www.ioirp.com International Journal of Innovative Research in Computer Science and Engineering (IJIRCSE)
ISSN: 2394-6364, Volume – 3, Issue – 1. March 2018

# PREDICTING STUDENT ACTION THROUGH ONLINE EXAMINATION IN ONLINE TRAINING

**Mrs.E.KANIMOZHIVEENA M.E, ASSISTANT PROFESSOR**

**Anandhi. K[**], Anusuya Devi. K[**], Hemavathi. N[**]**

[*]Assistant professor, Department of CSE,@gmail.com

ADHIYAMAAN COLLEGE OF ENGINEERING, HOSUR

[**] Final year students, Department of CSE, anadhipramila96@gmail.com

anusuyadevik18@gmail.com, hemy2251996@gmail.com

***ABSTRACT***

*Data mining is known to have a potential for predicting user performance. The main objective is to provide tutorial for the student who are weak in the particular subject, these has been done using data mining concept. Data mining is about finding new information in a lot of data. These performances firstly grouped into clusters. Then an extended automaton is created for each cluster based on the sequences of event found in the cluster performance. Then those data has been clustered based on the sequences of events found in the student's database. The proposed system provides a good reasonable prediction and tutorial for the students in order to guide them.*

## INTRODUCTION

EDUCATIONAL data mining has already achieved promising results, for example, with regard to the analysis of student performance or the prediction of student grades, especially in the field of web e-learning. However, there is hardly any research in the literature that has integrated data mining techniques into intelligent tutoring systems (ITSs) , for example, to provide customized tutoring for each student.

The present paper provides a collective student model that has been designed to anticipate the actions that students are likely to take while completing a practical assignment in an educational environment for procedural training. This model is created from activity records or logs collected from students with a similar background that previously completed the same practical assignment. As we will see later, an ITS equipped with this collective student model can use hints to stop students from making certain errors or from floundering with the practical assignment.

It is sometimes a good idea to let students make mistakes from which they learn. In other cases, however, it is better to give students the minimum amount of support that they need to progress independently towards problem solving and overcome their zones of proximal development. In this way, each student learns not from his or her mistakes but with a little bit of help. If necessary, the tutor gradually increases the level of support or scaffolding every time the student makes a mistake or gradually reduces the amount of help provided when the student makes progress. Another reason for helping students not to make mistakes is to prevent student frustration when they fail too often.

The proposed collective student model consists of several clusters of students, each of which contains an extended automaton. This automaton is a directed graph adapted for our purposes. As explained later, these clusters will help to provide automatic tutoring adapted to each student type. In order to confirm this claim, we validated the model using student logs collected in a 3D virtual laboratory for teaching biotechnology. This validation had two main goals:

i) verify that the prediction error is acceptable for tutoring purposes

ii) check whether clustering methods can classify students into groups that require different tutoring feedback. As we will see later, although students had a lot of freedom of action in this virtual laboratory, the model was reasonably reliable at predicting student actions and provided a useful classification of students into clusters according to their performance.

The structure of the remainder of the paper is as follows. Shows relevant works in the field of educational data mining. Section 3 describes the proposed ITS architecture, which would be able to leverage the collective student model detailed later in Section 4. Section 5 reports model validation detailing the method followed in this study and discussing its results. Finally, Outlines the conclusions of this research and some future work.

## RELATED WORK

The related work is divided into two sections. Briefly presents the main goals of educational data mining and mentions some of the key results with respect to web based e-learning systems. Focuses on systems for procedural training equipped with ITSs, whose student logs have been analyzed by means of data mining.

## EDUCATIONAL DATA MINING (EDM)

EDM tries to use data sourced from the repositories of different types of learning environments to better understand learners and learning. Some general applications of EDM are: communicate student activities and usage of online courses to educational stakeholders; help with course maintenance and improvement by analyzing usage data; analyze how well the domain is structured by student performance prediction; generate recommendations for students; predict student grades and learning outcomes; and model students. Given the scope of our research, the literature review will focus on the last three EDM applications.

Some researchers use data mining to provide hints, feedback or recommendations about which content is best for each student. Some of these use an ITS. The most frequently used data mining techniques for this purpose are association, sequencing, classification and clustering.

Other researchers try to predict different kinds of student learning outcomes such as final grades or dropouts. The most frequent data mining techniques used in this group are association, classification and clustering.

Student modeling has several applications such as the detection of student behavior or learning problems. This group most frequently uses the same data mining techniques as above, plus statistical analyses, Bayes networks, psychometric models and reinforcement learning.

One noteworthy paper in the last group processes Moodle logs to discover a specific student behavior model. They divide these logs into student groups with similar characteristics using a clustering method and then apply process mining to each cluster to create a model (represented by a directed acyclic graph) that shows the most frequent sequences of student actions. An interesting conclusion of this paper, which is relevant for our research, is that graphs, models or visual representations are easier to comprehend. Teachers and students find this summarized information more accessible. Therefore, this information could be very useful for monitoring the learning process and providing feedback.

As we find from the works referenced in this section, most research in EDM has focused on studying data or logs registered by web e-learning systems, like Moodle or MOOCs, or data collected from student curricula.

To the best of our knowledge, there is no any other proposal of predictive model in the literature to support procedural training environments that relies on data mining. Hence, next section will focus on a closed related area where we have actually been able to find some interesting contributions, procedural training environments equipped with ITSs, whose student logs have been processed through data mining.

