Involving Learner’s Emotional Behaviors in Learning Process As a Temporary Learner Model

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Abstract

It is essential for adaptive learning systems to have information about the learner. More information about the learner provides more precise deduction about learner’s knowledge, characteristics and preferences. This information is stored in learner model. Furthermore emotions play an important role in cognitive processes and therefore it must be regarded in online learning. Besides learner emotional behaviors should be considered different from other learner’s characteristics like knowledge and preferences. They also may be different in different sessions. Regular learner modeling focuses on prerequisite relationships for updating the learner model. But in the example based learning, learner ability for doing exercise must be regarded as well. In this case, learner’s emotional behaviors may lead to wrong updating of the learner model. On the other hand, learner inability in doing exercise may be related to his/her emotional state. Also, It may be temporary and only for this learning session. In such cases, learner model should not be updated by temporary results until the system ensures that they are right. In this work a new model for learner modeling will be represented that divides learner model into two parts: 1 – permanent learner model and 2 – temporary learner model. Permanent learner model stores information about learner knowledge and preferences, and it is utilized for other next sessions. Temporary learner model consists of some sort of information which is only useful in the current session. Information regarding learner emotional behaviors should be placed in the temporary learner model of our proposed model. When the learning system ensures that such information is not gathered from temporary emotional state of the learner, it could be placed them in the permanent learner model. This approach leads to more precise learner modeling for decision making.

Keywords: Learner Modeling, Temporary Learner Model, Permanent Learner Model, Emotions Recognition, Emotional Behaviors.

1. Introduction

E-Learning systems have been progressed and provided special features which make them more suitable for group learning. But e-learning systems are still behind face to face tutoring by a teacher to one student (Sarrafzadeh et al., 2003). One reason for this weakness is that they are not informed enough about learner’s characteristics. In the standard e-learning systems parameters being tracked and logged from the learner
behavior are few (Brusilovsky and Millán, 2007). Therefore, to enhance e-learning systems for personalized learning, it is necessary to increase logged parameters about learner during his/her learning process.

Another reason for this weakness is that many of the e-learning systems are not regarding learner's emotional states (Self, 1990; De Bra and Calvi, 1998; Cheung et al., 2003; Brusilovsky, 2003; Zhang et al., 2007). There are some previous works that have considered to recognizing emotions of learner (Ekman, 1999; Kopecek, 2000; Sebe et al., 2005; Osano, et al., 2006). However, they are studies focused on emotions recognition and are not regarding enough to e-learning. For making e-learning systems more effective, we should consider emotions of learner as well as his/her knowledge and other characteristics.

In this work we have represented a new model for learner modeling that divides learner model into two parts: 1 – permanent learner model and 2 – temporary learner model. Permanent learner model consists of regular learner model that stores information about learner’s knowledge and preferences. It is usable for other sessions during the learning process. Temporary learner model consists of some information about learner that is only useful for this session and is not usable for other sessions. Learner emotions are placed in this part.

The organization of this paper is as follow: After introduction, in the second section usual user modeling and emotional modeling will be described. Then, in the section 3, our proposed model for learner modeling will be represented. This model includes emotional model of learner in the context of temporary learner model. After that, updating method of the permanent learner model will be explained in section 4. 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. Finally, in Section 6, the conclusion will be presented.

2. Usual Learner Modeling and Emotional Modeling

There are some previous works in the context of user modeling. For example, Brosilovetsky (Brosilovesky, 2003) divides adaptive hypermedia into 3 parts, which is content model, user model and adaptation model. He is mentioned that we can store some information about user and his/her characteristics in the user model for future usage of them. De Bra (De Bra and Calvi, 1998) introduces user model as an overlay of content model, which can store some parameters such as user knowledge about specific concepts in the form of numeric values. Brosilovesky (Brosilovesky and Millán, 2007) classifies user models of different hyper media and educational systems on the basis of used characteristics. He mentions that Web-based adaptive educational systems (AES) mostly rely on learner knowledge and learning goals.

