Research Paper
Impact Factor - 2.262
Peer Reviewed Journal

IJMDRR
E- ISSN –2395-1885
ISSN -2395-1877

EDUDATA IN ADAPTIVE LEARNING SYSTEMS

S. Lakshmi Prabha* Dr.A.R.Mohamed Shanavas R.Nivetha*****

**Ph.D Research Scholar, Bharathidasan University & Associate Professor,Department of Computer Science, Seethalakshmi Ramaswami College, Tiruchirappalli, Tamilnadu, India,*

***Associate Professor, Department of Computer Science, Jamal Mohamed College, Tiruchirappalli, Tamilnadu, India,*

****Assistant Professor, Dept. of Computer Science, Seethalakshmi Ramaswami College, Tiruchirappalli, Tamilnadu, India,*

Abstract

Learning management systems, learning platforms, learning software and online learning systems —have the ability to capture streams of fine-grained learner behaviors, and the tools and techniques in data mining can operate on the data to provide a variety of stakeholders with feedback to improve teaching, learning, and educational decision making. This paper describes about the use of student log data from an e-learning system MATHSTUTOR for adaptive learning environment. Also briefs about the functionality of such adaptive learning system and use of EDM techniques in predictive modeling.

Keywords-Adaptive-learning, e-learning, LMS, EDM.

INTRODUCTION

E-learning is a means of education that incorporates self-motivation, communication, efficiency, and technology. Learners enjoy having the opportunity to learn at their own pace, and on their own time. Education is getting very close to a time when personalization will become commonplace in learning. The instructor is responsible for supporting student learning, but her role has changed to one of designing, orchestrating, and supporting learning experiences rather than "telling." The instructor elaborates and communicates the course's learning objectives and identifies resources and experiences through which those learning goals can be attained. Rather than requiring all students to listen to the same lectures and complete the same homework in the same sequence and at the same pace, the instructor points students toward a rich set of resources, some of which are online, and some of which are provided within classrooms and laboratories. Thus, students learn the required material by building and following their own learning maps.

In an online learning system, the student's dashboard shows learning resources, including lectures by a master teacher, sophisticated video productions emphasizing visual images related to the genetics concepts, interactive population genetics simulation games, an online collaborative group project, and combinations of text and practice exercises. Each resource comes with a rating of how much of the portion the learning map it covers, the size and range of learning gains attained by students who have used it in the past, and student ratings of the resource for ease and enjoyment of use. These ratings are derived from past activities of all students, such as "like" indicators, assessment results, and correlations between student activity and assessment results.

The student chooses a resource to work with, and his or her interactions with it are used to continuously update the system's model of how much he or she knows about the particular topic. After the student has worked with the resource, the dashboard shows updated ratings for each learning resource; these ratings indicate how much of the unit content the student has not yet mastered is covered by each resource. At any time, the student may choose to take an online practice assessment for the unit. Student responses to this assessment give the system—and the student—an even better idea of what he or she has already mastered, how helpful different resources have been in achieving that mastery, and what still needs to be addressed. The teacher and the institution have access to the online learning data, which they can use to certify the student's accomplishments.

This scenario shows the possibility of leveraging data for improving student performance. The data can be used for "sensing" student learning and engagement. This detailed behavior data can pinpoint cognitive events. The section II brief about the components involved in a learning system. The section III describes the data flow in an adaptive learning system. The section IV explains about the use of educate in an adaptive e-learning tool in mathematics. The implementation of the tool[MATHSTUTOR] is explained in [3].

LEARNING SYSTEM WITH SIX COMPONENTS

This section describes a prototypical learning system with six components:

1. **Content:**A content management, maintenance, and delivery component interacts with students to deliver individualized subject content and assessments to support student learning.

2. **Data Repository:** A student learning database (or other big data repository) stores time-stamped student input and behaviors captured as students work within the system.
3. **Predictive Model:** *A* predictive model combines demographic data (from an external student information system) and learning/behavior data from the student learning database to track a student's progress and make predictions about his or her future behaviors or performance, such as future course outcomes and dropouts.
4. **Dashboards:** A reporting server uses the output of the predictive model to produce dashboards that provide visible feedback for various users.
5. **Adaption Engine:**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.
6. **Intervention Engine:** An intervention engine allows teachers, administrators, or system developers to intervene and override the automated system to better serve a student's learning.

