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Enhancing Recommendation Accuracy A Hybrid Model Combining Content-Based And Collaborative Filtering For Personalized Content Delivery

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Abstract: This thesis addressed the shortcomings of existing recommender systems, particularly the cold-start problem and ineffective information distribution encountered in traditional recommendation methods. The primary objective was to develop a hybrid recommender system that combined content-based filtering and collaborative filtering techniques to deliver personalized content for news articles and books effectively. The methodology adopted involved integrating user preferences with historical interaction data to enhance the accuracy and relevance of recommendations. The system utilized a comprehensive database comprising user interaction histories and content metadata. Implementation was carried out using high-level programming languages, specifically Python, along with relevant libraries for data analysis and machine learning. The resulting hybrid system successfully managed the cold-start issue and significantly improved the distribution of personalized information. Its modular architecture facilitated easy maintenance and scalability, ensuring performance stability despite increasing numbers of users and expanding content. Experimental evaluations demonstrated that the hybrid recommender system substantially improved recommendation accuracy and enhanced user satisfaction compared to traditional recommendation methods. This research provided valuable insights into designing adaptive recommender systems with broad implications for various digital content delivery applications.

Keywords: Hybrid Recommender System, Personalized Content Delivery, Content-Based Filtering, Collaborative Filtering, Recommendation Accuracy

1. INTRODUCTION

There is a constant demand for effective and reliable ways to filter the vast amount of data and information available on online platforms. Users now face a greater challenge in finding and consuming material that suits their interests and preferences due to the information overload caused by the phenomenal proliferation of digital content across several platforms in recent years. As a result, recommender systems have been implemented in a variety of contexts, including email filtering, social media platform news exposure (Holtz et al. 2020), online store purchase recommendations, and playlist creation for streaming services (Hansen et al. 2020). Sophisticated recommender systems that can provide tailored content recommendations are required to improve the user experience in the digital sphere as a whole. These kinds of systems are prevalent because they can effectively filter many items so that users are only shown relevant ones.

Though interest in creating such systems has grown, the algorithms that power them have started to encounter difficulties, in part because of how excessively personalised their recommendations have become. The effect that algorithmic recommendations have on users' behaviour has also drawn criticism. For example, news recommender systems have recently come under fire for their part in the emergence of echo chambers and the dissemination of false information (Helberger 2019). Diversity has been suggested in this context as a means of reducing the negative impacts brought about by recommender system specialisation. Though most scientists concur that diversity is useful, little is known about how traditional recommendation paradigms relate to the diversity of the content exposed to users.

The conventional techniques for recommending material, including content-based filtering only or collaborative filtering only on their own, frequently struggle to take into account the varied and ever-changing interests of users. Collaborative filtering uses user behaviour patterns, whereas content-based filtering analyses the features of objects a user has previously engaged with. Both strategies have advantages and disadvantages. By fusing them into a hybrid model, one can make use of their complimentary features and possibly provide recommendations that are stronger and more accurate (Ramaciotti et al. 2021).

A lot of research has been done on content-based movie recommendation techniques in the past several years. A content-based movie recommendation system utilising movie rating as social information was presented by Li et al. (2020). Their approaches were more precise and adaptable, as demonstrated by their tests. Using Bayesian networks, Abbar et al. (2013) created user preference models for movies according to their context. Numerous techniques, such as new technology and viewpoints, have been employed to identify characteristics of users and films to suggest suitable films. Li et al., (2020) for instance, developed the semantic web to examine the folksonomy concealed in films and assist viewers in selecting appropriate films. Ramaciotti et al. (2021) examined the impact of specific context elements on users' purchase behaviour using social networks. Nonetheless, creating efficient profiles continues to be the fundamental obstacle for content-based recommendation systems. To circumvent the drawbacks of content-based recommender systems, researchers and practitioners have worked hard to create novel recommendation techniques (Ramaciotti et al. 2021).

