Improvisation of learning experience using Learning Analytics in eLearning

Uday Kumar Mothukuri, B Viswanath Reddy, P Naveen Reddy, Sarada Gutti, Kumar Mandula, Ramu Parupalli, CH.A.S.Murty, E.Magesh
Centre for Development of Advanced Computing(C-DAC)
Hyderabad, India
{muday, viswanath, pnaveen, gsarada, mkumar, ramup, chasmurty, magesh}@cdac.in

***Abstract*— As technology progresses, understanding online learner's behavior is the key for successful implementation of digital learning. The more we know about learners, the more tailored learning experiences will be. Analyzing the learner's preferences will help to predict the behavior of learner's so that required support and guidance can be provided on time. For achieving this much more efficient systems are required to process all types of the learner interactions with the learning management system during their each learning activity. This paper discusses the importance of learning analytics, and presents its usage in eLearning. It describes how learning analytics can help the learners, instructors and institutions to look into ongoing learning processes and how the online educational processes can be improved. It also depicts about the proposed system how the learning styles can be used for improving learning experience.**

Keywords—learning analytics; LMS; learning styles; MOOC; recommender system

I. INTRODUCTION

In general, the definition of eLearning is any form of online learning in which the instructor and learner are bridged through the use of Information and Communication Technologies (ICT), providing the flexible ways of learning from anywhere, anytime, at their own pace. It is the combination of various learning services and technologies for enhancing the learning experience under the guidance of teachers. Learning Management System (LMS) is a web-based platform and used to automate and centralize the administration of the eLearning activities such as enrollment, course delivery, tracking and reporting the learning progress. The key eLearning services of any LMS include user management, course organization, course delivery, online assessment, query handler, reporting, communication and collaboration services. An effective LMS should provide the learning environment to the learners, so that the administrators can easily manage users and administer other eLearning services.

However, the well-known problems in MOOC (Massive Open Online Course) environment are explored, such as the high dropout ratios and how these numbers can be reduced using various machine learning techniques [7]. The objectives of the research on MOOC platform is to look deep into learner progress, for example; predicting the student performance using clickstream data [5] or gauging the effectiveness of student's state with the provided educational resources and defined activities [6].

On the other hand the increase in the usage of these eLearning platforms tending to generate large amounts of data from the user interactions with the system. Learning Analytics may be used to take proactive action aimed at mitigating learning risks and improving learner's engagement and performance. By analysing these patterns through the analytics systems we can bridge the connections between phenomenally not related data and give better instructions. Learning Analytics also gives institutions the ability to improve the eLearning courses, custom tailor every eLearning activity, and gain valuable insights into learning behaviours and preferences. By using analytics tools, creators/instructors can fine tune eLearning strategy and ensure that every aspect of eLearning course is in-line with goals and objectives. Learning analytics mainly aims at visualizing students' learning information for students to reflect and enhance their learning and for teachers to interpret student learning and adopt intervention [4]. Greller and Drachsler [9] proposed a generic framework for learning analytics, intended to serve as a manual for setting up Learning Analytics services for the educational institution. This framework mostly focused on the internal connections between the six different dimensions and the impact of the analytics process on the end user and the content providers.

In our previous study we have introduced adaptive learning environment that deals with the learning style and prior-knowledge level of the students to provide personalized course content and learning path. The first approach introduced prior knowledge level modeling for providing recommended learning path and in the second approach; the ILS questionnaire is introduced for knowing the varied learning styles. In the other study we have introduced the recommendation system where we have addressed the issue of clustering the similar group of learners when there is a smaller user profile data set [2][3]. The instructor has need to provide different activities; learning services, as part of the learning path for different groups of learners.

In this paper presents how the learning analytics was used to build and frequently update the cognitive profile which holds the information of student's learning style, improving the learning experience by involving the instructor's intervention on need and providing the recommendations to increase the learner engagement with the system. Section 2 deals about the Learning Analytics in eLearning, and how learning analytics can be used to predict the learning styles during the learning process, respectively. Section 3 describes about the Learning Styles. In Section 4 we have presented the proposed approach with our LMS and how this can improve the learning

978-1-5386-1922-3/17/$31.00 © 2017 IEEE

experience. Finally, the paper concludes by describing the future work to be carried out.

