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Personalized Learning Environment in Higher Education through Big Data and Blended Learning Analytics

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Abstract*: Blended learning is seen as one of the effective ways of engaging learners in higher educational institutions. The e-learning platforms have further facilitated in adapting to learner centric approach of teaching learning. Analytics have played major role in revolutionizing various sectors including education. Blended learning analytics provides inferences which when utilized effectively by the educator and learner would enhance the teaching-learning experience. Huge amount of varied data is generated when learner and educator interact with e-learning platforms, this when coupled with other demographic information can be used to personalize the learning experience. This necessitates the need of a framework which can capture and use the digital data.

Keywords:* Big Data, *Blended Learning Analytics, Higher education, Personalized learning.

I. INTRODUCTION

Learning is not linear in nature. Thus, a generalized curriculum, pedagogy and teaching processes would not be able to meet the heterogenous learner's requirement [3]. It also would not be able to extrapolate the learning curve of a learner. Personalized learning can be looked upon as a solution to the varied learning demands of student community. Tailor-fit teaching learning approaches have definitely proven to be more successful when compared to the generalized approach. With the ease of availability of e-resources and platforms, there has been a steep rise in use of e-learning platforms in higher education [5]. This also has accelerated personalized learning approaches.

Blended learning model is being utilized by various universities to facilitate the learning needs of the students [10]. Learning analytics when applied in the blended learning environment provides opportunities to fine-tune the personalized approach of teaching-learning. There are many blended learning models which are being utilized in higher education. Few of them are self-blend, flipped classroom, rotation model, flexible mode courses, blended MOOC, blended online class, blended face-face class [4]. All these models are evolving to adapt to the requirements of higher education and so is educational technology. This paper proposes a framework for personalized learning using blended learning model "blended face-face class ".

II. PERSONALIZED LEARNING (PLE) THROUGH BLENDED LEARNING (BLE)

Technology has been a catalyst to the disruptive innovation happening in the field of higher education. Personalized learning also has evolved with technological intervention leading to new and flexible instruction practices [8]. These new instructional practices are more learner centric over traditional educator centric approaches. Technology backed personalized learning, the digital data along with demographic data of the learners can be utilized to devise learning plans which would tailor fit the needs of each learner [5]. Personalized learning involves multiple aspects of teaching-learning process like curriculum, evaluation process.

Personalization can happen in both traditional face-face teaching or with technology backed teaching. The former would require that the learner group to be small in number, to ensure personalization but leveraging on technology would allow the educator to cater to a large group of learners and still achieve personalization to a greater extent [17]. In this learner centric instructional approach, the learner is a collaborator in devising the learning path and is also responsible for the learning. This leads learners to be co-creators of content for teaching learning process along with educators [1].

Blended learning supplements the learner centric approach by providing on the go availability of resources and self-paced learning. The learning management systems (LMS) like Moodle provide a platform to facilitate personalized learning through blended learning approach. These e-platforms allow better engagement of learners and also leave a trail of digital data to analyze the behavior and patterns. Personalised learning would be affective only when recommendations or corrective measures are provided to both educators and learners at periodic intervals [11]. Analytics would facilitate in understanding learner behavior and learning pattern.

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A. Learning analytics in Blended Learning Environment

Educational data available in a blended learning environment is quite large.

The various interactions of learner and educator with LMS provide a deeper insight about the behaviour of learner, educator and the learning curve of the learner. The various log files available with the LMS along with other demographic and academic details of the learner helps the educator to personalise the teaching learning process [12]. Blended learning environment captures learner's behaviour and learning characteristics which supplements learner's profile. Learning Analytics (LA) is a good tool to enhance the teaching-learning process effectively[6]. The learner profile generated with help of these heterogenous data when analysed along with learning records provides deeper insight on learning characteristics and behaviour.

The varied learning behaviour and characteristics of the learner can be captured and analysed. This analysis helps to understand the effectiveness of instructional methodology and pedagogies. The areas of improvement would be easily identified and focused improvement on those areas would lead to better teaching learning environment [9]. Learner's also would be able to identify the areas of improvement more easily with learning analytics thus enhancing their learning curve. Visual analytics along with learning analytics helps in identification of learning patterns and learner's behaviour [5].

