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Elate – A New Student Learning Model Utilizing EDM for Strengthening Math Education

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Abstract— The increase of e-learning resources such as interactive learning environments, learning management systems (LMS), intelligent tutoring systems (ITS), and hypermedia systems as well as the establishment of school databases of student test scores has created large repositories of data. These data can be converted into knowledge for enhancing teaching and learning process. This paper proposes a new learning model ELATE (Enhancing Learning And Teaching) for strengthening Mathematics education in school level and proposes a frame work for using Educational Data Mining for knowledge management. This model utilizes Educational Data Mining (EDM) methods to provide results to the learners regarding their performance and skill level and to the teachers about their wards performance and their capabilities. The teachers can use the EDM results to motivate the slow learners and move the over practiced students to the next level. The ELATE frame work proposed in this paper has five levels processing to provide knowledge management services to stakeholders of educational institutions especially for the teachers and students.

Keywords— LMS, ITS, ELATE, Educational Data Mining

I. INTRODUCTION

Traditional classrooms in schools are turned into SMART classes where technology enhanced learning tools are used to assist the teacher in explaining the concepts visually. Now the Education is just not the process of filling mind with information. E-learning in education incorporates self-motivation, communication, efficiency, and technology. The e-learning transforms the schooling system into a student-centric one that can customize for different student needs by allowing all students to learn at their own pace and time. There are various kinds e-learning methods available in the form of CDs and DVDs, LMS, ITS, MOOC, for the e-learning purpose. Future trends are looking at training delivered on PDA's and cell phones. This new, form of education is called m-Learning or mobile learning. There are fundamentally two types of e-Learning: synchronous and asynchronous learning

A new form of learning known as blended learning is an amalgamation of synchronous and asynchronous learning methods. Using both online training through virtual classrooms and also giving CD's and study material for self-study is now being increasingly preferred over any single type of training. Educational technologies are a valuable tool for complementing the curriculum and personalizing learning experiences for students in new ways.

As the number of students increase in each class it is very difficult for the teacher to assess the students' mastery over the subjects accurately. The mathematics teacher has to assess the student level of understanding in each skill defined in each lesson. Only by identifying the weakness/strength of a student the teacher can provide extra coaching or promoting him to do the next lesson. Monitoring the students' performance and predicting their skill in mathematics becomes a vital to promote math education in school level. By using e-learning tools for teaching mathematics we can capture streams of fine-grained learner behaviors. The tools and techniques of EDM can operate on those data to provide a variety of stakeholders with feedback to improve teaching, learning, and educational decision making

To demonstrate how such adaptive systems operate, using the predictive models created by educational data mining, we propose a prototypical learning system ELATE (Enhancing Learning and Teaching) for math education and a frame work. This paper is organized as follows: section 2 lists the literature review, section 3 describes the proposed ELATE model and its components, section 4 describes the ELATE frame work, methodology is given in section 5, section 6 provides results and discussions and conclusion is given in the last section.

II. LITERATURE REVIEW

The process of Educational data mining is an iterative, Knowledge Discovery process which consists of Hypothesis formulation, Testing and refinement[2] (Figure-1). All those who take part in the educational process could gain by applying data mining on the data from the higher education system [1](Figure-2). These two papers explains how EDM is used in educational process.

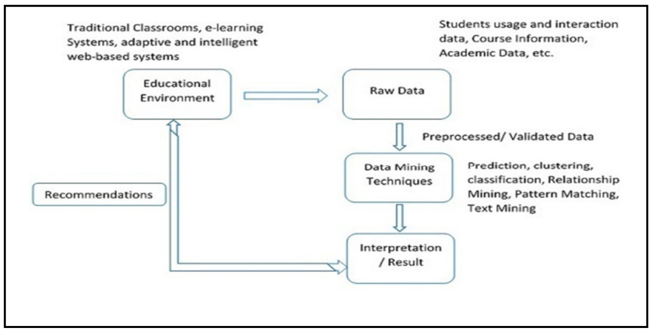

Figure 1. Educational Data mining Process[2]

