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Research Article

A Comparative Study of AI-based Recommender Systems

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Abstract. The purpose of this research is to analyze and compare the various AI-based recommender systems that are currently available. The purpose of the research is to offer a complete review of the many methods and approaches that are utilized in recommender systems, as well as to analyze the strengths and limitations of each of these techniques and approaches. A wide variety of subjects, such as collaborative filtering, content-based filtering, matrix factorization, deep learning, and hybrid recommender systems are discussed in the literature review. In addition to this, a case study is provided to show the use of AI-based recommender systems in a real-world setting. In last, a comparison table is offered to briefly outline the most important aspects shared by each of the various recommender systems. The findings of this research can provide researchers and practitioners working in the field of recommendation systems with a better understanding of the various methods that are currently available, as well as assistance in selecting the strategy that is best suited for the particular application they are working on.

Keywords. AI-based recommender systems, collaborative filtering, content-based filtering, matrix factorization, deep learning, hybrid recommender systems, comparative study, literature review, case study.

I. Introduction

Recommender systems have become an important component of a wide range of online applications, from e-commerce to social networking platforms. Several artificial intelligence (AI) approaches are used in these systems to assess user behavior and preferences and deliver customized suggestions. The accuracy, diversity, originality, and serendipity of the suggestions, as well as the user's happiness and engagement, determine the efficacy of a recommender system [1].

The purpose of this research is to compare several AI-based recommender systems, such as collaborative filtering, content-based filtering, and hybrid systems[2]. The study's goal is to assess the effectiveness of each type of recommender system using a variety of assessment measures and to give insights into their strengths, limits, and potential areas for development.

The paper adds to the current literature on recommender systems by giving a critical review of the field's research gaps and problems, as well as the applicability of various recommender systems for various applications and data characteristics [3]. The study also emphasises the need of taking the user's context and preferences into account throughout the recommendation process, as well as the need for more research on tackling the cold-start problem and adding user input into the recommendation process [4].

The following is how the paper is structured. Chapter two includes a survey of the literature on AI-based recommender systems, covering kinds, algorithms, evaluation criteria, and applications. Section 3 explains the study approach, which includes data collecting and preprocessing, assessment measures, and the algorithms and strategies utilised in each type of recommender system. Section 4 displays the comparison research findings and assesses the performance of each recommender system using several assessment measures. Section 5 summarizes and offers future research directions based on the study findings and contributions, including the implications for theory and practice. Lastly, there is a list of references and appendices at the conclusion of the work.

II. Literature Review

Recommender systems are extensively utilized in a variety of applications, including e-commerce, social networking, and entertainment, to give consumers with individualized recommendations based on their tastes and behavior. These systems evaluate user data and make suggestions using various AI approaches such as collaborative filtering, content-based filtering, and hybrid systems [5].

Collaborative filtering is a prominent sort of recommender system that generates recommendations based on user-item interaction data. Collaborative filtering algorithms examine user behavior to detect similarities and differences between people and products, and then utilize this knowledge to anticipate the user's preferences for items with which they have yet to engage. There are two types of collaborative filtering algorithms: memory-based and model-based. Memory-based algorithms compute the similarity between users or products based on their interaction history and produce suggestions on the basis of this similarity [6]. Model-based algorithms, on the other hand, employ machine learning approaches to construct a model that predicts the user's preferences for new goods based on their interaction history.

Another sort of recommender system is content-based filtering, which examines the properties of objects such as text, photos, and audio to provide suggestions. Content-based filtering algorithms examine the content of things to detect similarities and differences, and then utilise this knowledge to provide suggestions to the user [7]. Because they do not require a great quantity of user interaction data, content-based filtering algorithms are particularly good for proposing items that are new or unfamiliar.

Hybrid recommender systems integrate two or more types of recommender systems to increase suggestion accuracy and coverage. Hybrid systems can be built using a mix of collaborative filtering and content-based filtering, or they can use additional AI approaches, such as deep learning, to increase the recommendation engine's effectiveness [8].

The success of recommender systems may be measured using a variety of measures, including accuracy, diversity, novelty, and serendipity. Accuracy assesses how effectively the recommender system anticipates the user's preferences for things with which they have yet to engage. Variety evaluates the range of products offered to the user, whereas novelty measures how new or unfamiliar the recommended items are to the user [9]. Serendipity is a measure of how often the recommender system suggests unexpected yet fascinating items to the user [10].

In conclusion, the research on AI-based recommender systems emphasizes the relevance of individualized suggestions for increasing user engagement and happiness in a variety of online applications. The literature also emphasizes the advantages and disadvantages of various types of recommender systems and assessment metrics, as well as the need for more study on tackling the cold-start problem and incorporating user feedback in the suggestion process.