There are some previous works in the context of learner emotional modeling as well. There are 5 methods that computer could be utilized for recognition of learner's emotional behaviors:
1. Questions asking,
2. Deductions making based on learner’s behaviors (Cowie et al., 2001),
3. Learner’s voice processing (Kopecek, 2000),
4. Learner’s image processing (Ekman, 1999; Pantic and Rothkrantz, 2000),
5. Learner’s behaviors monitoring using sensors (Gunes and Piccardi, 2006).

All together, since now, there hasn’t been enough consideration for learner’s emotions in the e-learning systems.

In our proposed model, emotions are placed in the learner model as a temporary part. Furthermore, we have recommended that newly gathered information about learner should be placed in the temporary learner model at first. At the end of each session system can decide which information must be moved in the permanent learner model. We have utilized implicit parameters and asking questions for learner’s emotions recognition in our proposed model.

Our proposed model will be discussed in the next section.

3. Our proposed model

In our proposed model, learner model is divided into two parts: Permanent Learner Model and Temporary Learner Model (Figure 1).

Permanent learner model includes some information about learner’s previous knowledge, his/her skills in learning, interested goals, and so on. Temporary learner model includes logged information regarding learner's emotional attitudes during learning process. Learner tiredness, eagerness, and so on could be tracked to describe this part of the learner model. One of the most important issues is unexpected and short term emotional reflections which might be affecting the temporary model. Of course, these issues have no effect on the permanent model.

When learner starts a new session, the LMS can make use of information which is saved in permanent learner model to make appropriate decisions for content presentation. But all of the explanations made by the system’s reasoning should not be placed in the permanent learner model.

Obviously, in different sessions, the environmental conditions and the learner's emotional states may not be the same. Therefore, this difference can lead to some mistakes in the system’s reasoning. For instance, supposing the system wants to make decision on the basis of the number of learner’s mistakes in doing exercises. If the large number of mistakes is took place, the system will assume that the learner himself/herself is not prepared for starting the next chapter. But this reasoning may be caused by the emotional conditions. Such a case is not a permanent cause and should be considered as a temporary state. Logically, the system should not record this information as learner's inability.
In such situations, system should compare the acquired information with the previous ones to verify if there is any record of the same experience. If the answer is positive, then the permanent learner model will be updated. Otherwise, when there is a considerable difference between the acquired information and the related ones previously saved in the permanent model, system could assume that it is necessary to interrupt learner, and asking him/her explicitly about his/her emotional conditions.

In our proposed model, when the acquired characteristics have a large difference with previous recorded ones (for a particular learner), they are placed in the temporary learner model. Therefore, at the end of any session, system can decide if such information should be used for updating the permanent learner model, or it must be ignored. In fact, temporary learner model is like a filter (figure 2). Gathered information from this session must be passed from this filter. Validated information will be moved to permanent learner model for future usage. It will cause to save more precise information about learner in permanent part of the learner model.

In the other words all system's deductions about learner are placed in the temporary learner model at first. Then the system investigates that witch gathered information is reasonable. Then reasonable deductions are used for updating permanent learner model. In the next section we have explained our proposed method for updating permanent learner model.
4. Updating the Permanent Learner Model

We have used some implicit parameters for validation of information that is saved in the temporary learner model. The following sections illustrate how we can calculate the value of related parameters and then, how we can use them, in the filtering process of the learner model to develop the permanent learner model.

4.1. Implicit parameters

In this work, our focus is on two parameters: difference between mean time of doing exercises and average of predicted mean time, and difference between percent of occurred mistakes and average of predicted probability of making mistake in the solved exercises.

To using our method, predicted mean time and predicted probability of making mistake in each exercise must be saved in its meta-data. It should be predicted by a professional teacher. In the next section we will represent our recommended equations for calculating these parameters.

