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Online Students' Learning Behaviors and Academic Success: An Analysis of LMS Log Data from Flipped Classrooms via Regularization

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ABSTRACT: The main purpose of this study was to demonstrate the uses of regularization, a machine learning technique, in exploring important predictors for online student success. We analyzed student and learning behavioral variables from undergraduate fully-online flipped classrooms. In particular, students' instructional video watching behaviors at an instructional unit level were extracted from LMS (learning management system) log data, and Enet (elastic net) and Mnet were employed among regularization. As results, regularization not only showed comparable prediction performance to random forest, a nonlinear method well-known for its prediction capabilities, but also produced interpretable prediction models as a linear method. Enet and Mnet selected 17 and 19 important predictors out of 159, respectively, and could identify potential low-performers as early as the first instructional week of the course. Important variables rarely recognized in previous studies included complete viewings of the first video before class and repeated complete viewings of challenging contents after in-class meetings. Unlike previous studies, aggregate measures of video lecture views were not important predictors. Variables less frequently studies in previous studies were the number of non-mandatory quiz-taking and mobile lecture watching frequencies. Variables in line with previous research were student attitudes towards the course, gender, grade level, and clicks on learning materials postings. Many students turned out not to watch lecture videos completely before class. Further research on regularization and exploration of these variables with other potentially important predictors can provide more insight into students' online learning from a comprehensive perspective.

KEYWORDS: Flipped classroom, LMS log data, Regularization, Machine learning, Student success, Learning behaviors, Prediction models, Performance modeling, Pre-class activities, After-class activities, Final performance

I. INTRODUCTION

E-learning systems are gaining increased popularity due to their massive scalability and their immense potential of providing non-disrupted and affordable learning 24/7. Artificial Intelligence (AI) can significantly enhance e-learning systems through personalized content delivery to a learner. In contrast to a conventional e-learning system, where all the learners that are studying at a specific grade are delivered identical contents, an AI based adaptive and personalized e-learning system delivers specific and targeted content to each learner. A learner can experience improved learning through personalization, as the e-learning system can customize content delivery according to the strengths and weaknesses of the learner.There has been a considerable research on the personalization of e-learning. A review of this research area shows that most of the current AI-based personalized e-learning techniques are not integrated to create a more diverse, holistic personalized e-learning framework. In this article, we propose such a framework that integrates knowledge tracing, learning mode adaptation, and recommender systems for the delivery of personalized e-learning content. In this way, we can integrate different AI-based techniques that have been researched and validated. Creation of personalized e-learning platforms in this manner results into a comprehensive system that mitigates the issues and shortcomings of individual models.Personalization implies that each learner is assessed and taught individually. For this purpose, an AI-based system can be employed to assess a learner's level and determine appropriate contents. For instance, if a learner performs poorly on a specific topic, then the topic may be repeated – possibly through a different mode of content delivery. Similarly, if a learner demonstrates higher level of comprehension, then learner may be taught the next level of content, which are related to the subject.There are several methods of delivering personalized content, of which, adaptive learning and adaptable learning are the most widely employed. In the former approach, a recommendation strategy is built which delivers content according to the level of comprehension of the learner.

Requirements exist in determining appropriate level of a learner and to determine and recommend suitable content. In comparison, the adaptable learning technique is focused on delivering content through the preferred mode or medium of delivery. Since these preferences may be implicit, an adaptable learning system is needed to be artificially intelligent in determining the preferred modes.Delivering personalized content to a learner could be extremely significant for an effective e-learning system. This is specifically useful where online education supplements physical classes, for example, in the recent pandemic (COVID-19). In addition, personalized e-learning systems can also be implemented to educate masses, as it provides a cost-effective method to deliver education.A personalized content delivery system has many computer-science related challenges. It requires a smooth and capable mechanism exist through which learners can be continuously assessed and proper level of comprehension can be determined. Machine Learning (ML) and Deep Learning (DL) based models may be utilized to determine and match the appropriate level of content for the learner.