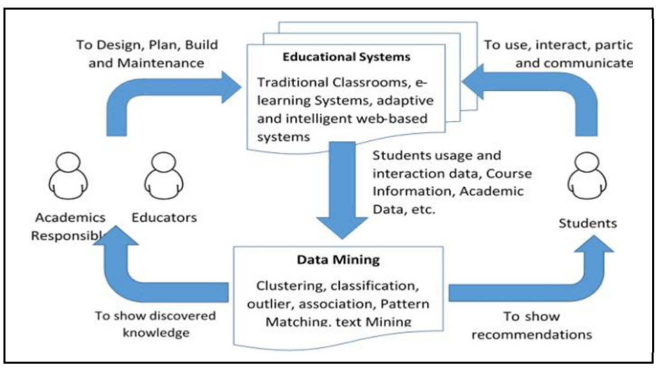

Figure 2: The cycle of applying data mining in educational systems [1]

Literature survey in this area reveals that [3][4][5] [17] the capabilities of applying DM or EDM methods depend on the domain it is used. The dataset used in these papers were derived from higher education students and tried to help the institution for predicting and improving the performance grade. The requirement of a model which cater to the needs of Indian school educational system was felt and was developed. And the proposed model in this paper takes an e-tutor environment in mathematics[16] where the active participation of students are stored as student log for further analysis.

III. ELATE MODEL

This section describes a learning model proposed for Math e-learning system. The model (Figure-3) has five components and two participants: learners (students) and Teachers. The five components are: 1) Math Tutor –the domain model 2) Student Learning database 3) EDM – performance evaluation 4) Dash Board/ Visual analytics 5) Adaptation engine.

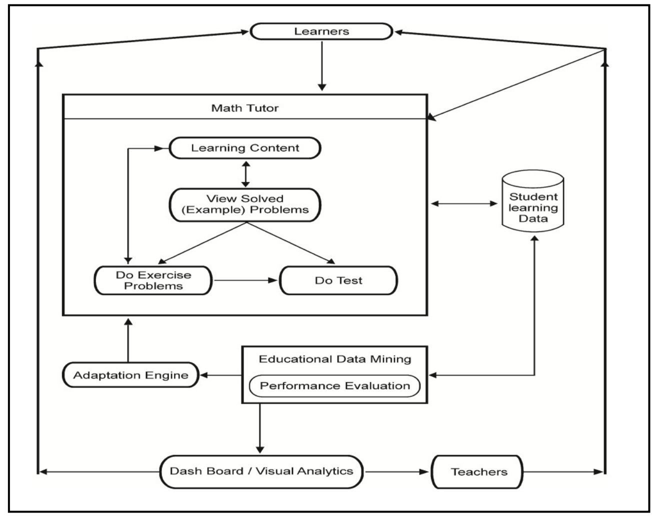

Figure 3. ELATE -Learning model for math e-learning system

Enrolling students is not depicted here. For this paper we assume that enrolled students are logging in and viewing the learning content. After viewing the lesson, solved problems are displayed one by one as teacher solves the problem in the class room. He can then move to exercise problems where he has to solve problems in steps. If a student does a mistake in a step Tutor immediately give a feedback 'wrong' and provide suggestion or hints. He can next move on to test his skill in that lesson by doing test. No hints /messages given to indicate right/wrong while performing test.

A student learning database stores the present status of student (like completed the learning material, completed how many problems in each category etc.), steps, results, feedback, number of hints used, time spent in solving exercise/test problems, login and logout time The performance evaluation is carried out with EDM methods to provide feedback to the Tutoring system through adaptation engine which personalize the content delivery to the student. An adaption engine regulates the content delivery component based on the output of the predictive model to deliver material according to a student's performance level and interests, thus ensuring continuous learning improvement.

The teacher look into the dashboard decides for a student or the class about his instruction to improve the performance in learning. He can instruct the student(s) or edit/include the contents in domain model. The students are allowed to complete all problems or skip some problems in viewing examples/exercise problems. But he has to do all in test. Students' demographic data can be stored in a separate database or can be included as a table in learning database. This model can be used as a general model suitable for all lessons in Math curriculum.

Inferring what content does a student know like specific skills and concepts or procedural knowledge and higher order thinking skills is known as user knowledge modeling. Knowledge can be inferred from accumulated data that represent the interactions between students and the learning systems such as correctness of student responses alone or in a series, time spent on practice, number and nature of hints requested, repetitions of wrong answers, and errors made. Such “inferences” can be made by a predictive computer model or by a teacher looking at student data on a dashboard.