III. PROPOSED WORK

A. Framework

The proposed framework captures learner data (demographic data, previous academic records) to create learner profile. This generated profile is the first input to the system. This profile would be updated at regular interval of time as the learner progresses in the course.

The heterogenous data as shown in fig 1 are of different forms and are captured during the entire course. The library and attendance logs coupled with student interaction with the educator (In Class and Off Class interaction) can be utilized to understand the learner needs. The Learning records of each learner contains all the interactions of the learner with blended learning system. This is one of the pivotal data which helps the analytical engine to provide effective recommendations

The fig 2 depicts the framework encapsulating the learning records, educator interaction and strategies and learner profile. The two-way interaction of the learner and educator with the environment ensures that the learner profile and learning records are updated to provide more accurate and efficient recommendations.

The analytical engine performs all the required steps to analyze the data fed into it and provides recommendations which lead to personalization of learning for the learner. It identifies the current learning stage (beginner, intermediate, advanced) of the learner which facilitates the personalized assignment and content recommendation by the educator. The educator interacts with the blended learning system to administer personalized recommendations which are also recorded. The learner also would interact with the BLE to obtain personalized learning. The interactions of the learner and educator with the BLE is captured and stored in the learning record. The assessment done at periodic intervals of time during the course, updates the learning records and the heterogenous data sources as shown in Fig 1. It updates the learner profile which allows the engine to capture the learning of the student in a periodic manner.

The engine would not only facilitate personalized learning but also capture the learning of each learner. The important outputs derived out of the engine are clustering of students which lead to personalization of learning and the learning curve of each learner. A rising learning curve indicates the improvement in the learning which is the expected output of any teaching learning process.

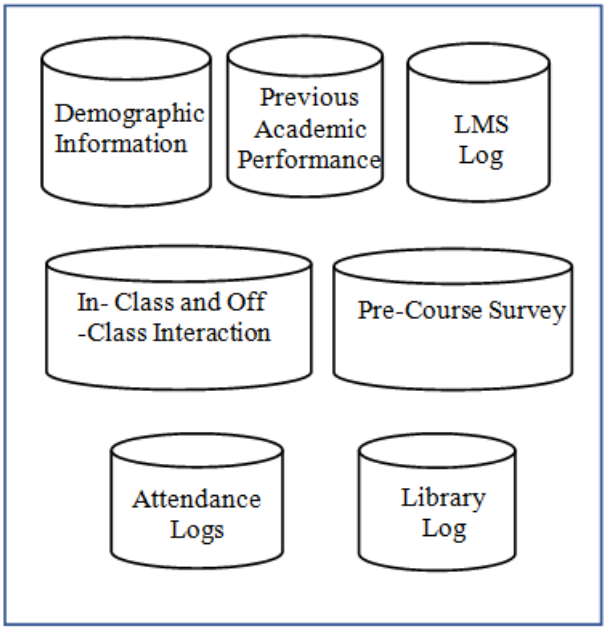

Fig. 1. Heterogenous Databases (Big Data)

B. Analytical Engine- Frequent Pattern Two Log Mean Cluster Bayes (FPTLCB)

The analytical engine named FPTLCB uses the following approaches and algorithms to handle the heterogenous learner data. The initial step of preprocessing the varied
data is through "Greedy Stepwise". Feature selection using the greedy approach provides quicker elimination of redundant and irrelevant features. The combination of forward selection and backward elimination is used to enhance the efficiency of the approach. The next step involves application of the proposed algorithm, Two-Log Mean clustering (TLMC) to group the learners.

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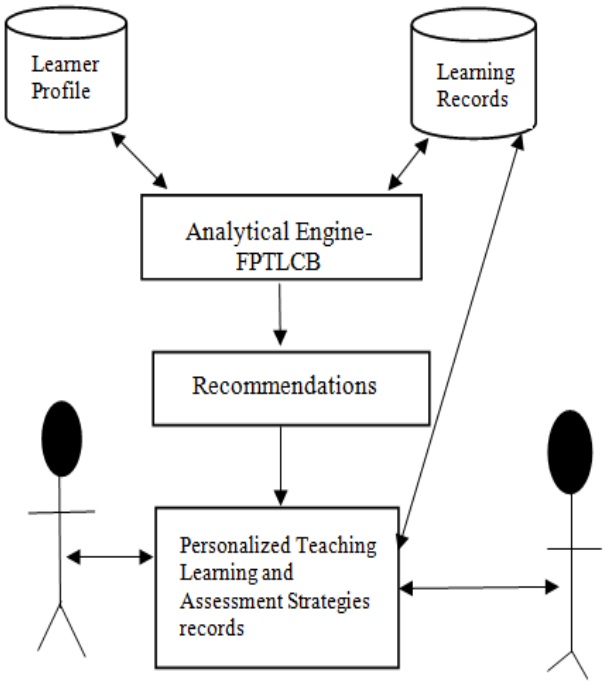