In addition to these six internal components, an adaptive learning system often uses the student information system (SIS) that is maintained by a school or institution as an external data source. Student profiles from the SIS are usually downloaded in batch mode, as they do not change often, and then are linked with performance data in the student learning database using student identifiers in compliance with applicable law. Student profiles contain background information on students that can be used to group them into specific categories.

DATA FLOW IN THE SYSTEM

The numbers in Figure 1 signify the data flow that creates feedback loops between the users and the adaptive learning system. The data flow starts with Step 1, students generating inputs when interacting with the content delivery component. The inputs are time-stamped and cleaned as necessary and stored in the student learning database according to predefined structure (Step 2). At certain times (not synchronized with student learning activities), the predictive model fetches data for analysis from both the student learning database and the SIS (Step 3). At this stage, different data mining and analytics tools and models might be applied depending on the purpose of the analysis. Once the analysis is completed, the results are used by the adaptation engine (Step 4) to adjust what should be done for a particular student. The content delivery component presents these adjusted computer tutoring and teaching strategies (Step 4) to the student. The findings also may flow to the dashboard (Step 5), and, in the last step in the data flow, various users of the system examine the reports for feedback and respond (using the intervention engine) in ways appropriate for their role.

These last steps complete feedback loops as stakeholders receive information to inform their future choices and activities.

EDUDATA IN MATHSTUTOR

MATHSTUTOR[3] is an e-learning tool designed for learning mensuration part of mathematics. Teachers register the students and provide IDs. When the students enter into the tutor his actions through keystrokes are stored for tracking. Students receive feedback on their interactions with

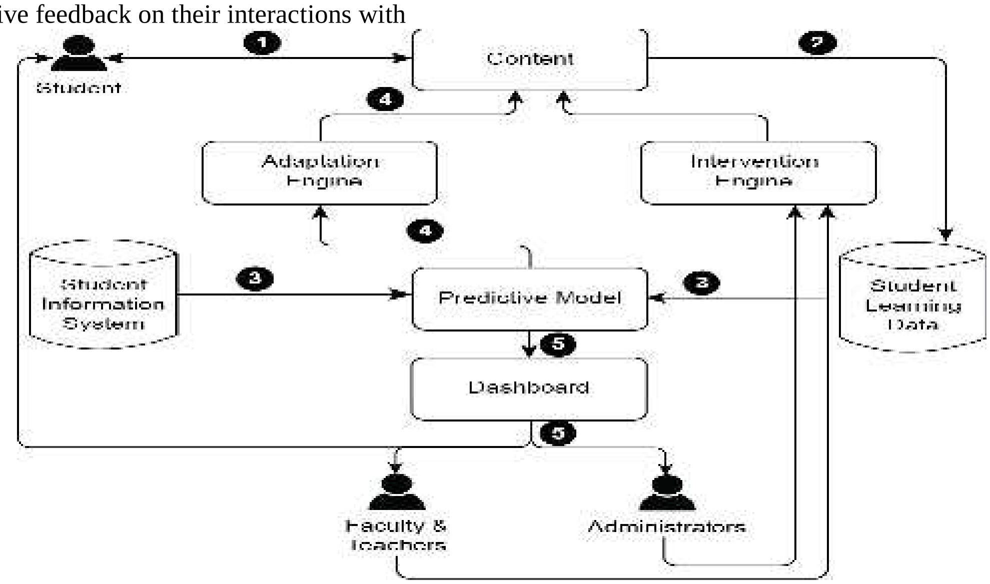

Figure 1.The components and data flow through an Adaptive Learning System

IJMDRR
E- ISSN –2395-1885
ISSN -2395-1877
Research Paper
Impact Factor - 2.262
Peer Reviewed Journal

the content they are learning through the adaptive learning system[Figure2]. The feedback typically includes the percentage correct on embedded assessments and lists of concepts they have demonstrated mastery on, but it also can include detailed learning activity information (e.g., hints requested and problems attempted)[Figure 3].

