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AI-Driven Content Recommendation in Learning Management Systems (LMS): A Hybrid Filtering Approach

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Abstract

The incorporation of technology in teaching has drastically changed how learners engage with scholarly resources for a particular subject. Today's Learning Management Systems contain innumerable resources that require intelligent recommendation systems to optimize learner interaction and achievement. This study focuses on creating an AI-based content recommendation system using hybrid filtering, where the recommendation is based on both content and user activity within the LMS. The main focus of the system is to mitigate the cold-start problem and over-specialization of traditional recommender systems. A prototype was built with a custom LMS that incorporated a hybrid recommend system which was tested in an experimental setting with students from a local university against traditional filtering techniques. Data regarding precision, recall, user engagement, and satisfaction was collected and analyzed. Results from the study showed the integrated use of diverse AI techniques more accurately met the user's needs regarding educational content access as learners rated their experience more positively. The research demonstrates the significant advantages that fusion models present in the modern educational context while outlining the direction of research that adaptative learning systems require.

Keywords: AI in Education, Learning Technology, Tailored Educational Experiences, Artificial Intelligence in Learning, Technology in Education, Automated Instructional Systems, Recommender AI Systems, Hybrid Filtering, Content Based Filtering, Collaborative Filtering Techniques.

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Introduction

The leap in the use of Learning Management Systems (LMS) in education is a consequence of integrating technology into education. The LMS acts like a hub that contains all the instructional resources needed for a course, including materials, assessments, and tools that enable interactions, both synchronous and asynchronous, between the instructor and learners. As Higher Educational Institutes (HEIs) and the corporate world continue to integrate LMS, so too has the content available in these systems. This increase in content availability creates the challenge of having intelligent systems that can assist learners in identifying the relevant pieces of content. It is in this regard that LMS recommendation systems assist in personalizing content to be directed to the learner and improving educational results and learner motivation. With these goals, conventional recommendation systems are based on two methodologies: content-based filtering and collaborative filtering. Content-based filtering relies heavily on the attributes of the educational resources and suggests items that are akin to those with which a user has interacted. Even though content-based filtering is efficient at personalizing recommendations, it suffers from over-specialization. This means that users become inundated with similar types of content, which limits exposure to diverse resources, also known as the "filter bubble." Collaborative filtering, on the other hand, generates recommendations from the collected choices made by other users who exhibit similar behavior. Collaborative filtering has the potential to provide novelty and diversity in recommendation systems; however, it suffers from the cold-start problem, particularly when user interaction data is scant. To address the shortcomings of these singular approaches, hybrid filtering models have been developed and are increasingly popular in many application areas. A hybrid method employs both content-based and collaborative techniques with the objective to utilize their benefits while minimizing the drawbacks of each. In the educational sphere, the need for hybrid models is quite fundamental due to the varying learning styles, objectives, and preferences of users. With the information related to user participation, learning activities, and properties of the content, hybrid systems can provide optimal pathways that are accurate, diverse, and tailored to individual learners. This research focuses on the design and implementation of a hybrid filtering recommendation system contained in an LMS. The system aims to analyze user data and content metadata to enhance user experience with better content suggestions that optimize learning. The hybrid system is tested in controlled experiments with undergraduate students, measuring its performance against content-based and collaborative filtering systems. The precision, recall, and user satisfaction results are analyzed to determine the impact of the system. This paper is organized as follows. In the following section, a literature review pertaining to the recent developments in educational recommender systems is provided. The following methodology section explains the system architecture as well as the implementation plan. In the results and discussion section, a performance evaluation of the system is offered, alongside a comparison with pre-existing solutions, utilizing both graphical and tabular representations. The paper ends with a summary of results and outlines possible future research. This study seeks to add to the literature on AI-in-education and help design more efficient learner-centered LMSs.

