International Journal of Research Publication and Reviews, Vol 5, no 2, pp 280-286 February 2024

International Journal of Research Publication and Reviews

Journal homepage: www.ijrpr.com ISSN 2582-7421

Adaptive Learning Platforms A Machine Learning Based Framework for E-Learning Recommender System Optimization

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A B S T R A C T

With the rapid evolution of online education, the demand for personalized learning experiences has grown significantly. This paper introduces an innovative approach to enhance e-learning platforms through the integration of a machine learning-based framework. The proposed system focuses on optimizing the Recommender System, leveraging adaptive learning techniques to tailor educational content to individual learner profiles. Through the analysis of user behavior and content features, our framework dynamically adapts recommendations, aiming to improve user engagement, knowledge retention, and overall learning outcomes. The study explores the efficacy of machine learning models, real-time adaptation mechanisms, and user feedback loops to create a comprehensive Adaptive Learning Platform. Preliminary results indicate promising advancements in personalization and effectiveness, offering a pathway for the future development of intelligent and responsive e-learning environments.

Keywords: Adaptive Learning, E-Learning, Recommender System, Dynamic Adaptation, Real time Learning.

1. Introduction

In the dynamic landscape of digital education, Adaptive Learning Platforms play a pivotal role in catering to the diverse needs of individual learners. Recognizing the imperative for personalization in the e-learning experience, this study presents an innovative framework that leverages machine learning to optimize Recommender Systems within Adaptive Learning Platforms. The primary aim is to enhance the effectiveness of educational content delivery by tailoring recommendations to the unique profiles and preferences of learners. Traditional one-size-fits-all approaches to education often fall short in meeting the diverse needs of learners. Adaptive Learning Platforms address this challenge by dynamically adjusting content delivery based on individual learning styles, pace, and preferences. Within this paradigm, the Recommender System emerges as a critical component, acting as an intelligent guide to curate and suggest relevant educational materials.

This research delves into the intersection of adaptive learning and machine learning, proposing a framework designed to optimize the Recommender System. By incorporating sophisticated machine learning models, the system adapts in real-time to user behavior, ensuring a personalized and engaging learning journey. The integration of user feedback mechanisms further refines the recommendations, fostering an environment where learners receive content tailored to their evolving needs. Adaptive learning is characterized as an instructional approach that makes use of advanced technologies, especially machine learning algorithms, to customize educational content, instructional approaches, and assessment methods for individual learners. The primary objective is to dynamically adjust the learning process in real time, taking into account each learner's performance, preferences, knowledge level, and learning style. By continuously analyzing learner data, including assessment outcomes, patterns of interaction, and progress monitoring, adaptive learning systems can offer timely and specific interventions. This ensures that learners receive the most pertinent and effective educational materials and activities. Due to their ability to convey educational information and adapt to the specific needs of students, adaptive learning systems are gaining increased popularity.

In general, Learning Management Systems (LMS) often fall short of meeting the specific requirements of individual learners based on their unique profiles. However, recognizing and incorporating learners' profiles into the system can significantly enhance the learning experiences and overall success of students (Imran et al., 2016). Introducing personalization features in LMS, recommender systems emerge as valuable tools for suggesting suitable learning objects to learners, thereby augmenting their learning journeys. Consequently, the generation of adaptive and personalized learning paths has become a pivotal focus in the design of learning environments (George & Lal, 2019; Hwang et al., 2020b; Raj & Renumol, 2021).

Within the realm of educational technology, the extraction of latent patterns from learner data is advantageous for refining online learning systems. Research on personalized learning, especially in the context of full-path recommendations, holds particular significance for advancing E-learning systems (Zhou et al., 2018). Online learners contribute substantial data with big-data characteristics, offering insights into their learning habits and facilitating the discovery of individual learning patterns (Chen & Zhang, 2014). The data generated within learning environments can be fed back into the system, contributing to learning evaluation and monitoring processes (Sachan & Saroha, 2022). Consequently, improvements in learning material recommenders enable more effective monitoring of student performance and adaptation to changes in their performance and learning preferences.