IV. ELATE FRAME WORK

The frame work shown in Figure-4 has five layers/levels to provide knowledge management services to the institutions which use Technology Enhanced Learning (TEL) for the course delivery. This frame work utilises EDM techniques to provide results discovered from data captured in the first level. For data transformation in the second level pre-processing is done on the data captured in first level and relevant attributes for further processing is selected using feature selection/feature abstraction.

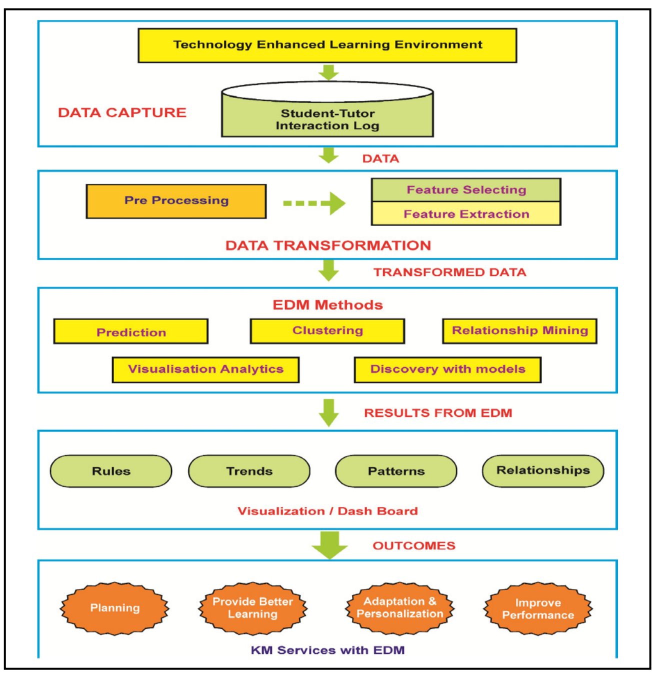

Figure 4. ELATE Framework for Knowledge Management service with EDM

In the third level EDM methods are applied on the transformed data and the results from these methods are shown as rules, trends, patterns and relationship. The outcomes of the fourth level is used by the stakeholders of TEL as knowledge management(KM) services to take intelligent decision making in planning, providing better learning, improving performance, adapting and personalising to the student needs. The Elate model in Figure 3 fits in this frame work.

V. METHODOLOGY

The researchers used MathTutor[16] as a technology enhanced learning tool to teach mensuration lesson of mathematics to the 6th grade students of Tamil Nadu, India. One hundred and twenty students participated in this study. The students completed the first lesson metric measures through this tutor. The student-tutor interaction log is considered for the research. The first level in ELATE frame captured the student log information of the example problems viewed, exercise problems solved and test problems attended by each student. In the second level of data transformation the captured data are pre-processed and necessary features are selected for the application of EDM methods. In the results and discussions section third and fourth level of the proposed model ELATE is illustrated through results taken from WEKA and DataShop[12] tools.

VI. RESULTS AND DISCUSSIONS

Learning systems typically track the state of student mastery at the skill or topic level and can provide this information to students so they know what to study and to teachers so they know the areas where they should concentrate for further instruction. Students receive feedback on their interactions with the content they are learning through the adaptive learning system. The feedback typically includes the percentage correct on embedded assessments and lists of concepts they have demonstrated mastery on is shown in Figure-5 using performance graph [10]. It can include problems attempted (correct/incorrect) as shown in Figure-6 for each student.

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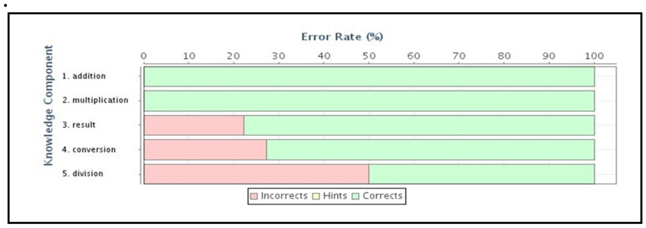

Figure 5. Performance of a student over five skills

Figure 6. Performance of a student in solving nine problems

The EDM algorithm J48 for Classification [13] is performed to classify students according to their score. The tree view (Figure-7) provides more insight into the activities of the students that affect their grade.