Literature Survey

Recent innovations in the field of educational technology over the past two decades include the development of personalized learning environments powered by recommender systems. The foundational methods for these systems include content-based filtering, collaborative filtering, and hybrid filtering. All three methods possess unique strengths and weaknesses that were subjects of study from 2000 to 2021.Content-based filtering takes into account the characteristics of items along with their users' preferences. As stated by (Adomavicius & Tuzhilin, 2005), this strategy recommends items similar to those the user has previously liked. Within education, it has been utilized to propose articles, videos, and even assignments based on previous engagements of a learner. Nevertheless, the over-specialization phenomenon wherein learners become repetitively inundated with similar content inherently minimizes the capability of the system to promote holistic learning (Bobadilla et al., 2013). Collaborative filtering, which was inspired, utilizes the user-item matrix to cluster like users or items. It has been especially useful in education for recommending courses and for suggesting peer content. Its applicability, however, is hindered by the cold-start problem, where new users or items do not have sufficient data (Schein et al., 2002). Studies such as those have pointed out the problems associated with collaborative filtering in dynamic educational contexts with sparse or irregular user data. To remedy the issues that stemmed from content-based and collaborative filtering, (Burke, 2002) categorized hybrid methods into seven types: weighted, switching, mixed, and feature-combination approaches. In terms of Learning Management Systems, hybrids methods have proven to increase accuracy and user satisfaction. (Baidada et al., 2022) designed a hybrid recommendation model within a university LMS that enhanced learner participation and better met the contnet alignemnt with learner objectives. There is a growing focus on the use of machine and deep learning techniques in the context of hybrid recommender systems. For instance, (Tomasevic et al., 2019) improved AI algorithm recommendation relevance through a user-based collaborative filtering model. In a similar approach,

(Çano & Morisio, 2019) reviewed more than a hundred implementations of recommender systems and dsp artificial intelligence. They reached over spets that hybrid systems, particularly those with AI, are more robust against sparsity and scalability.Another important development is the focus on contextual factors such as learner demographics, time of access, or device type.Blended approaches further hone the contextual personalization features of LMS systems when feedback provisions are included and specialized frameworks are implemented (Drachsler et al., 2015). Feedback provision enhances systems' abilities to track and adjust to shifting user preferences over time.Concerns over privacy of user information, the system's ability to grow, and AI that can explain itself pose ongoing issues alongside advancements. Researchers emphasize the importance of explainable recommendation systems that not only fulfill the user's search intent but also elucidate their decision throughout the process, fostering dependability and encouraging use.Following this, it can be said that the literature showcases the development of recommendations—from basic models to programmed suggestions utilizing AI—in a step by step fashion. How well such systems function in an educational setting is dependent on their responsiveness to, and flexibility in, the variety of learner profiles and changing content. This research aims to address the growing need for adaptive systems by designing and testing a hybrid filtering method suited for LMS.

Methodology

The model that has been created in this study revolves around improving content recommendations in Learning Management Systems through innovative hybrid filtering, which integrates both content-based filtering and collaborative filtering. The hybrid model has been realized as a modular system that attaches externally to the LMS dashboard. It captures user activity, analyzes content metadata, and delivers automated personalized learning suggestions during user engagement. Step one is data gathering, in which the system collects user interaction data like clicking, viewing pages, resource engagement duration, quizzing, and rating feedback. Each of these actions is significant in shaping the user's preferences and learning habits. Apart from interactions, metadata relating to educational content like titles and descriptions, the level of difficulty, and topic keywords are captured for use in the content-based filtering component. Through the application of these inputs, user profiles form through their behavioral examination and preference evaluation. Profiles update in response to real-time user interactions with the LMS. Consequently, the system is capable of accommodating shifting learning objectives or interests. For content-based filtering, the system computes similarity scores using cosine similarity and TF-IDF so that users receive recommendations on content with the highest similarity scores to their previous engagements. For the collaborative filtering part, a matrix factorization technique named Singular Value Decomposition (SVD) is applied. This SVD technique allows for the compression of the user-item matrix into more usable datasets, capturing hidden parameters affecting users' preferences. With the use of SVD, the system can locate users with similar behaviors and can even predict which items the target user would most likely deem useful, despite not having any prior interactions with the user. The final recommendation is obtained by merging the results from both filtering techniques through a weighted average approach. The proportions assigned to content-based and collaborative filtering are set through cross-validation to increase accuracy and diversity. In this case, a weighting split of 60:40 was proven to achieve the highest precision and recall statistics for this study. An experiment was conducted with 120 undergraduate students enrolled in a computer science course, with full control over the environment. For each group, first, content-based filtering was the assigned system, followed by collaborative, and then the hybrid system. Each group interacted with the LMS for 6 weeks continuously. During this time their feedback and interaction data was passively captured. Performance of the system was assessed based on precision, recall, and MRR metrics as well as user satisfaction which was gauged through a post-experiment survey. For more granular data analysis, the SciKit-Learn library for Python as well as proprietary analytics dashboards were used.