The rest of the paper is organized as follows. The problem statement and research questions are introduced in Sect. 2. Section 3 briefly explains the related works on the current domain from 2018 to 2023. Section 4 elaborates on the design of the knowledge and domain models. Section 5 describes the learning path recommendation model that is proposed in this paper. The subsections of Sect. 5 elaborate on the algorithm used for learning path generation. The experimentation procedure and results are presented in Sect. 6, and Sect. 7 discusses the developments in correlation with the research questions and states the limitations of the work. Section 8 concludes the current work with a discussion on future work.

2. Problem Statement & Research Findings

The primary aim of the adaptive learning path recommendation model is to furnish learners with personalized sequences of learning activities that best suit their needs (de Marcos et al., 2008). Therefore, the goal of this study is to identify a versatile model for personalized and adaptive recommendations, departing from the conventional "one-size-fits-all" approach. Chen et al. (2014) underscored the importance of improving access to learning resources to enhance learner performance and satisfaction. Furthermore, optimizing learner performance, considering factors such as learning time and scores obtained, results in more effective learning paths (Chen, 2011). Consequently, our focus revolves around learning duration, expected scores, adaptivity, and the acceptance of recommended learning resources. The research questions addressed are articulated as follows:

RQ1: Can we precisely predict the learning duration and expected score during the learning path recommendation process?

RQ2: What learner-centric personalization parameters contribute to the generation of adaptive and diverse learning paths in an e-learning environment?

3. Review of literature

In the contemporary educational landscape, technology plays a crucial role in learning, transforming e-learning into a global phenomenon. The vast expanse of information on the internet has made it imperative to leverage tools like the recommender system for efficient information retrieval with minimal effort. This system revolves around the learner's profile, which is crafted based on various parameters including current academic accomplishments and demographic details of the student. There will be a list of courses from which a user can opt. The recommendation system compares the profiles of user and the courses. A recommendation will be made based on the basis of similarity index between the profile of the user and the attributes of the potential courses. The two recommendation systems which have been successfully implemented are ‘Guess You Like: Course Recommendation in MOOCs’ implemented in China and ‘A Case Based Recommender System for MOOCs’ implemented in India. The work done by various researchers in the field of e-learning is given below.

Kulkarni, Rai & Kale (2020) have conducted one survey on e-learning. The researcher has highlighted that searching a topic on the web is time consuming process and a student has to put in lot of time and efforts. This tedious task can be eased by using recommender system for e-learning. The researcher has given the example of ancient Indian education system and the modern education system of these days. The researcher has put impetus on need of recommender system so that exact information can be retrieved from humongous records easily. The researcher has highlighted the benefits of e-learning for learners such as learning from anywhere, fast access to data, courses can be learned and revised also according to need, international courses are also available from the comfort of the house. The last and most important benefit is “User-pace” course. The user has proposed three level hidden Bayesian link Predication (3-HBP) model. This model is useful for ascertaining the user behavior and user relationships. George & Lal (2019) have analyzed the current state of educational recommendations. A detailed comparative study of ontology-based recommender systems and other recommender systems has been carried out to understand the current state of developments in recommender systems. Based on this study, the authors have concluded that most of the recommender system suffers from two inherent problems i.e. cold start and sparsity. The cold start problems arise due to initial lack of data. In absence of past data related to various courses and learners, it become difficult to provide inferences. The collaborative recommender system works on the past rating given by the system users. But the main cause of sparsity issue is insufficient feedback given by users. Generally, users don’t feel motivated to provide all the ratings and this result into incomplete data.

Murad & Yang (2018) studied Personalized E-Learning Recommender System using Multimedia Data. The researcher has analyzed that there are large number of e-learning environments which have gained popularity for delivering online lectures. The online learners have different academic and economic background. It is not a good practice to recommend the same learning material to all the students. The use of personalized e-learning can help to help to narrow down the list of recommendations. Milicevic, Ivanovic & Budimac (2017) have proposed personalization of the e-learning systems according to the learner’s needs and knowledge. The aim is to facilitate personalization of a learning content. Collaborative and social tagging techniques could be used for this Tensor factorization technique and it has been modified to gain the most efficient recommendation. This model is named as Intelligent Tutoring System (ITS) for programming course. Jing & Tang (2017) have studied Chinese MOOCs XuetangX known as “Guess you like” has 1000 courses and 60 lakh users in China. XuetangX, if a learner’s profile is incomplete, then this system can fetch the user’s profile from LinkedIn and generate a nearest match. This can solve the issue of cold-start in online mode. This system works in both online as well as offline mode.