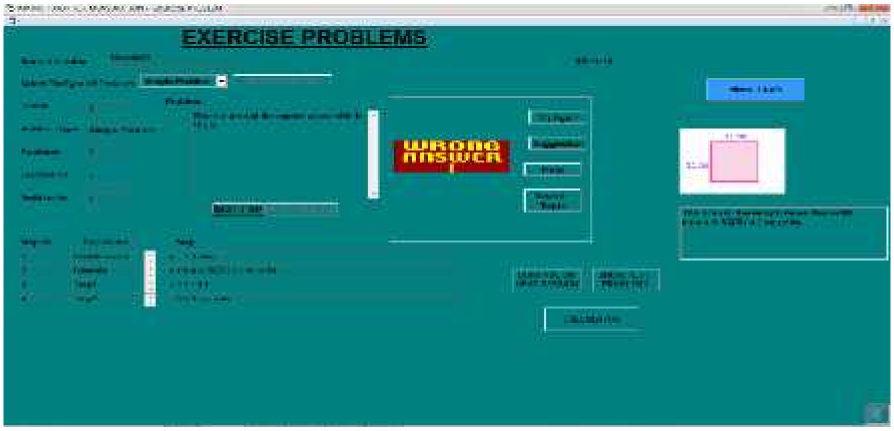

Figure 2.Screen Shot from MATHSTUTOR showing student interaction

Teachers receive feedback[Figure3] on the performance of each individual student and of the class as a whole[Figure4] 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. Teachers may choose to intervene with the system to adjust student learning pace or may assign additional learning materials targeting the skills that are not yet mastered.

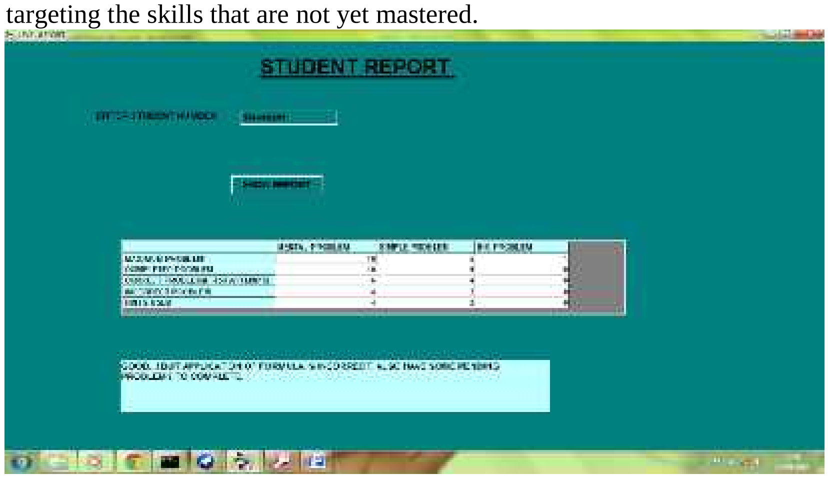

Figure 3. Screen Shot from MATHSTUTOR showing a student Performance

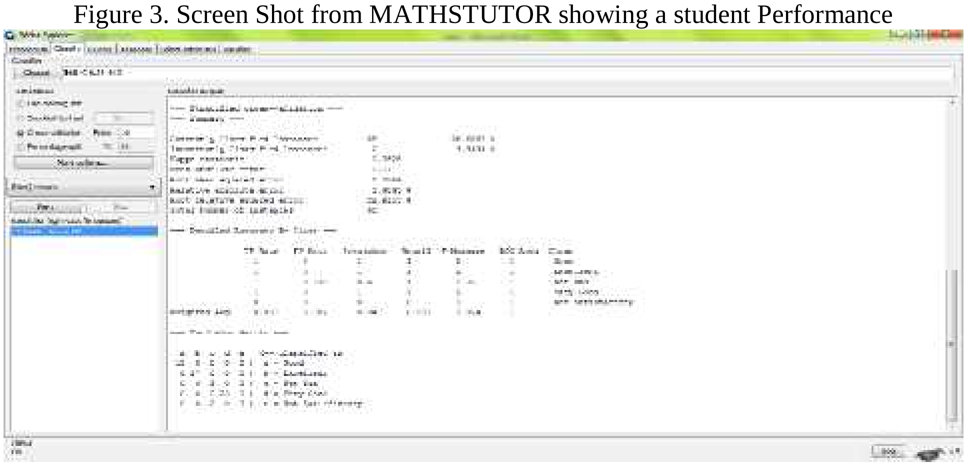

Figure 4. Clustering students using WEKA

IJMDRR
E- ISSN –2395-1885
ISSN -2395-1877

Administrators can look at detailed data across different classes to examine progress for all students at a school, to see what works and what does not in a particular classroom, and to do so with less effort.. Learning system data can support analyses of how well students learn with particular interventions and how implementation of the intervention could be improved. This part for administrators is under implementation.