II. LEARNING ANALYTICS

Learning analytics is the measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and the environments in which it occurs [1]. Learning analytics uses data about learners and their activities for helping the institutions to understand and improve the educational processes, and providing better support to learners. It combines the data analysis with student interaction in online education tools like Learning Management Systems, Virtual Learning Systems, etc., aiming to create a more integrated and customized learning experience. It uses intelligent data, student performance and analysis models to find out how learners learn and the institutions can use to improve their experience.

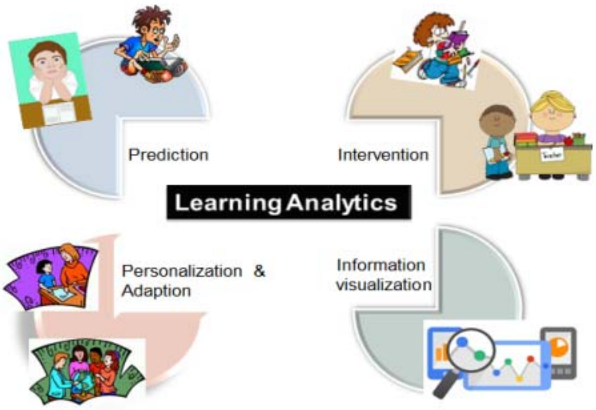

Figure 1: Benefits of using Learning Analytics in eLearning

A. *Benefits of Learning Analytics*

- Can predict
  - future student performance (based on past patterns of learning across diverse student bodies)
  - the most and least visited content resources for reviewing and improving the quality of the resources
- Intervene when learners are struggling to maintain the pace
  - providing necessary instructions on every activity
  - recommending the success stories for motivation and creating the interest
- Personalize the learning process for each and every student and encouraging improvements
  - providing the required type of content resources (video with subtitles, audio files, PDF with marking tools, saving the current learning position and loading the same on next visit, notes, etc.)
  - accessibility towards the widgets like calendars for displaying the activities ahead and completed, reminders for the planned activities, etc.
- Adapt teaching and learning styles via socialization, pedagogy and technology
  - Participation among the peer groups discussions for solving the assignments or gaining the knowledge
- Visualize the information processed in the form of user specific dashboards
  - Dashboards are acting as the progress monitors that can provide the complete picture of where the student is standing in the course

B. *Improving the quality of teaching*

Merging analytics with LMS leads to more comprehensive and in-depth evaluation of user's interaction with an eLearning system. In LMS the analytics produce information that helps administration in making decisions and policies, to monitor and measure learners' performance and assess them more accurately that will benefit learners and learning process.

For Instructors:

- It can furnish the instructor with better information on the quality of the content resources and activities assigned to the students, and on their assessment/assignment process.
- It also helps to identify and address the issues during their life cycle of the student learning process, and these interventions can help to build good relations among the peer group and the instructors.
- It can be used by instructors to monitor the live performance of their students while they are accessing a specific module; if required they can adapt their teaching methods, for example, they can identify the students who are struggling on a specific topic/activity based on the time they spent.

For Students:

- Can identify struggling students earlier
- Once a student has been identified who requires some attention, personalized interventions such as guidance or support from the instructor can be automatically provided to help those students.
- Providing the success stories can also acts as a motivation add-on

III. LEARNING STYLES

Learners' differ from one another in different ways, knowing their learning style will help to develop coping strategies to compensate for the weaknesses and capitalize on strengths [10]. The learning styles model developed by Richard Felder and Linda Silverman (Felder, 1993; Felder and Silverman, 1988) incorporates four major dimensions, namely Perception dimension (sensing/intuitive), Processing dimension (active/reflective), Input (visual/verbal) and Understanding (sequential/global). The Index of Learning Styles (ILS) is an on-line instrument used to assess preferences on four dimensions and they categorize the learners according to their way of processing information.

