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Developing of A Learning Content Recommendation System Using Collaborative Filtering Based on User Rating

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Abstract

The advancement of artificial technology has paved the way for personalized learning experiences through adaptive systems which could be built by developing a recommendation system. In education filed, a variety of learning material recommendation systems that employ user filtering algorithms has prompted a lot attention as well. These systems aim to enhance the learning journey by offering tailored learning content suggestions based on individual preferences. This research explores the design of recommendation of learning content system, focusing on user filtering algorithms to analyze user preferences. By leveraging techniques such as collaborative filtering and user-based filtering, the system can accurately predict and recommend relevant learning materials to users based on others rating. The system continuously refines itself in an effort to increase user satisfaction and recommendation accuracy, which will eventually contribute to more efficient and engaging learning experiences.

Keywords: *recommendation system, learning content, educational data mining, user rating, collaborative filtering*

1. Introduction

E-learning is becoming an essential component of today's educational system. A revolution in learning takes place into being through the use of e-learning, particularly in terms of acquiring and seeking information [1]. But, as expectations for learning and technological developments advance specially the existences of artificial intelligent technology, so does the appealing nature of online learning, which can be attributed to both the ease of information acquisition and the ongoing developments of technology, both of which have further improved the educational process. One of the most fascinating developments in e-learning is the creation of Adaptive Learning, an approach to education that enables customization of learning to meet each student's unique needs [2-6]. Adaptive learning-based learning is an important learning concept for answering increasingly complex learning problems. The diverse backgrounds and needs of students with increasing and diverse demands for knowledge mastery have necessitated a learning concept that can adapt to the needs of each individual student. Apart from that, the learning concept used also ensures that each student gets a learning experience according to their level. Apart from that, the adaptive learning-based learning concept is also able to increase retention and understanding of concepts for students by presenting material in stages according to students' abilities [7].

A recommendation method, which successively decides what to learn in the next step depending on the knowledge available at the time, is the engine of an adaptive learning system. It stands to reason that an effective recommendation system maximizes gains across the entire learning trajectory including deciding the strategies of offering the appropriate learning materials rather than concentrating just on the gain at the next stage [8]. A recommendation system that was designed has to able to adapt the unique preferences of each learner.

The success of developing a recommendation system has been proven to be successful in helping various problems, especially system personalization problems in various fields such as e-commerce systems and various social media platforms. Collaborative filtering is one of the popular methods used to develop recommendation systems. The collaborative filtering technique will produce recommendations for users based on the preference results of other users who are similar[9-11]. Similarity measurements can be done by measuring the similarity of the profiles of each user, for example age, gender and other background profiles. This collaborative filtering technique is called a user-based approach. Apart from that, another approach is to measure the similarity of users who have an interest in the same item[12-13]. In this technique, user ratings will be preference information used to measure similarity between users. The use of ratings on the same item to see similarities has been used by various companies such as Netflix to provide films to each user.

In the field of education, several recommendation applications have been developed. Samina Amin et al (2023) have proposed a recommendation system that takes into account similarity values while combining various machine learning techniques with content-based filtering methods[14]. Another study by Hazar et al (2022), was conducted to develop a recommender system that suggests and guides learners in selecting appropriate learning videos based on their individual requirements. This system is built on the principles of collective intelligence from internet user [15].

In this research, collaborative filtering based on user rating is used to recommend learning content in the salting learning process. In a learning process there are several learning outcomes that must be achieved, each learning achievement is delivered by problem-based learning and to solve these problems, several materials are available that can be used to help solve the problem. The recommendation system will provide material recommendations that suit the learner's preferences. Unlike previous studies, the evaluation conducted on the recommendation model is assessed using evaluation metrics that indicate the accuracy of the recommendation results. In this research, the evaluation process also considers the impact of these recommendations on the success of the learning outcomes.

In section 2, we will provide proposes method of the solution to build a recommendation system for learning materials. The proposed solution will be evaluated in Section 3 by implementing the recommendation system in a programming class. Conclusion and future works will be presented in Section 5.

