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Eliminating Anomalies in Learner Modeling Using Two-Partial Learner Model

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Abstract—Sometimes, gathered information from tracking learner interactions is not precise. In fact, existing e-learning systems only know the number of previewed pages precisely. They can deduce that how much the learner is mastered using some learner's characteristics such as time of doing exercises and the number of mistakes. But these deductions may be not precise. Because the time of doing exercises depends on learner's emotional states and environmental conditions. Thus we have introduced a new concept as two-partial learner model. Our proposed model divides learner model into two parts: Permanent Learner Model (PLM) and Temporary Learner Model (TLM). In the two-partial learner model, system's deductions are placed in the TLM at first. Then, system should validate accuracy of these deductions. Valid deductions are used in the updating of PLM for making them usable in other sessions. Otherwise, they should be ignored. Two-partial learner model is suitable for example-based educational systems. Because these systems are making deductions about the learner based on his/her interactions with the system.

***Index Terms*—Permanent Learner Model, Temporary Learner model, Two-Partial Learner Model.**

I. Introduction

Some researchers believe that nowadays e-learning systems are progressed than traditional teaching in which a teacher represents content to many students [1]. Intelligent tutoring systems offer many advantages over the traditional classroom scenario: they are always available, non-judgmental and provide tailored feedback [2], [3], [4]. They have proved to be effective, resulting in increased learning [5], [6], [7]. However, these systems are extremely weaker than face to face tutoring to one student. One reason is that e-learning systems use few parameters for tracking learner's interactions [8], [9], [10], [11], [12], [13], [14], [15], [16]. Another reason is that system's deductions about these parameter's values are not precise [10], [11]. Many of e-learning systems are not considering to learner's emotions and his/her environmental conditions [8], [9], [10], [11], [12], [13], [14], [15], [16]. While effecting of emotions and environment on learning process is obvious [17]. Although there is some researches about learner's emotions recognition [18], [19], [20], [21], [22], [23], [24], but e-learning systems don't consider to it as an important part of their teaching process.

In this work, we have proposed a new model for learner modeling. In the proposed model we have divided the learner model into two parts: Permanent Learner Model (PLM) and Temporary Learner Model (TLM). Permanent learner model is similar to regular learner model in the e-learning systems. The knowledge and the relevant information about the learner are maintained in the usual learner model [16]. TLM is like a filter. All system's deductions are placed in the TLM at first. During current session, system behaves with the learner according to this session's TLM. At the end of each session, validated deductions are used for updating the PLM. Our proposed model will lead to more precise deductions and thus it will lead to more adaptation in e-learning systems.

The organization of this paper is as follow: After introduction, in the second section our proposed model for learner modeling will be represented. After that, updating method of the permanent learner model will be explained in section 3. In this section computational method regarding parameters like average time of solving problems will be explained. The result of this computation is to validating this session's gathered information. In section 5 we will discuss about evaluation of model.

II. Our Proposed Model

In the proposed model, learner model is divided into two parts: Permanent Learner Model (PLM) and Temporary Learner Model (TLM). Permanent learner model is like the regular learner model in the e-learning systems. Temporary learner model is a temporary place in which emotions of learner and new deductions related to current session are put aside. TLM is like a filter. Learner emotions are related to current session and should be ignored after that. Furthermore, some deductions about learner's knowledge and mastery may be not accurate. Because emotional states and other temporary situations effect on parameters like learner's time of doing exercises and number of mistakes. So, it may be cause to incorrect deductions about learner's knowledge and mastery. Deductions that have a large difference with information in the PLM should not be utilized in the updating of the PLM. Our proposed learner model has been illustrated in Fig. 1.

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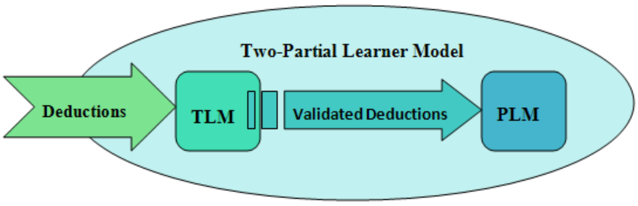

Fig 1: Two-partial learner modeling.

The information that is related to stable characteristics of learner is saved in the PLM. This information is about learner's Knowledge, interests, goals, average rate of doing exercises and so on. TLM consists of current session information before validation. Furthermore, emotional state of learner is temporary and should be kept in the TLM. Valid deductions of current session are utilized for updating the PLM.