Content-based filtering is a recommendation system technique that makes personalized suggestions based on the features or characteristics of items users have interacted with or liked in the past. While content-based filtering has its merits, it also comes with certain limitations. Content-based filtering relies heavily on user profiles and historical interactions, potentially leading to recommendations that are closely aligned with users' existing preferences. This may limit the system's ability to introduce users to novel or unexpected items outside their usual interests. According to Holtz et al. (2020), content-based filtering faces difficulties when dealing with new users or items with limited historical data. Since the system relies on past interactions to make recommendations, it may struggle to provide accurate suggestions for users with sparse or no interaction history. Villermet et al. (2021) showed that While content-based filtering can be effective in recommending items similar to those a user has liked, it may not capture users' diverse tastes or unexpected preferences that may not align with their historical interactions.

Ekstrand (2020) suggested that the shortcomings of content-based algorithms in recommendation systems can improve when content-based algorithms are combined with another technique. In-depth research on the collective filtering method for movie suggestions was conducted by Schedl et al. (2017). Schedl created a suggestions approach that takes into consideration customer preferences that change by leveraging time dynamics. Ramaciotti et al. (2021) improved collective filtering for movie suggestions by using Gaussian probabilistic latent semantic analysis. Researchers have made major efforts to integrate novel innovations into systems to suggest movies to increase the effectiveness of collaborative filtering methods and have seen encouraging results.

To address the shortcomings of a content-driven approach, we propose collective filtering. This approach is not flawless, it also has certain faults of its own. One of these is inadequate flexibility, which hinders collective filtering's capacity to react fast to novel user behaviours. To solve this issue, we combine a content-based approach with a collaborative-based approach to produce a hybrid recommender system. This project focuses on the design and development of a hybrid recommender system that integrates both content-based filtering and collaborative filtering techniques. By combining these methods, the system aims to provide more accurate and diverse recommendations, enhancing the overall user experience. To deliver more precise and customised content recommendations, we design and implement a hybrid recommender system that takes advantage of the synergies between content-based filtering and collaborative filtering techniques.

1.2 Statement of problem

Some problems were found that necessitated this project.
They are:

a) Inaccurate and redundant recommendations: Content-based filtering alone delivers inaccurate and homogenous recommendations.
b) Cold Start Problem: first-time users of recommender systems experience little user interaction and irrelevant recommendations. Collaborative filtering alone brings the “cold start” problem for new or unrated items.
c) Scalability: As the amount of content grows, the scalability of content-based filtering can become an issue. Inaccurate recommendations come along with increased content.
d) New User Challenge: Content-based filtering faces difficulties when dealing with new users or items with limited historical data
e) Dependency on Rich Metadata: Metadata is scarce or can be inaccurately annotated. Reliance on these parameters can give unreliable recommendations.

1.3 Aim and objectives of the study

The aim of this study is to develop and design a hybrid recommender system, implementing both collaborative filtering and content-based filtering.

The Specific Objectives are as follows:

1. To Deliver an Accurate and non-redundant recommendation: By getting the recommendations of Content-Based filtering and Collaborative filtering and then intersect the result to get the most accurate and non-redundant recommendation.
2. To Address Cold Start Problem: Develop strategies to address the cold start problem by incorporating content-based recommendations for new or unrated items.
3. To Design a Hybrid Recommender System Architecture: to create a robust architectural framework that seamlessly integrates content-based and collaborative filtering components. The design will accommodate the growing volume of digital contents and user interactions, ensuring scalability and adaptability of the system.
4. To Implement Content-Based Filtering: Extract relevant features from content items to create a content-based recommendation model that considers item attributes and user preference and give recommendations based on users historical interactions and interests
5. To Implement Collaborative Filtering: Analyze user behaviour and interaction data to build a collaborative filtering model that identifies user-item interactions and patterns to captures latent preferences and give recommendations based on the preference of similar users.