Bhaskaran, Marappan & Santhi (2021) have proposed a method which takes the important attributes of the learner and the educators in e-learning systems. In some scenarios, there is a need to make recommendations based on certain targeted attributes such as interests of the learner, ability, choice and aim of the learner. In this model, the intelligent recommender picks the important attributes for creating clusters. The proposed method is used to extract functional attributes of the learner. By using the concept of frequent sequencing, the recommendations are provided. The proposed method reduced the absolute mean error metric in cluster. Cao, Liu & Zhang (2020) have proposed a new method to overcome cold-start problem. The researchers have worked on community detection algorithm. The bipartite approach was used to identify the similarity between the user and the item. Louvain algorithm has been used to identify the community detection. Pearson correlation coefficient was used to calculate the single mode network. The researchers run the test cases on multiple datasets and eventually proved that the new approach had effectively improved the cold start problem.

Vimala & Vivekanandan (2019) has proposed the methods to improve the movie recommendations by using Collaborative filtering based system. K-L divergence based on fuzzy C-means has been used to enhance the movie recommendations. The enhanced square root cosine similarity has been used to compare the nearness of an active user with the benchmark criteria. The researcher has used three step processes to enhance the accuracy. The three steps are: Kullback-Leibler divergence based on collaborative fuzzy C-means user clustering, Computation of nearest cluster and identifying the recommended movies on the basis of user's ratings in the domain. Dahdouh, Dakkak, Oughdir & Ibriz (2019) shared the learning acquired after implementation of e-learning based ESTenLigne project. The system has its own set of issues related to ever increasing amount of data related to courses and students, the more number of pedagogical resources. The purpose of this recommender system was to provide useful recommendations to fresh graduates. The recommender system was developed using association rules to choose the most appropriate resource. The frequent item set concept is used to generate the useful transaction database. More relevant courses may be mined using the above said rules. Finally, a comparative study is conducted to prove the performance of MLib library with comparison to machine learning. Forouzandeh & Xu (2018) have proposed a Cuckoo algorithm on facebook data to overcome cold-start problem. The researchers have tried to work on the cold start cases where the past behaviors of user are not available on social media.When a user is using social media, then depending on the past behavior of user, it is really very easy to recommend the content and information to that particular user. But this task becomes challenging due to unavailability past data. At this stage, data mining techniques can play a crucial role to 18 suggest recommendations. The Cuckoo algorithm was proposed as a solution to cold start. The algorithm makes use clustering techniques and association rules. Musto, Gemmis, Semeraro & Lops (2017) have studied that multi-faceted information can be derived from the users' feedback. The research had used a framework to collect the inclination of the user. The example of restaurant had been cited to explain the various factors towards which a user may have some inclination e. g. quality of food, service available at the restaurant and ambience of the place, etc. In this type of example, a lot of information can be collected and this information may be used to predict certain recommendations for that particular user. The results have proved the insight behind this work and the issue of one-criterion recommendation was resolved.

4. Content Based Recommender System

The recommender system works by calculating the closeness between the attributes of the course and the attributes of the learner. The set of variables which will be showing closeness between the attributes of course and learner will be used for generating recommendations. Since, the course is having multiple attributes such as course title, university name, language, availability, and fees. Similarly the profile of the candidate is also having multiple attributes such as academic background, social background and financial status, etc. Hence, the Multi-Criteria Decision Making (MCDM) model seems best-fit for this scenario. The sentiment score will be added to further improve the recommendations. The sentiment score will add sentiment analysis in the existing recommender system and it will introduce human aspect also.

The proposed work for "Adaptive Learning Platforms: A Machine Learning-based Framework for E-Learning Recommender System Optimization" involves the development and implementation of a comprehensive framework aimed at enhancing the adaptability and effectiveness of E-Learning recommender systems. The framework integrates various machine learning techniques to create a personalized and dynamic learning experience for individual users. Below is an elaboration of the key components of the proposed work:

4.1 Data-driven Personalization:

The framework relies on extensive datasets derived from learner interactions within the E-Learning platform.

