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AI and ML Integration Using Collaborative Filtering in Movie Recommendations

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ABSTRACT

This study aims to integrate Artificial Intelligence (AI) and Machine Learning (ML) technologies with Collaborative Filtering (CF) to build a more accurate and personalized movie recommendation system. This system uses the Singular Value Decomposition (SVD) algorithm to reduce the dimensionality of data and generate rating predictions for users of movies they have not watched. This study implements a dataset from MovieLens to test the effectiveness of the model in providing recommendations. The experimental results show that the system successfully predicts user ratings with fairly high accuracy, reflected in the average Root Mean Square Error (RMSE) value of 0.85 for the five users tested. Although these results show good performance, challenges such as cold start problems and data sparsity are still major obstacles in producing more optimal recommendations. Therefore, this study also proposes the use of hybrid filtering, deep learning, and the use of external data to improve prediction accuracy and overcome these limitations.

1. INTRODUCTION

1.1 Formulation of the problem

In the digital era, the ever-increasing amount of content, including movies, often leaves users feeling overwhelmed when it comes to choosing what to watch. Conventional recommendation systems often fail to understand individual preferences accurately. This raises the need for more sophisticated methods to provide relevant and personalized recommendations. However, modern approaches based on artificial intelligence (AI) and machine learning (ML) provide more adaptive and personalized solutions. AI allows systems to analyze user data in depth, while ML provides the ability to learn preference patterns based on historical data. With this combination, recommendation systems can identify user preferences even without explicit input, through behavioral analysis such as click patterns, watch time, and ratings given [1].

Collaborative Filtering has been widely implemented in various applications in recent years. One example is an online shopping platform like Amazon, which uses this method to suggest products based on user tastes and purchasing patterns. Meanwhile, streaming services like Netflix have been using a hybrid recommendation system, which combines collaborative filtering and content-based filtering, since 2009. This strategy allows Netflix to provide more precise movie and series suggestions based on user preferences and the features of the content Recommendation methods are divided into three types, namely content-based filtering, collaborative filtering, and hybrid recommendation systems [2][3][4]. Content-based filtering is formed based on the belief that users tend to like products with the same characteristics as those they previously selected [4]. In addition, this approach can also utilize existing user data [5]. Collaborative filtering analyzes items based on preferences from other users [6]. Hybrid recommendation systems combine collaborative and content-based filtering to achieve better results [7]. Each approach has advantages and disadvantages, such as content-based filtering being limited in finding new items [8], while collaborative filtering faces problems such as cold start and lack of data [9][10][11].

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1.2 Research purposes

This study aims to investigate how collaborative filtering can be utilized in movie recommendation systems, assessing how well it provides tailored suggestions. It analyzes the role of artificial intelligence and machine learning in improving this approach. Furthermore, the study seeks to formulate suggestions for refining Collaborative Filtering-based systems (CF-based systems), ensuring an improved user experience and more precise content recommendations.

2. LITERATURE REVIEW

2.1 Artificial intelligence (AI)

Artificial intelligence is a fast-developing field [21]. Artificial intelligence (AI), especially through computational intelligence along with machine learning techniques and algorithms, has been organically utilized in creating recommendation systems [21]. Recommendation Systems (RS) are designed to help people find content that matches their preferences and interests within the large selection available. RS is a software program that offers users suggestions for things such as movies, music, careers, jobs,

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medicine, and education [22]. AI is a form of intelligence added to a system that can be arranged in a scientific context, also known as Artificial Intelligence or abbreviated as AI, and can be defined as the intelligence of a scientific entity. AI is a device similar to other devices, created to make life easier and improve the quality of life. Although artificial intelligence is a form of intelligent automation, sometimes the automation process needs to be placed behind the analysis [12].

Manual or semi-automated analysis processes can help systems understand context and nuances that may not be fully captured by existing AI models [12]. For example, in a movie recommendation system, even if AI is able to recognize patterns in user preferences, factors such as cultural trends, social issues, or other external influences may require human input or additional analysis to improve the accuracy of recommendations. In addition, the combination of AI-based analysis and manual methods can provide a more balanced solution, allowing the system to not only work automatically but also be more responsive to changes in user preferences and specific contexts. This is especially important in hybrid recommendation systems that combine the advantages of content-based and collaborative filtering methods to produce more accurate recommendations [17].