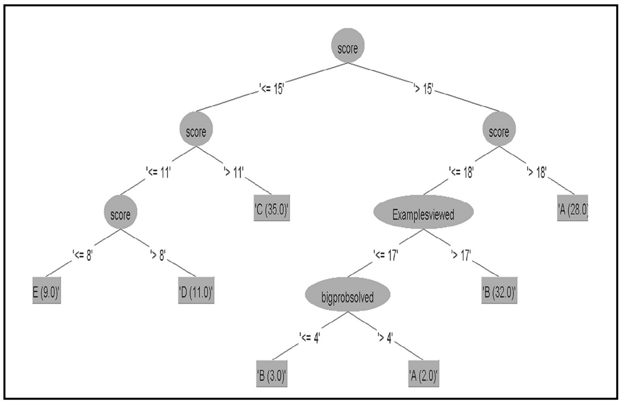

Figure 7. J48 classifer tree view

The teacher can further analyze whether number of hints used during problem solving affects the score of the students (Figure-8) using clustering method EM [13].

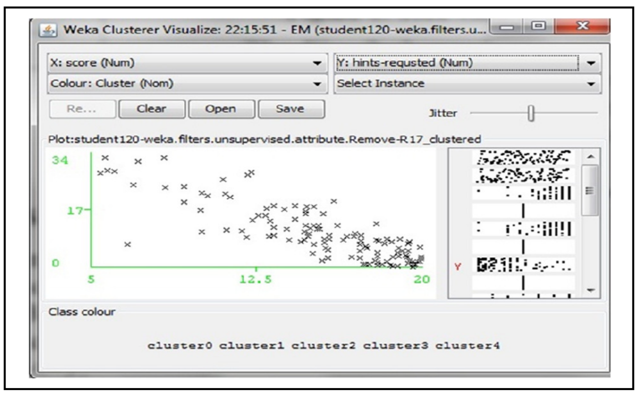

Figure 8. Score Vs Number of Hints used

The overall performance [14] in solving 32 steps in nine problems is shown in Figure-9. The teacher identifies the steps that the students made more mistakes from this curve.

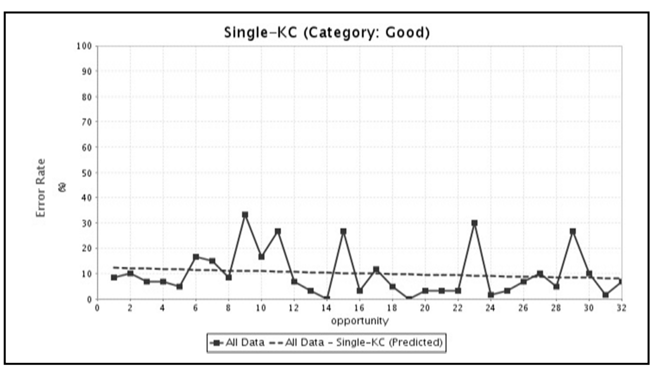

Figure 9. Learning Curve showing students performance in 32 steps

Teachers receive feedback on the performance of each individual student and of the class as a whole and adjust their instructional actions to influence student learning. By examining the feedback data, instructors can spot students who may need additional help or encouragement to spend more time on the content and identify areas where the class as a whole is struggling. The above outcomes from the fourth level of the ELATE frame work can be used by the teachers, students and administrators for intelligent decision making for improving performance and personalization.

VII. Conclusion

Educational data mining techniques in integration with learning systems can provide additional insight into the functions of teaching, learning and research. It acts as a tool for better decision making in the educational activities. The proposed model ELATE is semi automated in our research as the first level data capturing is done with a MathTutor and second level is processed with statistical techniques and WEKA. Third level once again utilizes WEKA for classification and clustering. DataShop tool is also used to find students performance in KCs and visualized through Learning Curve. The results of third and fourth levels are discussed in the results and discussions. The first four levels can be integrated in math learning system and the outcomes are used for personalizing, planning, and improving performance of the students.

Through ELATE model we can identify the existing knowledge and apply intelligence for better learning. This frame work can be utilized in personalized learning environment for providing appropriate feedback to the learners and teachers. The result from this research shows the effective use of the model in math domain to identify the skill level of the students. The same model can be used for any other e-tutoring environment. The demographic data of the students can also be incorporated to identify its influence in performance.

Acknowledgment *(Heading 5)*

For exploratory analysis, I used the PSLC DataShop, available at http://pslcdatashop.org (Koedinger et al., 2010).

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