4.2. Calculations on implicit parameters

We propose equation [1] for calculating difference between mean time of doing exercises and average of predicted mean time.
\[
\Delta T_{n+1} = \frac{(T_{n+1} - T_{p(n+1)}) + n(T_n - T_{pn})}{n+1}
\]

That \( \Delta T_{n+1} \) is new difference between mean time of doing exercises by learner and predicted mean time. \( T_{n+1} \) is mean time to doing exercises by learner for this session, \( T_{p(n+1)} \) is predicted mean time for this session, \( T_n \) is previous mean time, \( T_{pn} \) is previous mean of predicted time, and \( n \) is the number of previous sessions.

Our recommended method for computing difference between percent of mistakes and average of predicted probability of doing mistake in solved exercises is as follow. We propose equation [2] to calculating this parameter:

\[
\Delta f_{n+1} = \frac{(f_{n+1} - f_{p(n+1)}) + n(f_n - f_{pn})}{n+1}
\]

That \( \Delta f_{n+1} \) is new difference between percent of mistakes and average of predicted probability of doing mistake in solved exercises. \( f_{n+1} \) is percent of learner mistakes for this session, \( f_{p(n+1)} \) is average of predicted mistake probability for this session, \( f_n \) is percent of mistakes in \( n \) previous sessions, \( f_{pn} \) is previous average of predicted mistake probability, and \( n \) is the number of previous sessions. With the aid of these two parameters, we can estimate learner’s agility in doing exercises.

\[
Agility = \left( \frac{1 - f_{n+1}}{f_{n+1}} - \frac{1 - f_{p(n+1)}}{f_{p(n+1)}} \right) \times m_{new}
\]

That \( m_{new} \) is the number of exercises in new session. Then we can introduce agility factor as follow:

\[
AgilityFactor = \frac{((1 - f_{n+1})/T_{n+1} - (1 - f_{p(n+1)})/T_{p(n+1)})}{((1 - f_n)/T_n - (1 - f_{pn})/T_{pn})} \times \frac{m_{new}}{m}
\]

That \( m \) is average number of exercises in previous sessions. Negative or less than \( \alpha \) agility factor will lead to ignore this session’s results. It means that results of such a session should not be saved in permanent learner model. We will obtain an appropriate value for \( \alpha \) in our future work. Obtaining an appropriate value for \( \alpha \) will be discussed in section 5.
4.3. Filtering the Information

Regarded to learner’s unreasonable changes in time of doing exercises, percent of mistakes, and agility, system can recognize an unsuitable emotional or environmental state. When the system recognizes an anomaly, it can ask him/her some questions and determine its reason. But anomalies should not be saved in the learner model permanently, because it can make invalid conclusions. Thus, for obtaining more precise learner modeling and to achieve better adaptation, system can save results of this session in the temporary learner model at first, and then if no anomaly is detected it can move them to the permanent learner model. We have named this process as Irregular Conclusion Filtering.

If irregularity being detected is detected the system can use these unreasonable results for adaptation in the current session, but they should be ignored at the end of the session. For example if the number of mistakes in this session is considerably more than other previous sessions, system can represent easier exercises to learner. But this is only a temporary reaction. Therefore, at the end of the current session learning system can ignore its results.

5. Model Evaluation

At present we work on evaluation of our proposed model. We have selected mathematics course for our educational content. Our proposed model is under implementation, and evaluation will be done on a group of 50 students at BSc degree level. Exercises will be in various levels and predicted time for doing exercises will be saved in the meta-data of each exercise. Then preciseness of our proposed model will be compared with previous learner models.

Furthermore, by doing experiment we will investigate that how much each parameter is effectible by emotions and environmental states. And then we will recognize that what results must be detected as irregularities and must be ignored by obtaining an appropriate value for $\alpha$.

6. Conclusion

In this paper, we presented a new model for learner modeling designed for more accurate adaptability in E-learning systems. We explained how this model could improve the adaptability of educational environments. This improvement is feasible by dividing learner model into two parts: 1- permanent learner model and 2- temporary learner model. By saving irregularities in temporary learner model and ignoring them in other sessions, we can achieve more precise learner modeling and therefore more accurate adaptability. We are now in the implementation stage, and then the proposed models are under examination in evaluation and validation stages.
REFERENCES