CONCLUSION

Sample screen shots show the usage of edudata from MATHSTUTOR for effective teaching and learning.. 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 further instruction.. Researchers can use fine-grained learner data to experiment with learning theories and to examine the effectiveness of different types of instructional practices and different course design elements. Learning system developers can conduct rapid testing with large numbers of users to improve online learning systems to better serve students, instructors, and administrators. To research and build models in user modeling and domain modeling the data generated from learning systems utilizes Educational Data Mining techniques. Open source tools for adaptive learning systems, commercial offerings, and increased understanding of what data reveal are leading to fundamental shifts in teaching and learning systems.

REFERENCES

1. Baker, R. S. J. d. 2011. “Data Mining for Education.” In *International Encyclopedia of Education*, 3rd ed., edited by B. McGaw, P. Peterson, and E. Baker. Oxford, UK: Elsevier.
2. Brown, W., M. Lovett, D. Bajzek, and J. Burnette. 2006. “Improving the Feedback Cycle to Improve Learning in Introductory Biology Using the Digital Dashboard.” In *Proceedings of World Conference on E-Learning in Corporate, Government, Healthcare, and Higher Education 2006I,* edited by G. Richards. Chesapeake, VA: AACE, 1030–1035.
3. Prabha, S.L.; Shanavas, A.R.M., "Implementation of E-Learning Package for Mensuration-A Branch of Mathematics," 2014,IEEE, doi: 10.1109/WCCCT.2014.37.
4. Baker, R. S. J. d., A.T. Corbett, and V. Aleven. 2008. “More Accurate Student Modeling Through Contextual Estimation of Slip and Guess Probabilities in Bayesian Knowledge Tracing.” In *Proceedings of the 9th International Conference on Intelligent Tutoring Systems*. Berlin, Heidelberg: Springer-Verlag, 406–415.
5. Baker, R. S. J. D., and K. Yacef. 2009. “The State of Educational Data Mining in 2009: A Review and Future Visions.” *Journal of Educational Data Mining* 1 (1): 3–17.
6. Corbett, A. T., and J. R. Anderson. 1994. “Knowledge Tracing: Modeling the Acquisition of Procedural Knowledge.” *User Modeling and User-Adapted Interaction* 4 (4): 253–278. doi: 10.1007/BFO1099821.
7. Dawson, S., L. Heathcote, and G. Poole. 2010. “Harnessing ICT Potential: The Adoption and Analysis of ICT Systems for Enhancing the Student Learning Experience.” *International Journal of Educational Management* 24 (2): 116–128.
8. Köck, M., and A. Paramythis. 2011. “Activity Sequence Modeling and Dynamic Clustering for Personalized E-Learning. *Journal of User Modeling and User-Adapted Interaction* 21 (1-2): 51–97.
9. Hilbert T. S., Renkl, A., Schworm S., Kessler S., Reiss, K., “Learning to teach with worked-out examples: A computer-based learning environment for teachers,” Journal of Computer-Assisted Learning, Vol. 24, 2008, pp.316-332, DOI: 10.1111/j.1365-2729.2007.00266.x.
10. Siemens, G. Connectivism. “A learning theory for the digital age,” International Journal of Instructional Technology & Distance Learning, Vol. 2, No. 1, 2005, pp. 3–7, doi:http://www.itdl.org/Journal/Jan_05/article01.htm.
11. Scotty D. Craig, Michelene T. H. Chi, Kurt VanLehn, “ Improving Classroom Learning by Collaboratively Observing Human Tutoring Videos While Problem Solving,” Journal of Educational Psychology, Vol. 101, No. 4, 2009, pp. 779–789, doi: 10.1037/a0016601.
12. Mohammad Issack Santally,Alain Senteni, “Reconceptualisation of the Teaching and Learning Process through Computer-Mediated Frameworks,” International Journal of Instructional Technology and Distance Learning, Vol.2,No.1,2005, pp.23–38, doi:http://www.itdl.org/Journal/Jan_05/article03.htm., 2006, pp. 227–265, doi: http:// dl.acm.org /citation.cfm?id=1435353.