For example, if the system computes the average time of doing exercises and it is not reasonable regarding to PLM, it will ignore this information. In such a case the system supposes that this difference is for no suitable emotional state or other temporary situation and it is not a valid value. Otherwise, this value that has been stored in the TLM will be utilized for updating the PLM. It will lead to increasing preciseness of information in the PLM. Following section has been devoted to explaining our method for updating the PLM.

III. Updating Method for PLM

In this section, updating method of PLM in the two-partial learner model will be explained. We will explain it using two parameters: difference between mean time of doing exercises and average of predicted time, and difference between percent of doing mistakes by learner and average of mistake probability. Presupposed time of doing exercises and probability of mistakes are predicted by the professional teacher. It should be stored in the meta-data of each exercise. At the following subsection our proposed equations for computing and updating these two parameters will be discussed.

A. Computing parameters in the TLM

In this section equations for computing these two parameters are represented. Equation (1) has been utilized for computing difference between mean time of doing exercises and average of predicted time.

$$\Delta\overline{t}_{n+1} = \frac{(\overline{t}'_{n+1} - \overline{t}'_{p(n+1)}) + n(\overline{t}_n - \overline{t}_{pn})}{n+1} \qquad (1)$$

That $\Delta\overline{t}_{n+1}$ is new difference between mean time of doing exercises and average of predicted time. $\overline{t}'_{n+1}$ is mean time of doing exercises for this session, $\overline{t}'_{p(n+1)}$ is average of predicted time for this session, $\overline{t}_n$ is previous mean time, $\overline{t}_{pn}$ is previous mean of predicted time for previous sessions, and n is number of previous sessions.

For computing difference between percent of doing mistakes by learner and average of mistake probability, (2) has been recommended.

$$\Delta\overline{f}_{n+1} = \frac{((\overline{f}'_{n+1} - \overline{f}'_{p(n+1)}) + n(\overline{f}_n - \overline{f}_{pn}))}{n+1} \qquad (2)$$

That $\Delta\overline{f}_{n+1}$ is new difference between percent of doing mistakes by learner and average of mistake probability. $\overline{f}'_{n+1}$ is percent of learner's mistakes in this session, $\overline{f}'_{p(n+1)}$ is average of mistake probability in this session, $\overline{f}_n$ is percent of occurred mistakes in previous sessions, $\overline{f}_{pn}$ is average probability of mistakes in previous sessions and n is number of previous sessions.

.B Updating method for PLM

Parameters which mentioned above are stored in the TLM. As we mentioned above newly computed parameters are saved in the PLM or ignored after validation. We have defined agility factor for validating of them. Agility factor is a metric that show us difference of agility in the current session and learner's average agility. Equation (3) has been used for computing of agility factor.

$$AgilityFactor = \frac{((1-\overline{f}'_{n+1})/\overline{t}'_{n+1} - (1-\overline{f}'_{p(n+1)})/\overline{t}'_{p(n+1)})}{((1-\overline{f})_n/\overline{t}_n - (1-\overline{f}_{pn})/\overline{t}_{pn})} \times \frac{m_{new}}{\overline{m}} \qquad (3)$$

That m is average of exercises in previous sessions, and m_{new} is number of these session's exercises. Other parameters of this equation are defined in previous session. Negative or less than μ agility factor will cause to ignoring this session's results in the updating of PLM. Of course, results imply to two mentioned parameters and for other parameters another methods should be employed. We have been ignored other parameters in this work.

IV. Model Evaluation

For evaluating our proposed model we will investigate 50 students of BSc course. Our educational content is mathematics. Our purpose is recognizing that how much emotional states and environmental conditions are affecting on the agility factor. Then it will be cleared which parameters values should be considered as anomalies. Then, we will estimate that how much our proposed model will lead to increasing preciseness of learner modeling.

V. Conclusion

In this work we proposed a new model for learner modeling. Our proposed model is increasing preciseness of learner modeling by dividing learner model into permanent and temporary parts. Thus it will lead to improving adaptation in e-learning systems especially example-based educational systems. These systems are making deductions about the learner based on his/her interactions with the system [25], [26]. Thus, Two-partial learner model is suitable for example-based educational systems.

Furthermore, system which is using two-partial learner model can illustrate more precise information about students for the teacher. We are in the design stage, and our proposed learner model will be developed and evaluated.

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