Table 1: Dimensions of the FSLSM model

Active learners are categorized for retaining and understanding information better by doing something with the learned material such as; discussing, applying or explaining it to others.	Reflective learners tend to think about the concepts quietly first and they like to work alone.
Sensing learners prefer to learn facts and study concrete learning materials. In order to learn from concrete material, sensing learners tend to like solving problems with standard approaches and dislike complicated problems	Intuitive learners are more comfortable with abstract materials
Visual learners remember best what they see, such as pictures, diagrams and movies	Verbal learners learn better from written and spoken explanations
Sequential learners prefer to learn in a linear way and in order to find solutions they tend to follow logical stepwise learning paths. sequential learners are more interested in the details	Global learners tend to learn in large jumps and absorbing learning materials randomly, they are interested in overviews and find connections between different areas

IV. PROPOSED SYSTEM

As part of the proposed system, one of our LMS (Megh-Sikshak) is used for capturing the learner actions. During the time of user registration, the static (ILS) questionnaire is presented for identifying the initial learning style. However it is identified that the results captured from the static questionnaire are not fair enough for the continuous learning, where the learning styles need to be updated during the learning process. For achieving this we have embedded the Learning Analytics Capturing Agent (LA-C) in all the eLearning services provided to the learner. This agent will capture all the actions performed in the checkpoints configured in the LMS and provide the inputs to the Learning Analytics Engine for updating previously captured Leaning Styles.

The following are the various services offered by the proposed system.

1) Administration: This service will provide the management interface for the super admin/institute admin to manage users and courses. It supports single and bulk user registrations through predefined template and reminders through SMS/Emails. Instructor privileges can be obtained through a proper channel. An authenticated user can view all the courses published in the LMS.

2) Course Management: This service will provide the interface for designing the course structure and to upload the various types of content resources like html, PDF, video, SCORM packages, Non-SCORM zip files, downloadable files, external references like YouTube, etc. Once the courses are published any user can register into the course by selecting the courses from the list of available courses.

3) Content Delivery: The service provides to deliver the course content at schedule times (progressively based on schedule dates). It also allows discuss/post comments on the selected topic.

4) Assessment: This service allows the instructors to create, schedule, deliver and report practice problems, quizzes and assignments. A separate interface is provided for creating the questions, practice problems, quizzes and assignments.
Each learner can view the quizzes and assignments assigned by the instructor and can take multiple attempts (if allowed), can resume the unfinished quizzes and can view the correct answer report after the completion.

5) Communication:

- Announcements: This service provides to add announcements in the course dashboard for the specified duration. It also has a provision to send Email/SMS alerts to the users under a course.
- Discussions: This service allows the users to share their knowledge throughout the course or to discuss about a content/topic and also allows sending a question to the instructor/learner for clarification
- Reminder/Notification service: This service provides the functionality to send an Email/SMS alerts based on the desired check points in the application.

6) Performance Evaluation: This service allows in auto-evaluating the objective quizzes and classifies the user is pass/fail in the specific course/module/topic. It provides the interface for the instructors to view and submit the feedback/scores for the manually evaluated assignments. It also has a provision to issue the online certificate based on evaluation criteria.

7) Learning Analytics: This service captures the required data from all the services and logs into the server for further processing. It can provide various reports such as active/inactive users, course related activities, etc. to the admin, institute admin, instructor and learner based on the requirements. Using the e-Learning services offered through the LMS to the learner, all the required interactions are captured and accumulated as user entities. These entities are later processed and represented to the identified roles to intervene and engage for effective learning.