2. Methods

In designing a material recommendation system, it must be guided by the collaborative filtering process and the learning scenarios that have been designed. So that all content and features have been created to accelerate the achievement of learning goals that have been designed effectively. In general, there are two main steps:

a. Content grouping based on project work checkpoints.

There are nine projects work checkpoints that have been designed in the learning system while each student can access material recommendations from the 52 materials designed at each checkpoint. However, not all material will be recommended because not all material is basically relevant to the checkpoint, so a grouping process is carried out first to be able to group existing materials into 9 groups according to their respective checkpoints.

b. Design of User-Based Collaborative Filtering

The recommendation system was built using a user-based collaborative filtering technique, which is the technique will recommend material according to the results of collaborative accumulation of rating calculations or assessments given by all system users.
In Figure 1, when the first user who uses the system and is faced with checkpoint 1, the system will by default provide sequential recommendations according to the material index with a rating of 0 because no one has given a rating yet, and the first user gives a rating to material A and material B. Because he gave material B a rating of 4, so that for the next user, the order of the material displayed will change and material B will be in first place (see Figure 2).

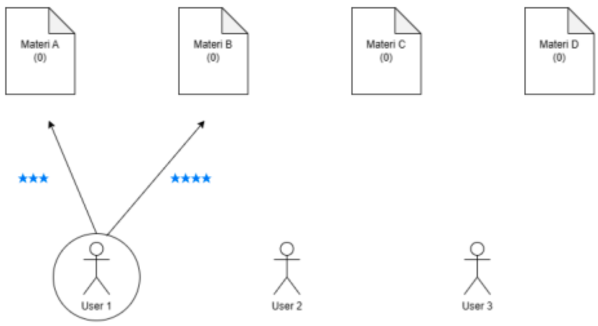

Fig. 1: Step 1 First user provide rating for the available materials according to his preferences

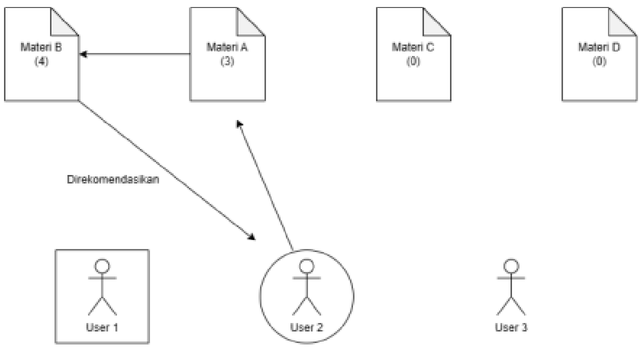

Fig. 2: Step 2 The second user will be recommended content based on the selections made by the first user

User 2 gets a list of materials based on ratings, so if for example User 2 chooses Material A first, then after he accesses Material A then he will be recommended by the system to read Material B because User previously had similarities to User 2 (Figure 3).

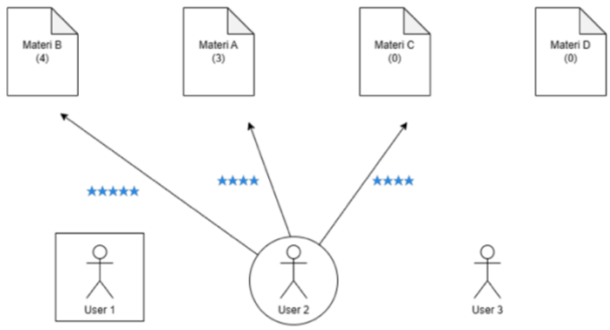

Fig. 3: Step 3 User 2 will provide ratings for the available materials according to his preferences.

When User 2 has been given material recommendations according to the User's similarities, then after that he will give a rating to the material he has accessed, and the rating will be accumulated from the giving of all Users who have given ratings, then the order of the material will change according to the rating value from top to bottom. and material that does not yet have a rating or the number of ratings is the same (in this case 0), it will still be recommended to only sort it according to the material index.