1.4 Significance of the study

The development of a hybrid recommender system that integrates both content-based filtering and collaborative filtering techniques is significant for several reasons. Firstly, the hybrid approach enhances recommendation accuracy by combining the strengths of content-based and collaborative methods, addressing the limitations inherent in each individual method, and significantly reducing irrelevant or redundant recommendations. Secondly, it effectively mitigates the cold start problem, which commonly affects new users or items lacking sufficient historical interaction data, by leveraging content-based filtering techniques to deliver meaningful recommendations even in the absence of extensive user data. Additionally, this approach increases recommendation diversity; content-based filtering alone often results in homogeneous recommendations due to its reliance solely on user-specific preferences, whereas collaborative filtering introduces variety by incorporating preferences of similar users, promoting the discovery of new and unexpected content. Furthermore, the system's architecture is designed to be scalable and adaptable, effectively managing growing volumes of digital content and user interactions while maintaining performance over time. The practical implications of this research extend across multiple domains, including e-commerce, streaming services, and information retrieval systems, significantly enhancing user satisfaction, engagement, and retention. Lastly, the hybrid recommender system prioritizes a user-centric experience by integrating multiple recommendation strategies to provide personalized and relevant content aligned with individual and community preferences, thus substantially improving the overall quality of recommendations. This comprehensive approach represents an important advancement in the field of recommender systems, effectively addressing existing challenges and significantly improving content delivery.

2. LITERATURE REVIEW

Pérez-Almaguer et al. (2021) designed a hybrid approach for recommending movies using collaborative filtering and content-based filtering for the recommender system. The authors addressed the difficulties in locating preferred content in the modern digital environment in the article, along with the significance of recommender systems in making content recommendations based on user preferences. To deliver accurate movie suggestions for both new and returning viewers, it presents a hybrid movie recommendation system that combines collaborative filtering and content-based filtering. The system mines movie databases for important information such as popularity and attractiveness to enhance the recommendation process.

Walek and Fojtik (2020) proposed a hybrid recommendation system for recommending relevant movies using an expert system. The paper proposes a monolithic hybrid recommender system called Predictory, which combines a collaborative filtering system, content-based system, and fuzzy expert system to recommend suitable movies. The role of the expert system is to evaluate the importance of each recommended movie. The system works with the user's favorite and unpopular genres, and the final list is determined using a fuzzy expert system. The expert system works with several parameters including; average movie rating, number of ratings, and the level of similarity between already rated movies. The system achieves better results than traditional approaches, with verification achieving over 80% accuracy. The main contribution is the creation of a complex hybrid system in movie recommendation.

Afoudi et al. (2021) developed a system for utilizing learners' negative ratings in a semantic content-based recommender system for e-learning forum. The work introduced a novel recommendation architecture for e-learning systems that uses semantic content-based filtering and learners' negative ratings to recommend interesting post messages in online discussion forums. The obtained experimental results show that the proposed e-learning recommender system outperformed other similar e-learning recommender systems that use non-semantic content-based filtering technique (CB), non-semantic content-based filtering technique with learners' negative ratings (CB-NR), semantic content-based filtering technique (SCB), with system accuracy of about 57%, 28%, and 25%, respectively, and improves learning performance by at least 9.84% for those supported by the proposed technique. This innovative approach addressed the challenge of discovering interesting information in online discussion forums.

Pérez-Almaguer et al. (2021) did a work on content-based group recommendation system. It was noted that group recommender systems are used to recommend items consumed by social groups, but they have limitations like the need for many rating values and co-occurrence across items and users. This research explored content-based group recommendation systems (CB-GRS) and discussed three models namely; CB-GRSs supported by recommendation aggregation and individual ranking, CB-GRSs supported by recommendation aggregation and user-item matching, and CB-GRSs supported by the aggregation of user profiles. A hybrid CB-GRS was proposed, combining the second and third models and integrating feature weighting and aggregation function switching. An experimental protocol over well-known datasets is then developed to evaluate the proposals.