Machine learning algorithms are employed to analyze and interpret individual learning patterns based on historical data.

The goal is to understand user behaviors, preferences, and performance metrics, forming the foundation for personalized recommendations.

4.2 Dynamic Content Recommendation:

The framework incorporates real-time adjustments to content recommendations based on ongoing user interactions.

It responds to changes in a learner's progress, interests, and evolving educational goals to ensure the relevance and challenge level of recommended content.

4.3 Collaborative Filtering Techniques:

The proposed work utilizes collaborative filtering techniques, which consider not only an individual's behavior but also tap into collective data from the learning community.

By identifying similarities between learners with comparable interests and learning trajectories, the system enhances the precision and diversity of recommendations.

4.4 Continuous Feedback Loop:

A critical aspect of the framework is the establishment of a continuous feedback loop.

Learner feedback, performance metrics, and interaction data are systematically integrated back into the machine learning model.

This feedback loop ensures that the system evolves over time, becoming more accurate and refined in its recommendations.

4.5 Adaptive Learning Paths:

The framework aims to create adaptive learning paths for users based on their unique needs and preferences.

As users progress through the learning materials, the system dynamically adjusts the sequence and difficulty of content to optimize the learning journey.

4.6 User Engagement Strategies:

The proposed work considers strategies to enhance user engagement by delivering content in a way that aligns with individual learning styles.

The system may incorporate multimedia elements, interactive components, and varied instructional approaches to keep users actively involved in the learning process.

4.7 Scalability and Efficiency:

The framework is designed to be scalable, accommodating a growing user base without compromising the efficiency of personalized recommendations.

Machine learning models and algorithms are optimized to handle large volumes of data and deliver timely responses to user interactions.

The overarching objective of the proposed work is to revolutionize E-Learning experiences by creating a highly adaptive and personalized environment. By leveraging machine learning techniques, the framework seeks to contribute to the ongoing evolution of education technology, offering learners tailored content that maximizes engagement, understanding, and retention.

5. Content-based recommender system optimization using k-l divergence technique

A recommendation system works as an information filtering engine. The purpose of a recommendation system is to predict the inclination of a user towards a course based on the past behavior of the user. In these days, there are plenty of recommender systems available in all walks of life. Generally, the recommender systems can be grouped into 4 major categories. The first one is content-based recommender system which works by comparing the attributes of two entities. The second is collaborative filtering recommender system which works on the basis of ratings of the user related to an item or an event. The third is knowledge based recommender system which gives recommendations according to the queries made by the user. The fourth is hybrid recommender system (Reddy & Govindarajulu 2018). When a recommender system uses more than one principle cited above, then it can be categorized as hybrid recommender system (Reddy & Govindarajulu 2018, Thakar, Mehta & Manisha 2015). The description of e-learning system is defined in chapter 3 along with the proposed recommender system. It has used the sentiment score associated with individual courses during recommendations. The proposed method uses the cosine similarity measuring technique for finding the similarity between two vectors i.e. whether two vectors are in same direction or in opposite direction. In this chapter, to compute the similarity with multi-dimensional attribute of student and course, K-L divergence (Kullback-Leibler divergence) technique is used. Student attributes and course attributes are probabilistic in nature. Thus, it require probabilistic difference measuring techniques for finding the suitable course list to the s36 tudents. In this section, “an efficient method to improve the accuracy of the course recommendations” is proposed