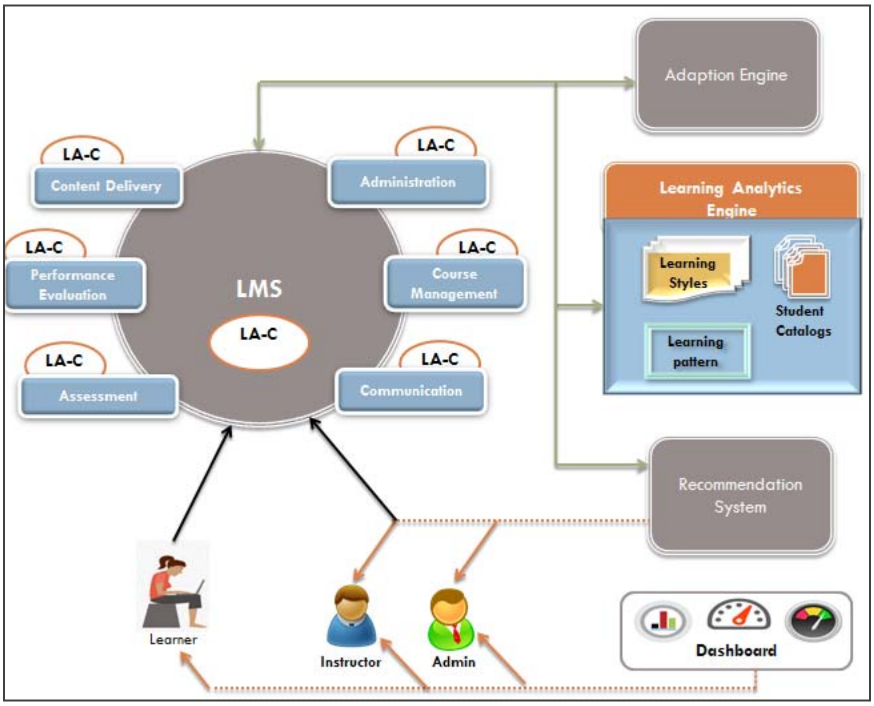

Figure 2: Proposed System

In the first phase of the proposed system, various parameters required for learning analytics would be captured invisibly to infer learning style of the user and captured learning style of each user is stored in the repository. Using initial learning style, the recommendation engine provides the right content type to each individual. At each learning phase, learner actions are tracked using the Learning analytics (tracking agent) for updating the learning style, updated only if any change is identified in the learning style and recommendation would be provided to the learner based on his/her learning style & behaviour. Learner's activities and their behaviour would be continuously measured, monitored so that learning environment can be adapted to meet their requirements. Learning analytics engine uses the data captured about learners and their activities to help the institutions understand and improve educational processes and provide better support to learners.

The learning cycle through an LMS gives the immense data to look into the insights of all the courses designed for the learners. The process of gathering the data has to be initiated from the point of publishing the course and made open for the enrolments. The analysed information from the system will help to improve each and every aspect of the course or the process flow of the system. In the MOOC environment once a course is published, the number of users viewed the course will look for the details such as intended for, course description, duration, authors/instructors of the course, course ratings, reviews & feedback that can drive towards the successful course enrolment. Which is nothing but how many users came back and enrolled with the course after viewing the success stories of the previous batch. Each successful enrolment depends on the response of the previous batch that has completed the course.

C. Adaption Engine:

This engine helps in providing the personalized learning environment by adapting towards the learning style. During the content delivery the appropriate types of content is provided along with the prescribed course material, in assessment for better performance the system will prompts the instructor that certain questions may require images/diagrams for specific set of learners, during the assessment delivery the system will displays the supporting images uploaded by the instructor, the system will adapts towards the login time and provides the notifications/reminders to fulfil the schedule, etc.

D. Recommendation System:

Based on the patterns recognized, system will provides the dashboard of each learner and generates the recommendations for each pattern identified. It also allows the instructor to intervene on the necessary stages of learning process. Patterns like, how many times student have logged in, time spent on each topic (content), type of content visited (video, PPT, PDF, etc.), number of assignments taken (completed, uncompleted), number of times viewed the recommended content, how often used the hints, number of successful and unsuccessful exercises, social sharing, interactions with other learners or with instructors etc. are used for dynamic modelling of learning styles. The below table depicts the patterns generated based on the learner/student actions and the appropriate learning styles predicted based on the FSLSM.

For example, in user management and course delivery services, capturing learner's activity (Fig: 3) helps the instructor to track whether a learner is active or inactive and also track the progress. Accordingly, recommendations can be provided to the learner by sending an alert through email/SMS.

In this way students can be retained and motivated for completing the course related activities.

Table 2: Various identified patterns and the predicted Learning Styles using FSLSM