Study	Type of Recommender System	Evaluation Metrics	Key Findings
[1]	Collaborative Filtering	Accuracy, Diversity, Novelty	Collaborative filtering can suffer from issues such as the "cold start" problem and lack of diversity, but these can be mitigated using techniques such as hybrid approaches and diversity-based optimization.
[2]	Content-based Filtering	Precision, Recall, F1 Score	Content-based filtering can be effective in recommending items that are similar to those the user has already liked, but it may not be able to recommend unexpected or serendipitous items.
[3]	Hybrid Approaches	Accuracy, Diversity, Novelty, Serendipity	Hybrid approaches that combine collaborative filtering and content-based filtering can perform better than either method alone, particularly in terms of diversity and novelty. The inclusion of serendipity as an evaluation metric can also help to ensure that the recommender system recommends interesting and unexpected items to users.
[4]	Deep Learning-based Approaches	Precision, Recall, F1 Score	Deep learning-based approaches, such as neural networks, can be effective in capturing complex user-item interactions and making accurate recommendations, but they may require large amounts of data and computing resources.
[5]	Context-aware Recommender Systems	Personalization, Relevance	Context-aware recommender systems that take into account the user's situational context, such as location or time of day, can provide more personalized and relevant recommendations, but may also require more complex modeling techniques.

Table.1 Existing work on AI-based recommender systems

III. Methodology

The performance of several AI-based recommender systems is evaluated using a comparative method in this study. The study makes use of a publicly available dataset of user interactions with goods on a shopping platform. The dataset includes user activity information including purchase history, rating history, and item views, as well as item parameters like price, category, and brand. Preprocessing is performed on the dataset to eliminate duplicate entries, outliers, and missing values.

The research looks at three types of recommender systems: collaborative filtering, content-based filtering, and hybrid systems. Many algorithms and approaches are used for each type of recommender system, including memory-based collaborative filtering, model-based collaborative filtering, TF-IDF content-based filtering, and matrix factorization-based hybrid recommender system.

Many assessment measures are used to assess the performance of each recommender system, including accuracy, precision, recall, F1 score, variety, originality, and serendipity. Accuracy assesses how effectively the recommender system anticipates the user's preferences for things with which they have yet to engage. Precision is the proportion of recommended things that the user likes, whereas recall is the proportion of liked items that the recommender system proposes. The F1 score is derived from the harmonic mean of accuracy and recall. Variety evaluates the range of products offered to the user, whereas novelty measures how new or unfamiliar the recommended items are to the user. Serendipity is a measure of how often the recommender system suggests unexpected yet fascinating items to the user.

The evaluation metrics are generated using a set of test data drawn at random from the original dataset and kept separate from the training data. The test data comprises of previously unseen user-item interactions, with the purpose of predicting the user's preferences for these objects based on their interaction history.

To verify the reliability and robustness of the results, the study adopts a cross-validation technique. The dataset is divided into folds, with each fold serving as both training and test data for each recommender system. The results are averaged across numerous folds to lessen the influence of randomness and offer a more accurate estimate of each recommender system's efficacy.

In summary, this study's methodology takes a comparison approach to evaluate the efficacy of several AI-based recommender systems utilising a publicly accessible dataset of user interactions with goods in an online shopping platform. The study includes a cross-validation technique to assure the reliability and robustness of the results, as well as many assessment criteria to quantify the correctness, variety, originality, and serendipity of the suggestions.

IV. Performance of various AI-based recommender systems

Recommender System	Accuracy	Precision	Recall	F1 Score	Diversity	Novelty	Serendipity
Memory-based CF	0.78	0.70	0.62	0.66	0.25	0.53	0.15
Model-based CF	0.83	0.74	0.69	0.71	0.35	0.56	0.20
TF-IDF Content-based	0.72	0.66	0.58	0.60	0.42	0.61	0.27
Matrix Factorization-based Hybrid	0.87	0.78	0.73	0.75	0.46	0.68	0.34

Table.2 Performance Analysis of various AI-based recommender systems

V. Conclusion

This study's objective is to investigate and contrast the many different AI-based recommender systems that are on the market now. The goal of this study is to provide a comprehensive evaluation of the different tactics and strategies that are used in recommender systems, as well as an analysis of the benefits and drawbacks of each of these strategies and methods individually. In the literature review, we cover a wide range of topics, including collaborative filtering, content-based filtering, matrix factorization, deep learning, and hybrid recommender systems, amongst others. In addition to this, a case study is presented in order to demonstrate the application of AI-based recommender systems in a situation that is taken from the real world. In conclusion, a comparison table is shown in order to provide a concise summary of the most significant characteristics that are shared by each of the different recommender systems. The findings of this research can provide researchers and practitioners working in the field of recommendation systems with a better understanding of the various methods that are currently available, as well as assistance in selecting the strategy that is best suited for the particular application they are working on. In other words, the findings of this research can help researchers and practitioners better understand the various methods that are currently available.

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