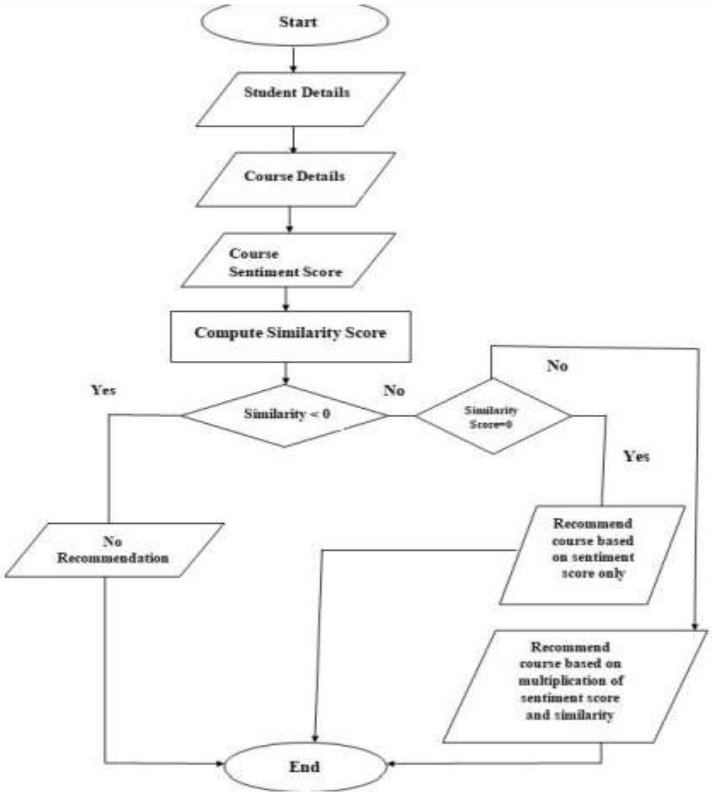

Figure 1: Flow Chart for Generating Recommendation System

Simulation based study has been applied for the proposed algorithm. Course attributes and student attributes have value ranging between 1 to 9. These values are generated randomly using uniform distribution. Similarly, sentiment score has two values score and magnitude. Sentiment score provides the measure of emotions contained in user's feedbacks. Its value ranges from -1 to +1. -1 represents total negative emotions whereas +1 represents total affection towards that subject whereas magnitude gives the amount of text data analyzed for computing the sentiment score.There a number of API's are available on the internet that can be used to compute the sentiment score from the text data. In this analysis, sentiment scores are also randomly generated by using uniform distribution

6. Conclusion

In conclusion, the development and implementation of the proposed "Adaptive Learning Platforms: A Machine Learning-based Framework for E-Learning Recommender System Optimization" hold great promise for revolutionizing the landscape of online education. By integrating advanced machine learning techniques into E-Learning platforms, the framework aims to create a dynamic and personalized learning environment tailored to the unique needs of individual users.The key components of the framework, including data-driven personalization, dynamic content recommendation, collaborative filtering techniques, and a continuous feedback loop, collectively contribute to the adaptability and effectiveness of the recommender system. The emphasis on creating adaptive learning paths ensures that users receive content that aligns with their learning preferences, leading to a more engaging and impactful educational experience.

The incorporation of collaborative filtering not only considers individual behaviors but also taps into the collective wisdom of the learning community, enhancing the precision and diversity of recommendations. The continuous feedback loop ensures that the system evolves over time, becoming more accurate and refined as it learns from user interactions and feedback. The framework's focus on scalability and efficiency is crucial in catering to a growing user base without compromising the speed and accuracy of personalized recommendations. This scalability is essential in accommodating the evolving demands of online education and ensuring that the system remains effective and responsive.

In essence, the proposed framework represents a significant step towards the realization of adaptive learning platforms that leverage machine learning to transform online education. As technology continues to advance, the integration of intelligent algorithms in E-Learning recommender systems becomes increasingly vital, offering a pathway to enhanced learning outcomes, increased user engagement, and a more efficient educational experience. As this framework is implemented and refined, it is expected to contribute substantially to the ongoing evolution of adaptive learning technologies and their integration into mainstream education.

References

Imran, H., Belghis-Zadeh, M., Chang, T. W., Kinshuk, & Graf, S. (2016). PLORS: A personalized learning object recommender system. Vietnam Journal of Computer Science, 3, 3–13. https://doi.org/10.1007/s40595-015-0049-6

George, G., & Lal, A. M. (2019). Review of ontology-based recommender systems in e-learning. Computers & Education, 142, 103642.

Hwang, G. J., Xie, H., Wah, B. W., & Gašević, D. (2020b). Vision, challenges, roles and research issues of artificial intelligence in education. Computers & Education: Artificial Intelligence, 1, 100001.

Raj, N. S., & Renumol, V. G. (2021). A systematic literature review on adaptive content recommenders in personalized learning environments from 2015 to 2020. Journal of Computers in Education. https://doi.org/10.1007/s40692-021-00199-4

Zhou, Y., Huang, C., Hu, Q., Zhu, J., & Tang, Y. (2018). Personalized learning full-path recommendation model based on LSTM neural networks. Information Sciences, 444, 135–152.