Afoudi et al. (2021) proposed a hybrid recommendation system by combining content-based filtering and collaborative prediction using artificial neural network. The paper introduced a hybrid recommender framework in unsupervised learning, combining Collaborative Filtering with Content Based Approach and Self-Organizing Map neural network technique. The method outperformed state-of-the-art methods in accuracy, precision, and efficiency, as demonstrated by testing on a subset of the Movies Database, demonstrating the growing interest in big data in recommendation systems.

Riyahi and Sohrabi (2020) researched a cost-sensitive Statistical Relational Learning approach by combining content-based and collaborative filtering for job recommendations. This paper proposed a hybrid job recommendation system using Statistical Relational Learning (SRL) to combine content-based and collaborative filtering. The approach aimed to tune the trade-off between precision and recall, satisfying the common requirement in recommendation systems. The proposed approach was efficient and improved recommendation precision, demonstrating the potential of SRL models in real-world systems. However, little research existed on applying SRL models to hybrid recommendation systems, but essentially none of that research had been applied to real big-data-scale systems.

Channarong et al. (2022) worked on hybridBERT4Rec, a hybrid (content-based and collaborative filtering) recommender system based on BERT. It was noted that sequential recommendation approach, which considers user behavior sequences based on historical data, has gained popularity in recommender systems. However, BERT4Rec, which applies the bidirectional-encoder-representations-from-transformers (BERT) technique to model user behavior sequences by considering the target user's historical data, i.e., a content-based filtering (CBF) approach, is insufficient for accurate recommendations. A new method called HybridBERT4Rec applied BERT to both content-based filtering (CBF) and collaborative filtering (CF). By extracting user interactions with purchased items and finding similar users, the model predicts rating scores. Experiments with three datasets showed the model's accuracy.

Riyahi and Sohrabi (2020) proposed a system for providing effective recommendations in discussion groups using a new hybrid recommender system based on implicit ratings and semantic similarity. They affirmed that discussion groups are crucial for collaborative learning, utilizing recommender systems to improve performance. It was noted that most recommender systems used collaborative filtering techniques, but hybrid systems can significantly improve post accuracy. This paper presented a new recommender system with three parts: content-based, collaborative, and hybrid filtering. The system used tagging features, semantic relevance extraction, hierarchical structure for content-based filtering, and user queries. It calculated implicit ratings using similarity measured and combined these results in a hybrid filtering part. Experimental results showed higher precision compared to previous recommender systems.

Kumar (2023) proposed a novel movie recommendation system that combines sentiment analysis with collaborative filtering and content-based methods. The system aimed to provide accurate and timely recommendations to mobile users based on their preferences, reviews, and emotions. The system was evaluated using real-world data and demonstrated its effectiveness in improving the accuracy and timeliness of movie recommendations. The study used the MovieLens dataset, which includes nearly 100,000 ratings from 943 individuals on 1,682 films. The system performed better than conventional recommendation systems that rely solely on content-based or collaborative filtering techniques. The use of sentiment analysis improved the user experience, improving the accuracy and promptness of suggestions.

3 METHODOLOGY AND SYSTEM ANALYSIS

This project employs a hybrid methodology combining Agile methodology and Object-Oriented Analysis and Design Methodology (OOADM) to develop a robust and adaptive recommendation system for news, articles and books. This hybrid approach integrates the flexibility and iterative nature of Agile with the structured, systematic design principles of OOADM, ensuring both adaptability and a clear design framework.