II. PROPOSED SYSTEM

There is intrinsic bias present in the functionality of recommendation systems due to the fact that the data these systems are trained on are observational data and not experimental. Also such recommendation systems often do not perform well due to the concept drift between the data of the training phase and the testing phase This information is essential for the development of personalized e-learning systems. This data and information need to be gathered at an appropriate level of granularity. The higher the granularity, the finer the trained machine learning based personalized e-learning system In that sense, definition and identification of significant as well as measurable evaluation metrics also need to be done in order to better map the aforementioned traits. These parameters may include time taken to attempt a specific problem, number of attempts on a given problem user or performance on different devices, type of evaluation etc This refers to the analysis of each recommendation in terms of its efficacy and contribution towards the learning goal of each learner. Currently, there are no evident ways to evaluate the recommendations provided, at each point during the user journey, other than going back to the user and gathering their feedback or assess the overall performance of the user after the completion of the learning path.

III. SYSTEM OVERVIEW

Personalization implies that each learner is assessed and taught individually. For this purpose, an AI-based system can be employed to assess a learner's level and determine appropriate contents. For instance, if a learner performs poorly on a specific topic, then the topic may be repeated – possibly through a different mode of content delivery. Similarly, if a learner demonstrates higher level of comprehension, then learner may be taught the next level of content, which are related to the subject. There are several methods of delivering personalized content, of which, adaptive learning and adaptable learning are the most widely employed. In the former approach, a recommendation strategy is built which delivers content according to the level of comprehension of the learner. Requirements exist in determining appropriate level of a learner and to determine and recommend suitable content. In comparison, the adaptable learning technique is focused on delivering content through the preferred mode or medium of delivery. Since these preferences may be implicit, an adaptable learning system is needed to be artificially intelligent in determining the preferred modes.

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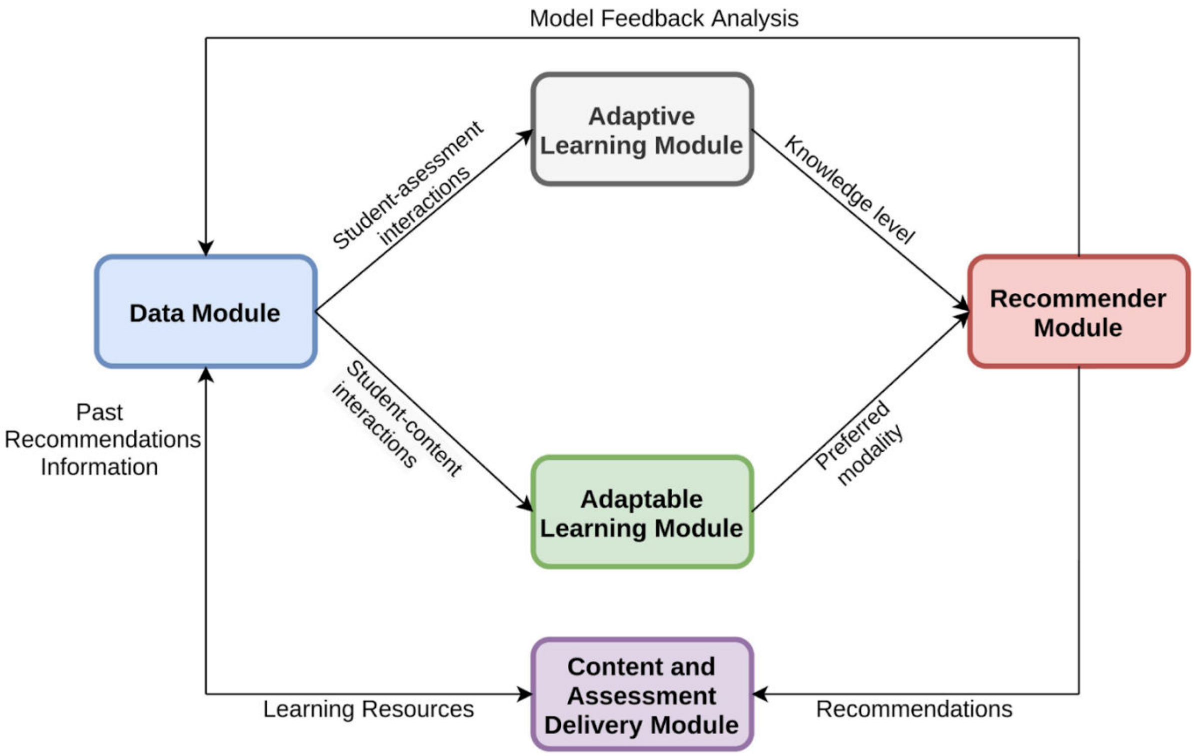