Sachan, D., & Saroha, K. (2022). A review of adaptive and intelligent online learning systems. ICT Analysis and Applications. https://doi.org/10.1007/978-981-16-5655-2_24Return to ref 2022 in article.

de Marcos, L., Martínez, J. J., & Gutiérrez, J. A. (2008). Swarm intelligence in e-learning: a learning object sequencing agent based on competencies. In Proceedings of the 10th annual conference on Genetic and evolutionary computation (pp. 17–24).

Chen, W., Niu, Z., Zhao, X., & Li, Y. (2014). A hybrid recommendation algorithm adapted in e-learning environments. World Wide Web, 17(2), 271–284.

Chen, L. H. (2011). Enhancement of student learning performance using personalized diagnosis and remedial learning system. Computers & Education, 56(1), 289–299.

Christudas, B. C. L., Kirubakaran, E., & Thangaiah, P. R. J. (2018). An evolutionary approach for personalization of content delivery in e-learning systems based on learner behavior forcing compatibility of learning materials. Telematics and Informatics, 35, 520–533.

Article Google Scholar

Ciloglugil, B., & Inceoglu, M. M. (2018). A learner ontology based on learning style models for adaptive e-learning. International conference on computational science and its applications (pp. 199–212). Springer.Return to ref 2018 in article

Clark, R. M., Kaw, A. K., & Braga Gomes, R. (2021). Adaptive learning: Helpful to the flipped classroom in the online environment of COVID? Computer Applications in Engineering Education. https://doi.org/10.1002/cae.22470

Article Google Scholar

Cun-Ling, B., De-Liang, W., Shi-Yu, L., Wei-Gang, L., & Jun-Yu, D. (2019). Adaptive learning path recommendation based on graph theory and an improved immune algorithm. KSII Transactions on Internet & Information Systems.

Deng, Y., Huang, D., & Chung, C.-J. (2017). Thoth lab: A personalized learning framework for cs hands-on projects. In Proceedings of the 2017 ACM SIGCSE technical symposium on computer science education (pp. 706). ACM.

Dharani, B., & Geetha, T. V. (2013, July). Adaptive learning path generation using colored Petri nets based on behavioral aspects. In 2013 International conference on recent trends in information technology (ICRTIT) (pp. 459–465). IEEE.

Dorça, F. A., Araújo, R. D., De Carvalho, V. C., Resende, D. T., & Cattelan, R. G. (2016). An automatic and dynamic approach for personalized recommendation of learning objects considering students learning styles: An experimental analysis. Informatics in Education, 15(1), 45–62.

Essalmi, F., Ayed, L. J. B., Jemni, M., & Graf, S. (2010). A fully personalization strategy of E-learning scenarios. Computers in Human Behavior, 26(4), 581–591.

Farrell, C. C., Markham, C., & Deegan, C. (2019). Real time detection and analysis of facial features to measure student engagement with learning objects. IMVIP 2019: Irish Machine Vision & Image Processing

Felder, R. M., & Silverman, L. K. (1988). Learning and teaching styles in engineering education. Engineering Education, 78(7), 674–681.

Google Scholar

George, G., & Lal, A. M. (2019). Review of ontology-based recommender systems in e-learning. Computers & Education, 142, 103642.Return to ref 2019 in article

Article Google Scholar

Gomede, E., de Barros, R. M., & de Souza Mendes, L. (2021). Deep auto encoders to adaptive E-learning recommender system. Computers and Education: Artificial Intelligence, 2, 100009.

Google Scholar

Hwang, G. J., Sung, H. Y., Chang, S. C., & Huang, X. C. (2020a). A fuzzy expert system-based adaptive learning approach to improving students' learning performances by considering affective and cognitive factors. Computers and Education: Artificial Intelligence, 1, 100003.

Google Scholar

Hwang, G. J., Xie, H., Wah, B. W., & Gašević, D. (2020b). Vision, challenges, roles and research issues of artificial intelligence in education. Computers & Education: Artificial Intelligence, 1, 100001.