Pattern ID	Pattern	Learning Style
AC-100	Less time to complete a content resource	Active
AC-101	More number of logins into the LMS	Active
AC-102	Less number of visits to complete a content material	Active
AC-103	Less number of requests to the instructor	Active
AC-104	More number of practice exercises taken	Active
AC-105	More number of discussions made related to each content resource	Active
RE-100	More number of jumps within the content resource	Reflective
RE-101	More time to complete each content resource	Reflective
RE-102	Less number of logins	Reflective
RE-103	Less number of practice exercises taken	Reflective
RE-104	Less number of discussions	Reflective
SE-100	More number of re-visits on each content resource	Sensitive
SE-101	More number of attempts for each practice exercise	Sensitive
SE-102	More number of reviews of each question during the quiz/practice exercises	Sensitive
SE-103	More number of changes in the answers during the quiz	Sensitive
SE-104	More time to complete quiz/practice exercise	Sensitive
SE-105	Less number of assignments completed	Sensitive
IN-100	Less number of re-visits on each content resource	Intuitive
IN-101	Less number of reviews of each question during the quiz/practice exercises	Intuitive
IN-102	Less number of changes in the answers during the quiz	Intuitive
IN-103	More number of practice exercises in less time	Intuitive
IN-104	More number of assignments completed	Intuitive
VI-100	More number of video lectures visited	Visual
VI-101	More time spent on the images in the content resource	Visual
VI-102	More number of successful question attempts having images	Visual
VI-103	Less time spent on questions having images	Visual
VI-104	Assignment submission with more number of images and less description	Visual
VE-100	More number of visits on the Text based content resources	Verbal
VE-101	Less number of successful question attempts having images	Verbal
VE-102	Submission of assignments with more detailed description	Verbal
VE-103	More number of successful question attempts which are text based	Verbal
SQ-100	Less number of jumps within the content resource or course material	Sequential
SQ-101	Less deviation in the learning process	Sequential
SQ-102	More number times quiz was resumed	Sequential
SQ-103	Less number of jumps during the quiz/practice problems	Sequential
GL-100	More number of jumps within the content resource or course material	Global
GL-101	More deviation in the learning process	Global
GL-102	More number of jumps during the quiz/practice problems	Global

E. Dashboard:

The proposed system consists of a dashboard module which assists the instructor in analysing the learners. The analysed information from dashboard is made available to the instructor and the instructor who can design and develop personalized learning path which includes type of learning services, activities and e-content which will be provided to the learners.

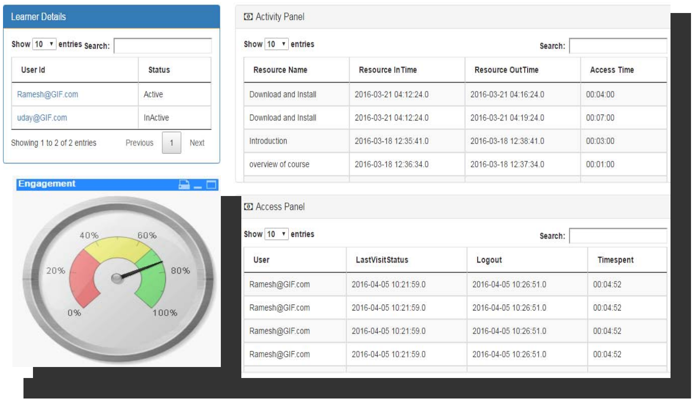

Figure 3: Instructor Dashboard to view the individual learner progress

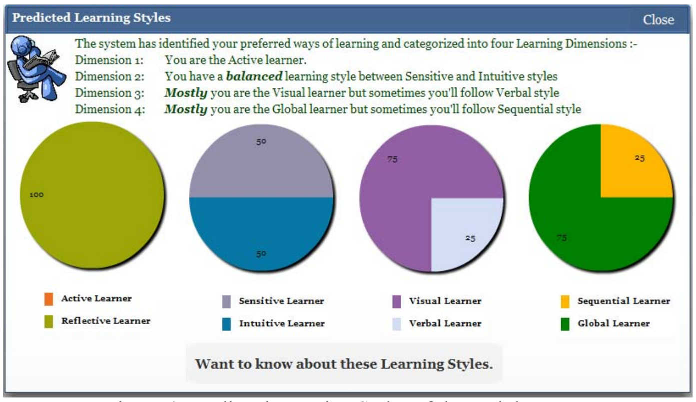

Figure 4: Predicted Learning Styles of the each learner

The following dashboard module helps learners to get better picture about their learning performance by comparing current and past performance.


Figure 5: Learner Dashboard to review his/her learning progress and credits achieved for every successful completion of the course

V. Conclusion and Future Work

This paper proposed an model of using learning analytics in e-Learning to help the users in personalizing their own learning interests based on the number of resources, participation in assessment and communication services for providing suggestions to instructors and learners. Future work will extend this research by integrating and exploring other prediction and recommendation algorithms for providing more personalized learning experience. Furthermore we are also planning towards monitor observational cues, such as gesture, posture, etc., of the learner to obtain information about a learner's affective states.