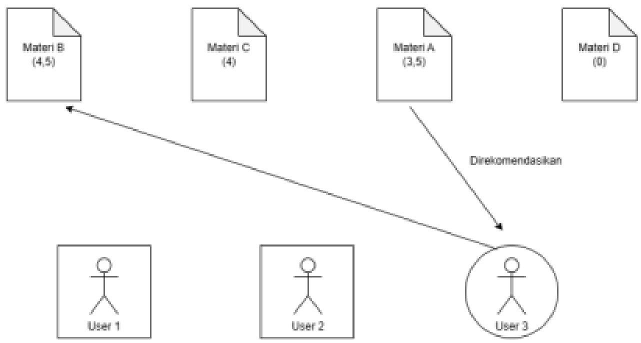

Fig. 4: Step 4 User 3 will be recommended content based on the selections made by pervious user

After User 2 gives a rating, then when User 3 chooses Material B, then Material A will be prioritized for recommendation because has similarities with User 2 and User 1 who initially had an interest in reading Material A first compared to Material C which had a higher rating, although in the end Material C would still be recommended but its priority level was below Material A. When User 3 gives a rating to the material that has been rated, then the rating on the material will be accumulated with the rating just given by User 2, and User 4 will receive the order of material as in Figure 5.

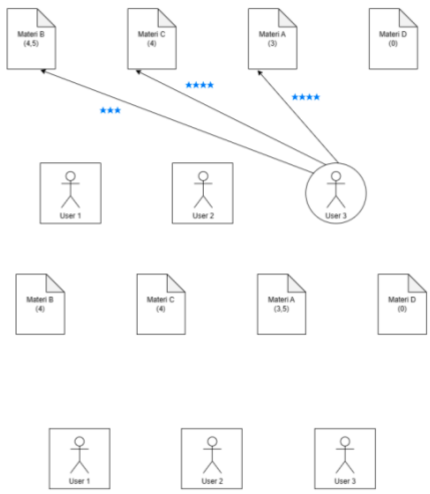

Fig. 5: User 2 will provide ratings for the available materials according to his preferences.

3. Result and Discussion

3.1. Implementation

We have developed a learning media that features a website-based material recommendation system based on previously designed layouts. In this application, students can engage in independent learning, guided by a project work manual included in the app, while benefiting from automatic material recommendations at each step of their learning journey. For each recommended material, students can provide an assessment or rating on a scale of 1 to 5, indicating how relevant the material is to their needs. Below is the interface display resulting from the development of the material recommendation system, as illustrated in Figure 6.

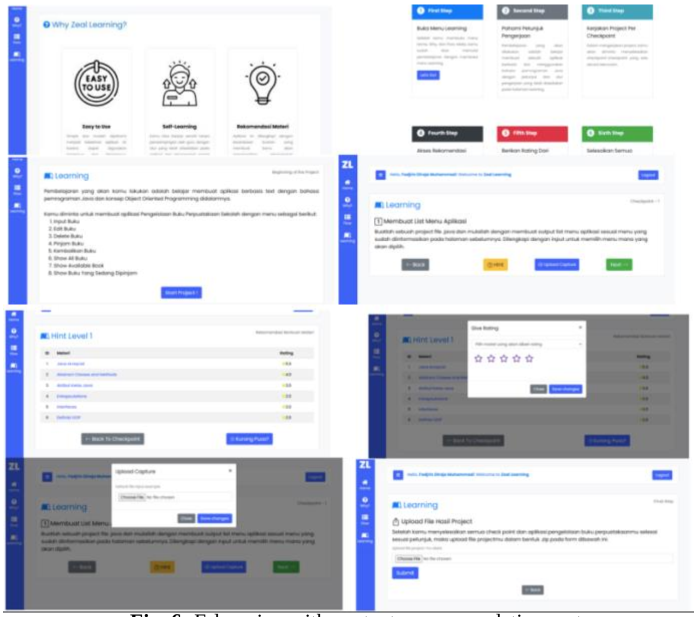

Fig. 6: E-learning with content recommendation system

3.2. Evaluation

The evaluation process was conducted in two phases: first, assessing the accuracy of the recommendations in relation to the content materials that meet students' needs, and second, examining the overall impact of the system on the learning process. To determine the accuracy of the recommendations, measurements were taken based on the average ratings provided by each student for the materials recommended in each topic.