Fig. 2. Blended Learning Analytics Framework

The algorithm would input the number of clusters to be formed, lift rations set (LRS) and follow the steps given below:

I. Randomly select TLMC items from LRS as the early cluster centers.
II. Repeat until no variation:
1. Re-assign or assign every item to the cluster to which the item is the maximum interrelated on the Two Log mean of the items in the cluster;
2. Update the cluster Two Log means, i.e., evaluate the Two Log means of the items for every cluster.

The last stage involves identifying the patterns and factors affecting the learning. The Frequency Pattern growth algorithm is efficient in identifying the repeatedly co-occurring features. This would provide the educator the needed recommendations to personalize the learning. The cyclic process of feedback, interaction and recommendation allows the environment to evolve itself over the multiple iterations to create an efficient personalized learning environment

C. Data Description

As the personalization of learning can be considered for a single subject or course in curriculum, a programming course was opted for data collection. Undergraduate students of computer science study many programming courses hence for a period of three years data was collected for Java programming course. Out of 4678, 3240 records of undergraduate students were taken after removing missing values and cleaning the data.

D. Performance Evaluation

The proposed algorithm TLMC when compared with the K-means algorithm proved better. The following figures indicate the performance with help of average silhouettes.

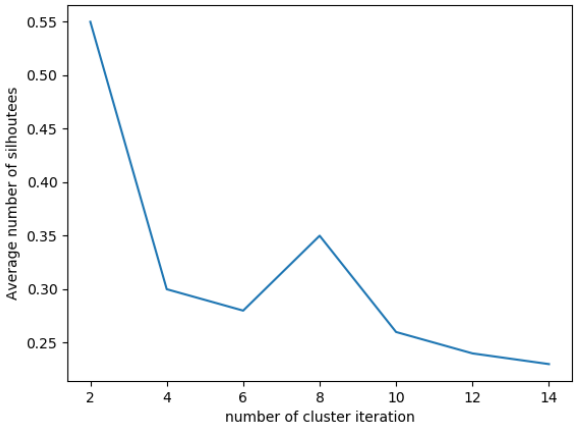

Fig. 3. Two Log Means

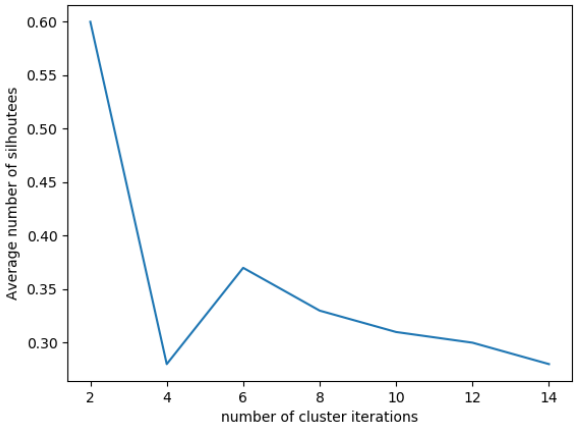

Fig. 4. k means

Average of silhouette for k-means shows that the average value takes several iterations but it doesn't have reduced low in their cluster's iterations. But in our two-log means, the silhouette value is achieved with smaller number of iterations and also it maintains its value in the corresponding iterations. The figure 5 shows the relationship between the library hours and the academic performance which is one of the tangible outputs of the engine.