Fig 1: System Architecture

IV. MODULES

- Data Collection Module
- Adaptive Learning Module
- Adaptable Learning Module
- Recommender Module
- Content and Assessment Delivery Module

MODULES DESCRIPTION:

4.1 Data Collection Module:

The data module stores the learning content and summative assessments. These are delivered to a learner by the content and assessment delivery module and as recommended by the recommender module. The data module also maintains a database that stores personal information of a user, assessment records, learning style, prior knowledge and the previous recommendations as recommended by the engine depicted. These attributes are computed for every learner and are used iteratively to generate personalized learning path for each learner. Learner interaction data is generated when a learner interacts with the e-learning platform. There are two possibilities for these learner interactions, such as, data for a new learner, and data for an existing user.

4.2 Adaptive Learning Module:

Proposed framework for personalized e-learning, the Adaptive Learning Module is tasked with the determination of knowledge levels of every learner across all the knowledge-components present in a curriculum. Knowledge level of a learner can be discovered from the underlying learner and e-learning system interactions. A sequential machine learning algorithm can be trained on this learner-interaction data to first estimate the latent knowledge-states of a learner and then the corresponding knowledge-levels. The dependency graph of knowledge components of a sample curriculum and an arbitrary prior knowledge vector of a learner, a vector encoding the prior knowledge of a student is shown on a 0-1 scale, where 0 means no prior knowledge and 1 denotes complete expertise of the knowledge component.

4.3 Adaptable Learning Module:

The Adaptable Learning Module determines the preferred mode of learning for a learner. It can be perceived that an individual learner's learning preferences are implicit, subjective, and hard to be inferred from raw data. Therefore, in

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order to identify learning mode preferences, latent variables are to be devised and extracted from the raw learner interaction data available in the e-learning databases. As an example of a latent variable, we suggest a three-dimensional data structure, termed as performance cube with a representation. A student-content interaction is the learning content viewing and attempting of an assessment for the same content. This derived dataset of performance cubes is analyzed for effective content modalities in an unsupervised way. For instance, an association rule mining algorithm or a neural embedding based algorithm can be used to find the relationship between the learning modalities and performance, when applied to the interactions present in the performance cubes.

4.4 Recommender Module:

Recommender Module is incorporated with Adaptive Learning Module and Adaptable Learning Module to provide personalized learning content recommendations. In this module, Deep Learning based Recommendation Engine (DLRE) is designed to provide two major recommendations: rating prediction and top-N item ranking for the learning content. DLRE takes input of user-item interaction matrix which contain learners (L) in a row, modality (M) in a column and probability of preferred mode (P), which is used for rating. DLRE is trained on this input data for rating prediction and item ranking. Rating prediction is a numerical value, Rij, indicating the predicted score of item j for user i whereas Item ranking is a list of the top N items that the learner will find most beneficial.

4.5 Content And Assessment Delivery Module:

The main task of the content and delivery module is to deliver the content as per output of the Recommendation Module. The module delivers appropriate content to a learner and sends information related to performance and other attributes to the data module. Depending upon the recommendations, the module also selects personalized content. Proposed framework encompasses five modules which are capable to deliver efficient personalized learning to an individual. The framework incorporates state-of-the-art techniques, which are capable to determine needs of an individual learner and deliver content accordingly.