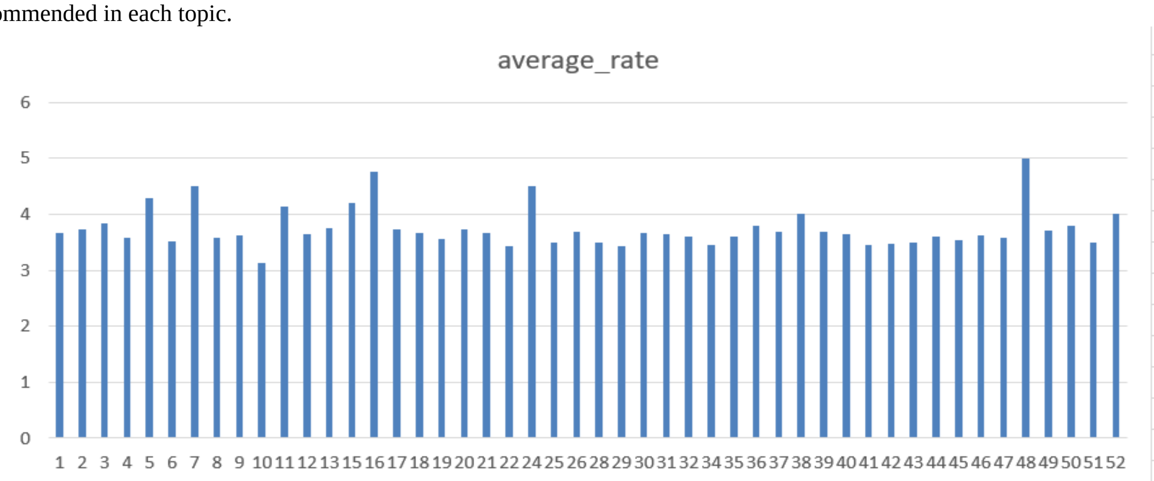

Fig. 7: Average rating of recommended material in all topics

Based on the results of these calculations, it can be concluded that material number 48 received the highest rating, with a score of 5 (five). Material number 16 (received the second highest rating, scoring 4.75. In third place, material number 24 was rated at 4.5. The overall average rating for all materials is 3.74.

To examining the impact of system on learning process, the evaluation was conducted using the One-Group Pre-test – Post-test design methodology. In this phase, we calculated the improvement observed after the treatment, which involves the use of the material recommendation system learning media, comparing results from before and after its implementation. During this stage, we also collect data to generate experimental findings. The N-gain test was conducted to assess the improvement in student learning outcomes following the treatment with the material recommendation system. An analysis of the overall pretest and posttest results indicates a notable increase, as illustrated in Figure 7.

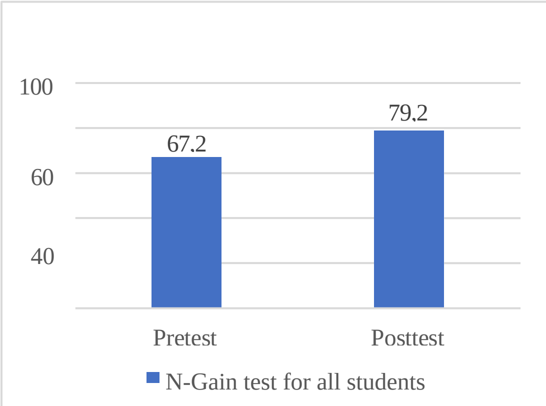

Fig. 7: N-gain results for all students

4. Conclusion

This research shows that artificial intelligence technology can support personalized learning experiences through adaptive systems, such as recommendation systems. Content recommendation systems aim to enhance the learning journey by offering customized content suggestions based on individual preferences. This research explores the design of learning content recommendation systems with a focus on user filtering algorithms to analyze user preferences. By utilizing techniques such as collaborative filtering based on user ratings, this system is able to predict and recommend relevant learning material to users based on ratings from other users. The system continually makes improvements to increase user satisfaction and recommendation accuracy, ultimately contributing to a more efficient and engaging learning experience. Further research can be carried out by exploring additional or hybrid filtering techniques that combine collaborative filtering and content-based filtering to increase recommendation accuracy. Using a combined approach can provide better results in predicting user preferences.

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