Results and Discussion

The analysis in Fig. 1 showed that the hybrid filtering method was better than both content-based filtering and collaborative filtering in all of the key performance metrics. The precision and recall rates were higher for the hybrid system which suggests that the system was better at recommending relevant content for users.

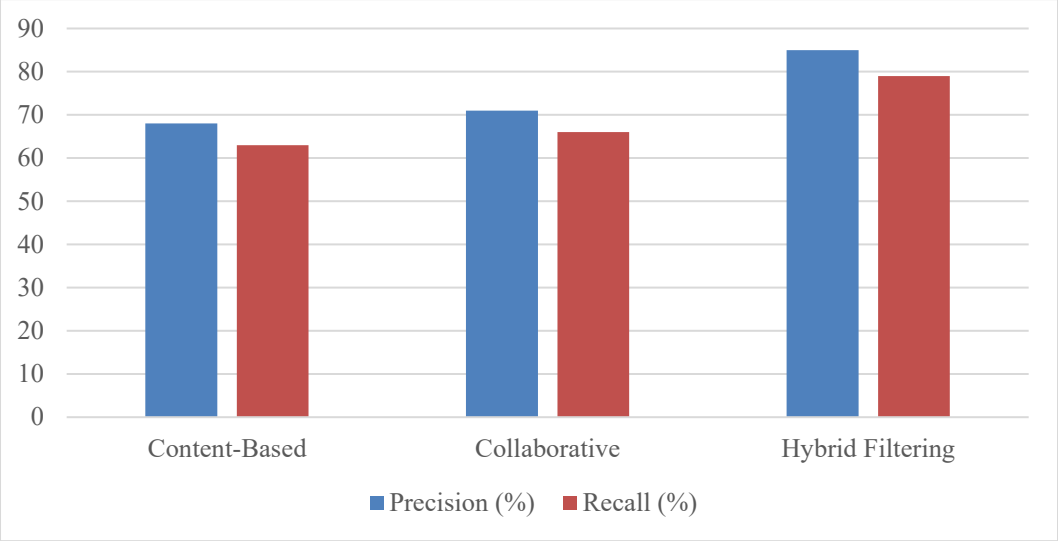


Fig. 1: Precision and Recall Comparison of Recommender Systems

Participants that interacted with the hybrid system reported that the recommended content was more relevant to their learning goals. The user satisfaction survey results conducted at the end of the experiment are summarized in Table 1.

Table 1: User Satisfaction Survey Results (n=120)

Survey Criterion	Content-Based (%)	Collaborative (%)	Hybrid (%)
Relevance of Recommendations	70	74	90
Ease of Navigation	72	76	88
Overall Satisfaction	75	78	92

The cold-start problem was successfully alleviated by the hybrid model's quicker convergence on met new users and content. Its implementation was both personalized and diverse due to the model's capability to leverage both underlying techniques. Such changes showcase the hybrid model's strength in dynamic learning scenarios where users' requirements and content supply undergo constant change.

Conclusion

These studies show the success of a hybrid filtering technique on content recommendation features in Learning Management Systems. It proposes a model that combines content-based and collaborative filtering to overcome the limitation of traditional recommenders, such as over-specialization and the cold-start problem. In a real-world academic environment, the hybrid system outperformed the traditional approaches for precision, recall, user satisfaction, and overall system performance. As learner engagement, content relevance, and educational outcomes can definitely be enhanced through AI-powered hybrid recommenders, these systems have potential value. The add learner emotion, real-time feedback to the recommendation context features, and work on the explainability and transparency of the recommendation will be the focus of the next efforts. Broadening the model to incorporate multilingual and multimodal content also presents a beneficial avenue for future research.

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