V. EXPERIMENTAL RESULT

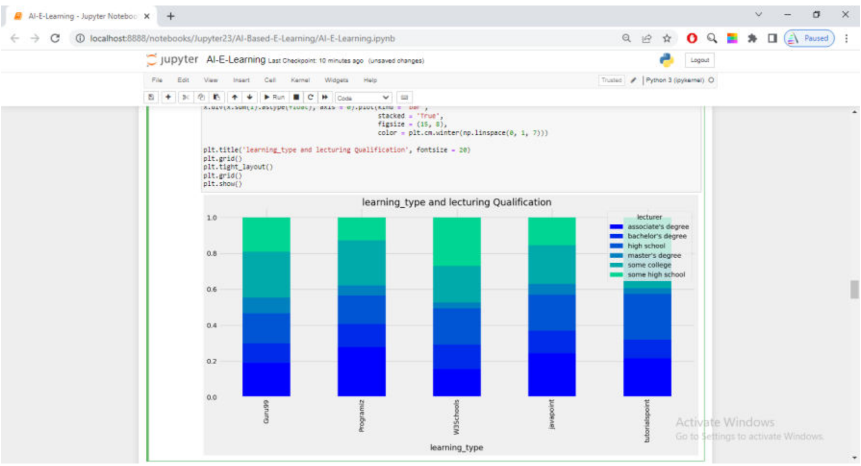

Fig 2: Comparison of learning type and lecturing Qualification

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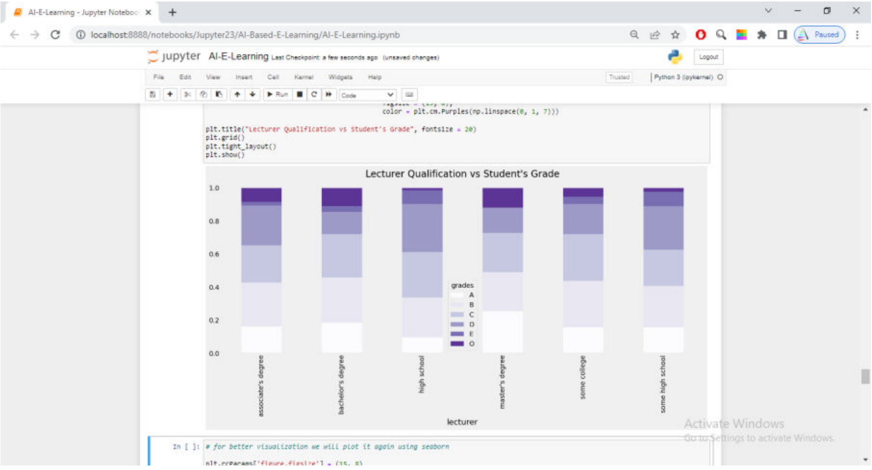

Fig 3: Comparison Lecturer Qualification and their corresponding grades

VI. CONCLUSION

The development of AI-based personalized e-learning systems require a holistic approach, comprising of thorough analysis of available data and e-learning data sources. These requirements should be properly synthesized and the necessary data should be extracted from the e-learning databases. Understanding the student learning process is essential for the development of an adaptive and personalized e-learning system. A good starting point for the understanding of this process is to model the sequential assessments' responses using a recurrent machine learning model. The trained model will explain the past student behaviour along with the forecast of the performance on future assessments, as demonstrated by the ``Adaptive Learning Module'' of the proposed framework. This basic model can be improved with the introduction and enrichment of the existing e-learning data by incorporating diverse variables related to consumed learning resources. Such relevant data variables will aid in implementing the ``Adaptable Learning Module'' and the ``Recommendation Module'' as discussed in Section V. Integrating different intelligent e-learning components this way provides a basis for the overall personalized e-learning solution. We have outlined a set of requirements and associated challenges and subsequently presented a holistic framework for personalized e-learning. The presented framework is designed to be an example of an intelligent e-learning system that integrates complementary components in order to first learn to determine comprehension levels of a student and then suggests learning resources as per the determined student level.

VII. FUTURE ENHANCEMENT

The continuous implementation and utilization of personalized learning framework can iteratively improves the personalization model. Utilization of data should also follow compliance to ensure data privacy. Evaluation of learner and the overall framework is significant. For this purpose, iterative rounds of evaluation of the framework may help towards improvement of the overall system.

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