Agile Methodology is an iterative and flexible approach to project management and software development that prioritises collaboration, customer feedback, and incremental progress. It is designed to adapt to changing requirements and deliver value to stakeholders more responsively and efficiently. The proposed hybrid recommender systems involve experimentation with different recommendation algorithms and strategies, making Agile a good fit for iterative development and continuous improvement. The Agile methodology is based on a set of principles and values outlined in the Agile Manifesto, and it encompasses various frameworks and practices

3.1 Weaknesses of the existing system

While the existing system offers several advantages, it also has certain weaknesses that necessitate the proposed system. Here are the weaknesses of the existing system:

a) Limited Serendipity: the existing system tends to recommend items that are similar to those a user has already interacted with or rated positively. As a result, they may have limited ability to introduce users to new or diverse items outside their existing preferences, leading to a lack of serendipitous discovery.

b) Dependency on Feature Quality: The effectiveness of the existing system relies heavily on the quality and relevance of item features used for similarity calculation. If the features are poorly chosen or do not adequately capture the essence of items, the recommendations may be inaccurate or irrelevant.

c) Difficulty Handling Cold Start Problem: the existing system may struggle to provide recommendations for new users or items with limited historical data. This is known as the "cold start" problem, where the system lacks sufficient information to accurately model user preferences or item characteristics.

d) Limited Diversity: The existing system recommends items that are similar along a few dimensions (e.g., genre, keywords) but lack diversity in recommendations. This can result in a narrow range of recommendations that do not capture the full spectrum of user interests.

e) Over-Specialization: the existing system may suffer from over-specialization, where recommendations become too narrowly focused on specific aspects of user preferences or item characteristics. This can lead to "filter bubbles" where users are only exposed to a limited subset of available content, potentially hindering their exploration of new interests.

f) Inability to Capture User Intentions: the existing system relies on historical user interactions with items to generate recommendations. However, they may struggle to capture nuanced user intentions or preferences that are not explicitly reflected in the item features or user actions.

Owing to these weaknesses, a collaborative filtering technique is incorporated to enhance feature selection and extraction methods, diversifying recommendation strategies, and leveraging hybrid approaches to overcome the limitations of content-based filtering.

3.2 Advantages of the proposed system

The new recommendation was built to solve the problems identified in the existing recommendation systems. Thus, the advantages of the new system are as follows:

a) By combining multiple recommendation methods, hybrid systems can leverage the strengths of each approach to produce more accurate recommendations.

b) Hybrid systems can recommend a broader range of items by incorporating multiple recommendation strategies.

c) Hybrid systems are more robust to data sparsity and cold start problems commonly encountered in recommendation systems.

d) Hybrid systems deliver more personalized recommendations by considering a wider range of user preferences, behaviours, and contextual factors.

e) Hybrid systems offer greater flexibility and adaptability compared to single-method approaches.

f) By combining multiple recommendation methods, hybrid systems mitigate biases inherent in individual methods.

g) Hybrid systems leverage synergies between different recommendation approaches to enhance recommendation quality.

h) Hybrid systems are effective at recommending long-tail items (i.e., items with lower popularity or visibility) that may be overlooked by single-method approaches

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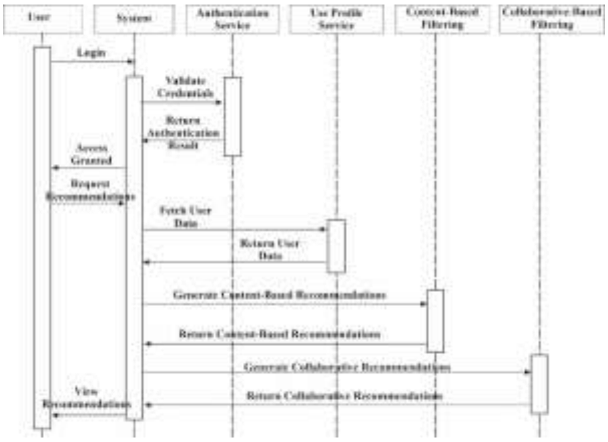