2.2 Machine Learning (ML)

Machine Learning (ML) is a subfield of AI that enables systems to learn from data and improve their performance without explicit programming. In the context of recommendation systems, ML is used to learn user interaction patterns and develop accurate predictive models. Machine Learning (ML) enables recommendation systems to capture hidden patterns from user interaction data, such as search history, click behavior, and personal preferences. The model then leverages these patterns to provide relevant recommendations, either in real-time or based on historical analysis [13] [14] [15]. Benefits of ML in Recommendation System:

1. Personalization: Providing a unique experience for each user
2. Data Efficiency: Maximizing the use of historical data for better predictions [1].
3. Increased User Satisfaction: Accurate recommendations increase user loyalty to the platform
4. Increased Revenue: In e-commerce, relevant recommendations encourage impulse purchases and increase sales.

2.3 Relationship Between AI And ML

AI and ML have a close relationship, with ML serving as a key component that enhances AI capabilities. In recommendation systems, AI orchestrates various analytical processes, while ML processes big data and predicts user preferences based on historical patterns. “The integration of AI and ML in recommendation systems enables a deeper analysis of user behaviour, resulting in more personalized and efficient recommendations" [1].

2.4 Impact of AI and ML Integration in Recommendation Systems

1. Increased User Loyalty: Relevant recommendations make users feel valued and understood, which can increase platform retention.
2. Operational Efficiency: Automating analysis and decision-making allow systems to work faster and more accurately.
3. Revenue Growth: In e-commerce, effective personalization drives impulse purchases and increases shopping cart value [1].

2.5 Latest Trends in AI and ML Integration in Recommendation Systems

1. Leveraging Large Language Models (LLMs)
   LLMs, such as GPT-4, are used to enhance the ability of recommender systems to understand user context and preferences in greater depth. Toolkits such as RecAI have been developed to facilitate the integration of LLMs into recommender systems, making them more versatile and user-centric.
2. Recommender AI Agent Development
   AI agents that integrate LLMs with traditional recommendation models enable more interactive and personalized interactions with users. Frameworks like InteRecAgent use LLMs as the brain and recommendation models as the tools to create more responsive and intuitive systems.
3. Multi-Modal Data Integration
   Recommender systems are beginning to leverage different types of data, such as text, images, and audio, to provide more accurate and contextual recommendations. This approach allows for a more comprehensive understanding of user preferences.

3. METHODOLOGY

This study uses an experimental method to evaluate the effectiveness of the integration of Artificial Intelligence (AI) and Machine Learning (ML) in improving the performance of a collaborative filtering-based recommendation system. Experimental methodology is a very common approach used in scientific research, including in the field of computer science [16]. In the context of this research, experiments allow the authors to systematically test various hypotheses and compare the performance of different algorithms [17]. The research was conducted through several stages including dataset selection, data pre-processing, algorithm implementation, and performance evaluation.

The first stage is dataset selection. The dataset used is MovieLens 100k, which contains 100,000 movie rating data from more than 900 users for 1,682 movies. This dataset was chosen because of its structured nature, high quality, and is often used as a benchmark in recommender system research [18]. In the second stage, data pre-processing is carried out to ensure that the data is ready to be used in experiments. This process includes data cleaning, data transformation into a user-item matrix, and dividing the dataset into training data (80%) and test data (20%). This step is important to overcome the sparsity problem and ensure that the algorithm can work optimally [19]. The third stage is the implementation of the collaborative filtering algorithm. This study uses two main approaches: User-Based Collaborative Filtering (UBCF) and Item-Based Collaborative Filtering (IBCF). In addition, ML-based algorithms, such as Singular Value Decomposition (SVD), are integrated to improve prediction accuracy. This process includes algorithm programming, parameter optimization, and the application of cross-validation techniques to reduce the risk of overfitting. The fourth stage is the evaluation of model performance. The evaluation method is carried out using the Root Mean Square Error (RMSE) metric, which is a measure of prediction error in a recommendation system. The resulting models are compared based on the RMSE value to determine the best algorithm [20]. This study is quantitative in nature with the aim of testing the hypothesis that the integration of AI and ML can improve the performance of collaborative filtering-based recommendation systems.

4. RESULTS AND DISCUSSION

This study aims to explore the integration of Artificial Intelligence (AI) and Machine Learning (ML) in the Collaborative Filtering (CF) method to improve the movie recommendation system. The results of this study show the RMSE Value for users 1 to 5 based on the comparison between actual and predicted ratings:

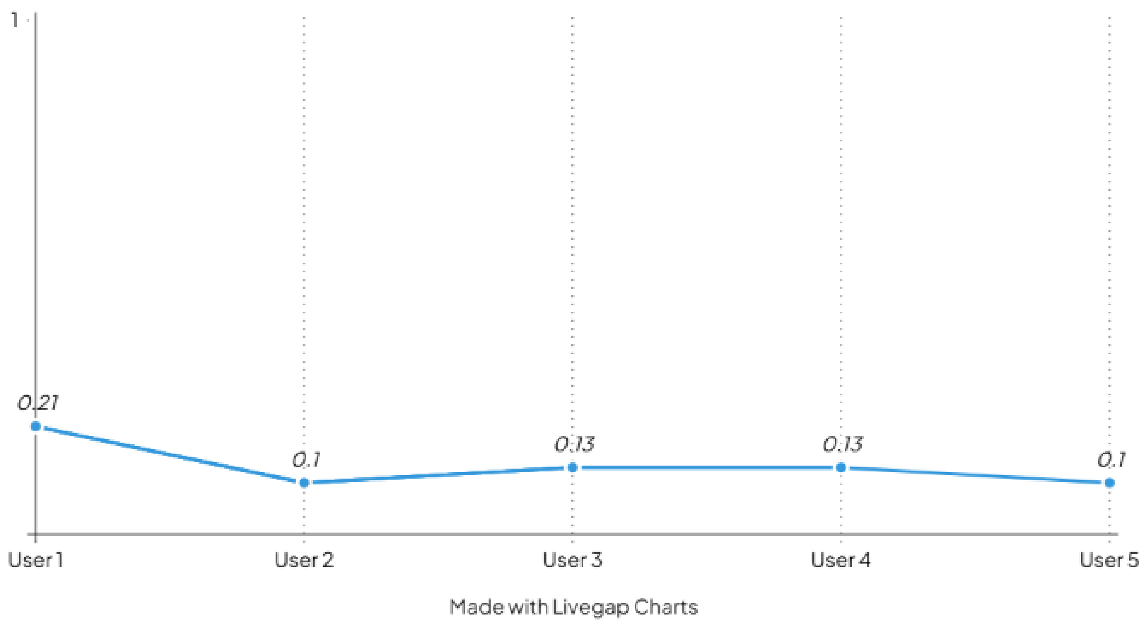

Figure 1. RMSE comparison diagram

A lower RMSE (Root Mean Squared Error) value indicates that the model can predict the ranking more accurately. RMSE measures the average of the squared errors between the actual values and the predicted values, meaning that the lower the RMSE value, the smaller the difference between the prediction and the actual values. Therefore, as the RMSE value approaches zero, the model's predictions are closer to reality.

In the context of the results obtained, users 2 and 5 have the lowest RMSE values, which are 0.10. This shows that for these two users, the difference between the actual rating and the rating predicted by the model is very small. The model successfully captures the user's preferences and behavior patterns, providing fairly accurate recommendations. The accuracy of the model in predicting this rating allows the recommendation system to provide recommendations that are more relevant and in accordance with the user's wishes. On the other hand, User 1 had a slightly higher RMSE value of 0.21. Although this RMSE value was still relatively low, the difference between the actual and predicted ratings indicated that the model might have had difficulty fully capturing this user's preferences or rating patterns. This could have been due to several factors, such as a lack of representative data on User 1's preferences or the model's inability to handle irregularities in the rating patterns provided by Users 1–5. Some factors that can affect the RMSE (Root Mean Squared Error) value are as follows:

1. Data Quality: Complete and accurate data results in more precise predictions, while data with missing values or bias increases RMSE.
2. Data Size: Models with more data can better capture patterns, while small or unrepresentative datasets can increase RMSE.
3. Algorithm Used: More complex and optimized algorithms, such as SVD, tend to produce lower RMSE.
4. Model Limitations: Issues such as cold start and sparsity can lead to higher RMSE if not handled properly.

5. Overfitting or Underfitting: Overfitting results in poor predictions for new data despite low RMSE on the training data, while underfitting causes the model to not capture patterns well, increasing RMSE.
6. User Rating Patterns: Users with more consistent and predictable preferences produce lower RMSE than users with more diverse preferences.

5. CONCLUSION

Collaborative filtering is an effective approach in movie recommendation systems, especially with the support of AI and ML. The results of this study indicate that collaborative filtering makes a significant contribution in improving the relevance and efficiency of recommendations. By utilizing other users' rating patterns, the system is able to generate more personalized recommendations that are in line with individual preferences, thereby increasing user engagement and decision-making efficiency. However, challenges include the cold-start problem for new users and data sparsity, which can affect prediction accuracy. To overcome these weaknesses, some suggestions that can be applied are:

1. Combining collaborative filtering with content-based filtering to harness the strengths of both methods, thereby addressing the issues related to cold-start and sparsity.
2. Leveraging external data, such as reviews or information from social media platforms, to enrich existing data and improve recommendation accuracy.
3. Adopting deep learning techniques such as autoencoders to handle big data more efficiently and generate more accurate recommendations.
4. Applying data encryption methods to protect users' personal information, which can strengthen the security and trust of users in the recommendation system.

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