ACKNOWLEDGMENT

We are grateful to Centre for Development of advanced Computing(C-DAC), a scientific society under Ministry of Electronics & Information Technology (MeitY), Government of India for supporting the research work carried out in eLearning domain.

REFERENCES

[1] https://en.wikipedia.org/wiki/Learning_analytics

[2] Uday Kumar M, Mamatha J, Sandesh Jain and Dhanander K Jain,learning Styles and Knowledge based Personalized Online Learning Services, IADIS International Conference,WWW/Internet, 2011

[3] Nava Jyothi, Kaveri Bhan, Uday Mothukuri, Sandesh Jain, Dhanander Jain, "A Recommender system assisting instructor in building learning path for Personalized Learning System", IEEE Fourth International Conference on Technology for Education, 2012

[4] M. A. Chatti, A. L. Dyckhoff, U. Schroeder, and H. Thüs, "A reference model for learning analytics", Int. J. Technol. Enhanced Learn., vol. 4,nos. 5_6, pp. 318_331, 2012.

[5] C. Brinton and M. Chiang, "MOOC performance prediction via clickstream data and social learning networks," in Proc. IEEE Conf. Comput.Commun., 2015, pp. 2299–2307.

[6] P. J. Mu˜noz-Merino, J. A. Ruip´erez-Valiente, C. Alario-Hoyos, M. P´erez-Sanagust´ın, and C. Delgado Kloos, "Precise effectiveness strategy for analyzing the effectiveness of students with educational resources and activities in MOOCs," Comput. Human Behav., vol. 47, pp. 108–118, 2015.

[7] M. Kloft, F. Stiehler, Z. Zheng, and N. Pinkwart, "Predicting MOOC dropout over weeks using machine learning methods," in Proc. Workshop Anal. Large Scale Social Int. MOOCs, 2014, pp. 60–65.

[8] J. A. Ruiperez-Valiente, G. Alexandron, Z. Chen, and D. E. Pritchard, "Using multiple accounts for harvesting solutions in MOOCs," in Proc. 3rd ACM Conf. Learn. Scale, 2016, pp. 63–70.

[9] W. Greller and H. Drachsler, "Translating learning into numbers: A generic framework for learning analytics," J. Educ. Technol. Soc., vol. 15, no. 3, pp. 42–57, 2012.

[10] Felder, R. Brent, R –Understanding Student Differences–Journal of Engineering Education 94– pp. 57–72 – (2005)

[11] Sabine Graf, Kinshuk, Qingsheng Zhang, Paul Maguire And Victoria Shtern, "An Architecture For Dynamic Student Modelling Of Learning Styles In Learning Systems And Its Application For Adaptivity" , IADIS International Conference on Cognition and Exploratory Learning in Digital Age (CELDA 2010)

[12] Maria Virvou, Efthimios Alepis, Sotirios, "A learning analytics tool for supporting teacher decision", Information, Intelligence, Systems and Applications (IISA), 2015

[13] Shuang Li, Chen yu, Jingjing Hu, Yao zhong, "Exploring the effect of behavioural engagement on learning achievement in online learning environment", International Conference on Educational Innovation through Technology, 2016

[14] K Govindarajan, V Suresh Kumar, Kinshuk, "Dynamic Learning Path Prediction- a learning analytics solution", IEEE 8th International Conference on Technology for Education, 2016

[15] Y. V. Nieto, V. G. Diaz, "Academic Decision Making Model for Higher Education Institutions using Learning Analytics", 4th International Symposium on Computational and Business Intelligence, 2016

[16] Thomas F. Hawk, Amit J. Shah, "Using Learning Style Instruments to Enhance Student Learning ", Decision Sciences Journal of Innovative Education, Vol 5 N0-1, 2007

[17] Farman Ali Khan, Sabine Graf, Edgar R. Weippl, A Min Tjoa, "Identifying and Incorporating Affective States and Learning Styles in Web-based Learning Management Systems",Interaction Design and Architecture(s) Journal - IxD&A, pp. 85-103, 2010.