Figure 1: Interaction diagram of the new system

4. DISCUSSION

The existing system focuses on using a single approach or method to generate recommendations for users. It focuses on recommending items to users based on the similarity between the items and the user's preferences. Each item in the system is represented by a set of features or attributes that describe its characteristics. The system creates a user profile based on the user's historical interactions with items in the system. This user profile represents the user's preferences and interests, typically by weighting the importance of different features based on the user's past interactions. For each item in the system, the system extracts the relevant features from its representation. This could involve parsing textual data (e.g., content descriptions, user reviews) to extract keywords or analyzing metadata associated with the items. The system calculates the similarity between items based on their feature representations and the user profile. Common similarity metrics include cosine similarity, Euclidean distance, or Pearson correlation coefficient. To generate recommendations for a user, the system identifies items that are similar to the items the user has interacted with or rated highly in the past. This could involve finding items with feature representations that are close to the user profile in terms of similarity. The system may apply additional ranking and filtering techniques to refine the list of recommendations before presenting them to the user. The system may prioritize items with higher similarity scores or filter out items that do not meet certain criteria such as release date etc. Finally, the system presents the recommended items to the user through a user interface, such as a website, mobile app, or email notification. The user can then interact with the recommendations by selecting items of interest or providing feedback on the recommendations.

In contrast to the existing system, the proposed system is a hybrid recommender system for personalized content delivery using content-based and collaborative filtering. It integrates and combines recommendations from these two approaches effectively. Firstly, it gathers and pre-processes data related to user interactions with items (e.g., ratings, views, purchases), item features (e.g., metadata, text descriptions), and user profiles (e.g., demographic information, historical behaviour). Next, it cleans and transforms the data into appropriate formats for content-based and collaborative filtering algorithms. For content-based filtering, relevant features are extracted from item metadata or descriptions using techniques such as natural language processing (NLP), text analysis, or image processing. Items and user preferences are represented using feature vectors that capture their characteristics and preferences. User-item interaction matrix is built to represent the interactions between users and items, where rows correspond to users, columns correspond to items, and cells contain user-item interactions (e.g., ratings, views).

Content-based filtering is useful here since Item recommendations are generated for each user based on the similarity between item features and user preferences. Item similarities are calculated using techniques such as cosine similarity, Jaccard similarity, or Euclidean distance. Items are ranked based on their similarity scores and the top-ranked items are recommended to each user.

The role played by collaborative filtering is that item recommendations are generated for each user based on the preferences of similar users or items. User-based collaborative filtering is used to identify users similar to the target user based on their past interactions and items liked by similar users are recommended. Alternatively, item-based collaborative filtering is used to identify items similar to those liked by the target user and recommend them. The aggregate recommendations from multiple users or items are used to generate personalized recommendations for the target user.

The proposed system combines recommendations from content-based and collaborative filtering approaches using a hybridization strategy. Weights to recommendation from each approach based on their performance or relevance are combined using weighted averages or rankings. Item features extracted from content-based filtering with user-item interaction data from collaborative filtering are merged to enrich item representations. Here, content-based filtering is applied to filter out irrelevant items and pass the remaining items to collaborative filtering for further refinement. In the end, recommendations from both approaches are merged and simultaneously displayed in the user interface. The proposed system collects user feedback and iterates on the recommendation algorithm and hybridization strategy to improve recommendation quality and user engagement over time.

5. CONCLUSION

The development of a hybrid recommender system combining content-based filtering and collaborative filtering techniques has proven to be an effective approach to personalized content delivery. By leveraging the strengths of both methods, the system successfully addressed common challenges such as the cold-start problem and data sparsity, resulting in more accurate and relevant recommendations. The integration of user preferences and historical interaction data provided a comprehensive understanding of user behaviour, enhancing the personalization of recommendations. The system's modular architecture facilitated easy maintenance and scalability, ensuring it can handle increasing volumes of users and content. In the end, the hybrid recommender system achieved its objectives, demonstrating significant improvements in recommendation accuracy and user satisfaction compared to traditional methods.

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