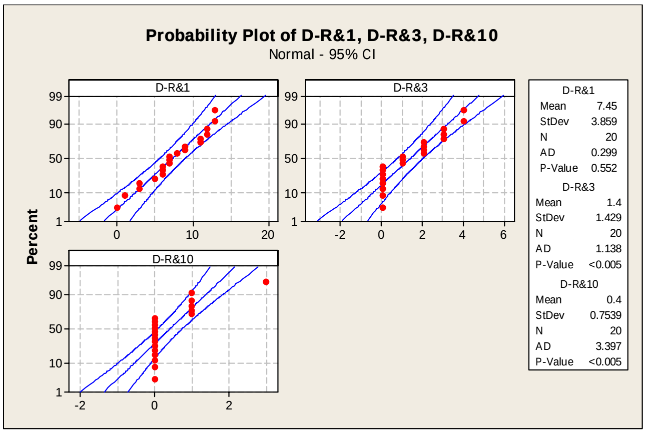

Fig. 2: Difference between real class and detected class when Rate of learning is the most valuable figure.

VI. CONCLUSION

In this paper we have proposed that system should behave differently by different classes of learners. We have classified the learners based on three metrics: learning rate, emotional affectability and environmental affectability. Moreover, we have proposed a method for detecting the class of each learner based on our recommended metrics. We have proposed that teaching method should be adapted by learners' characteristics for each class. Also, a teaching method should be utilized for more than one class. Finally, we have evaluated our proposed method.

Future works could be in these contexts: obtaining more precise values for α, β, δ, λ, θ, σ and designing a suitable teaching method for each class.

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