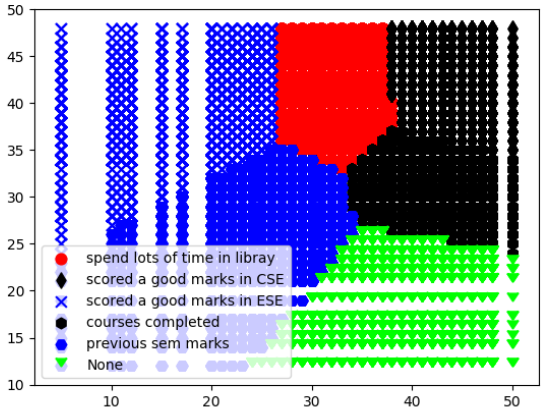

Fig. 5. Relationship between hours spent in library and performance

IV. CONCLUSION

The educational institutions are storing the digital and digital exhaust data of students. This data termed as Big Data due to the heterogeneity, can provide deeper insights of learning patterns. Equipped with this the educators can personalize the learning experience and can maximize the learning. This paper presents an efficient approach to create personalized learning environment in higher education.

REFERENCES

1. Cantabella, M., Martínez-España, R., Ayuso, B.,Yáñez, J. A., & Muñoz, A. "Analysis of student behavior in learning management systems through a Big Data framework.",Future Generation Computer Systems, 2019, 262-272.
2. Kavitha, W. Jaisingh , "A Study on the Student Experiences in Blended Learning Environments R.K ", International Journal of Recent Technology and Engineering (IJRTE) "Volume-7 Issue-4S, November 2018.
3. Rahul Chandra Kushwaha, Achintya Singhal , "Online Learning: An Emergence of New Model of Education ",International Journal of Recent Technology and Engineering (IJRTE) Volume-7, Issue-6, March 2019
4. Andino Maseleno, Noraisikin Sabani, Miftachul Huda, Roslee Ahmad4, Kamarul Azmi Jasmi, Bushrah Basiron , "Demystifying Learning Analytics in Personalised Learning ",International Journal of Engineering & Technology, Issue 7,Vol 3 2018, 1124-1129.
5. Khawla Alhasan, Liming Chen and Feng Chen , "Mining Learning Styles for Personalised eLearning "IEEE Smart World, ,2018.
6. Billy Tak Ming Wong, "Learning analytics in higher education: an analysis of case studies", Asian Association of Open Universities Journal, 2017,Vol. 12 Issue: 1, pp.21-40
7. R..Swathi, N.Pavan Kumar,L.KiranKranth ,L.KiranKranth ,L.Sethu Madhav, Dr. R. Seshadri, "Systematic Approach on Big Data Analytics in Education Systems", International Conference on Intelligent Computing and Control Systems ICICCS ,2017
8. Said Rabah Azzam, Ylber Ramadani ,"Reforming Education Sector through Big Data" ,IEEE conference on Cloud computing and Big Data analysis,2016
9. Dr. Manju Jose , Ms. Preethy Sinu Kurian , Mr. Biju V. ,"Progression analysis of students in a higher education institution using big data open source predictive modeling tool,", 3rd MEC International Conference on Big Data and Smart City,2016
10. Sarka Hubacko**va** , & Ilona Semradova ,"Evaluation of Blended Learning ", Procedia - Social and Behavioral Sciences , 2016.
11. Carolina Mejia,Sergio Gomez ,Laura Mancera , Sibylle Taveneau," Inclusive Learner Model for Adaptive Recommendations in Virtual Education , IEEE 17th International Conference on Advanced Learning Technologies,2017.
12. Tulasi.B, Suchithra.R, "Big Data Analytics And E Learning In Higher Education",International Journal on Cybernetics & Informatics (IJCI) Vol. 5, No. 1, February 2016
13. K. Sin, L. Muthu, "Application of big data in education data mining and learning analytics–A literature review", ICTACT J. Soft Computing vol 4, 2015.
14. Eman AbuKhousa, Yacine Atif,,"Big learning data analytics support for engineering career readiness", International Conference on Interactive Collaborative Learning (ICL),2014.
15. Phillip D. Long,George Siemens,"Penetrating the fog: analytics in learning and education", Italian Journal of Educational Technology (IJET) ,Vol 22,2014
    Dilpreet Singh ,Chandan K Reddy,"A survey on platforms for big data analytics", Journal of Big Data, volume 2, Article number: 8 ,2014.
16. Picciano, Anthony G., "The Evolution of Big Data and Learning Analytics in American Higher Education", Journal of Asynchronous Learning Networks, v16 n3 p9-20 Jun 2012

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