**ARCHITECTURE** In order to leverage the presented collective student model, we propose an extension of a previous ITS architecture, the

www.ioirp.com

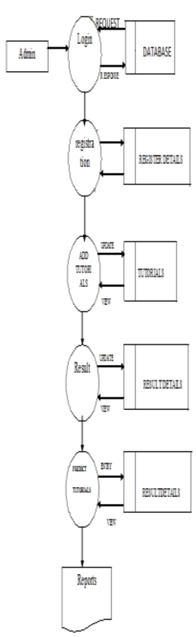
International Journal of Innovative Research in Computer Science and Engineering (IJIRCSE)
ISSN: 2394-6364, Volume – 3, Issue – 1. March 2018

MAEVIF architecture which is depicted in Figure 1. MAEVIF is a multi-agent architecture that is an adaptation of the classic ITS architecture for learning environments specialized in training. Within the extension of MAEVIF, this model encompasses a new agent, called Collective Student Agent.

Of the MAEVIF agents, let us focus on the Student Modeling Agent. The Student Modeling Agent contains an adaptive, extensible and reusable student model that infers the student knowledge state using a pedagogiccognitive diagnosis with non-monotonic reasoning abilities. The purpose of this agent is to discover each student's learning status, that is, what he or she does or does not know about the subject. This can serve as support for the personalized automatic tutoring of each student. In this way, if the student model contains enough information on a particular student, it will provide good predictions of his/her behavior. For example, if the student model knows that a student recently performed a task correctly, it is very likely that this student will perform the same (or a very similar) task correctly again.

One disadvantage of this student model is, however, that, if queried about the attainment level of a particular

LEVEL:1



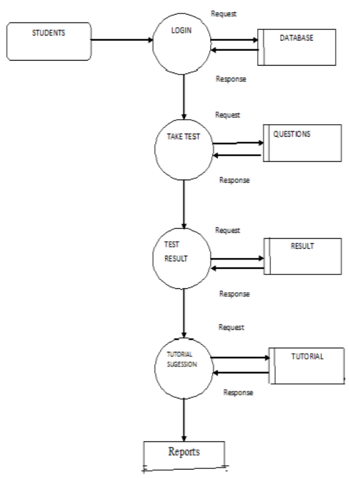

LEVEL:2

MAEVIF architecture with the new agentlearning objective, it will need a lot of background information about the student with respect to that learning objective in order to give a reliable enough response, and this information will often not be available. For example, this may be the case if it is the student's first attempt at an exercise. This may constitute a problem when the tutoring agent needs to predict the student's next actions, because if the student modeling agent is not confident enough that the student knows which actions to take next, it will not be able to provide a good prediction.

As this paper shows, if the student model does not possess enough information on a particular student, the collective student model will be a reasonably good alternative. The collective student model comprises summarized data on past student action events that are used to predict the actions that a student under supervision is most likely to take next. The premise for creating this model is that the behavior of past students doing a practical assignment should be similar to current students with the same training completing the same practical assignment.

**PROPOSED SYSTEM:**

EDM tries to use data sourced from the repositories of different types of learning environments to better understand learners and learning . communicate student activities and usage of online courses to educational stakeholders; help with course maintenance and improvement by analyzing usage data; analyze how well the domain is structured by student performance prediction; generate recommendations for students; predict student grades and learn




ing outcomes; and model students. Given the scope of our research, the literature review will focus on the last three EDM applications. Some researchers use data mining. There are several data mining studies using data collected from these two environments, but they do not report whether or not the results of these studies have been used to improve the tutoring services. For example, data from Assessment were used to create a model to predict when a student is about to ask for a hint . EDM is applied in Cognitive Tutor Algebra I to create a model that detects student attitudes/feelings such as engagement, concentration, confusion, frustration, and boredom solely from student interactions within the tutor. To the best of our knowledge, there is only one learning environment for procedural training equipped with an ITS that relies on EDM

## EXISTING SYSTEM:

This is because the most frequent transitions and the most visited states reflect the most common behavior of the students in the practical assignment. Therefore, the predictions based on such transitions and states are more reliable.

## CONCLUSIONS

The paper presents a model that can predict student actions in procedural training environments. Additionally, this paper explains how this model is integrated into an ITS architecture and how it can be used to improve the tutoring feedback by anticipating student errors as long as this is pedagogically convenient.

The collective student model is created from student logs by clustering logs and computing an extended automaton for each resulting cluster. We should highlight that there are few ITSs in the literature that rely on data mining techniques to enhance their tutoring feedback.

The proposed model has been validated using the student logs collected in a 3D virtuallaboratory for teaching biotechnology. As a result of this validation, we concluded that the model can provide reasonably good predictions and support tutoring feedback that is more adapted to each student type.

An application that displays the collective student model would be very useful for facilitating the definition of the tutoring strategy. In this way, the instructor could visualize when students make more mistakes or which part of the practical assignment students find easier. Based on this information, the instructor could decide where and what tutoring feedback the ITS should provide. Additionally, this could also help the instructor to improve his or her own teaching.

Another line of future work will be to validate an ITS built upon the proposed model in order to evaluate the tutoring feedback induced by the proposed model.

## REFERENCES

[1] C. Romero and S. Ventura, "Educational data mining: A survey from 1995 to 2005," *Expert Systems with Applications*, vol. 33, no. 1, pp. 135–146, 2007.

[2] C. Romero and S. Ventura, "Educational Data Mining: A Review of the State of the Art," *IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews)*, vol. 40, no. 6, pp. 601–618, 2010.

[3] R.S. Baker, "Educational Data Mining: An Advance for Intelligent Systems in Education," *Intelligent Systems, IEEE*, vol. 29, no. 3, pp. 78–82, 2014.

[4] L.S. Vygotsky, *Mind in society: The development of higher psychological processes*. Harvard university press, 1978.

[5] A.M. Olney, "Scaffolding Made Visible," in *Design Recommendations for Intelligent Tutoring Systems*. Orlando: U.S. Army Research Laboratory, 2014, Sch. 26, pp. 327–340.