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Hybrid-Based Movie Recommender System: Techniques, Case Studies, Evaluation Metrics, and Future Trends

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Abstract - The necessity for sophisticated recommender systems in the movie recommendation sphere has become particularly pronounced, generating a more personalized movie recommendation due to people nowadays who like to watch movies online. Efficient recommender systems make use of advanced machine learning (ML) techniques in the pursuit of accurate and meaningful recommendations. This paper endeavours to give a comprehensive overview of technologies known as recommender systems, concentrating on ML methods found at the base. Different strategies have been applied in this work, which include collaborative filtering (CF), content-based filtering (CB), hybrid approaches, Generative AI and so on. The merits and demerits of each technique are listed and explained briefly. In addition, the actual application's results are also presented in this paper. To evaluate the performance of the techniques, some of the important datasets that are used in evaluating recommender systems are also discussed along with measurement metrics to determine the effectiveness of technique. Example metrics used are Root Mean Square Error (RMSE), Mean Absolute Error (MAE) and so on. This paper synthesizes existing research to evaluate the advantages and limitations of diverse recommendation techniques, which aims to give suggestion on how to improve the design of movie recommendation systems so that the performance of the technique can be improved.

Keywords—Content-based Filtering, Collaborative Filtering, Hybrid-based, Machine Learning, Recommender System, Evaluation Metrics, Movie Recommender.

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1. INTRODUCTION

The rapid evolution of technology has revolutionized the way people consume entertainment. Online movie streaming services have emerged as a dominant force in the entertainment industry, reshaping audience preferences and consumption patterns. Users will now be able to watch movies online instead of going to cinema which can help users save money when compared to services that require user to pay per movie watched. However, there are limitations on those online platforms which are unable to perform accurate recommendations. Therefore, a movie recommender system is developed to help perform recommendations on movies which best matches user preferences. A

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recommender system is a system that makes suggestions that is related to users based on their previous interaction such as liked, commented, watched and so on. This enables it to generate a more personalized recommendation based on their responses which enhances the user's experience. Numerous recommender systems exist online, and many utilize ML techniques to enhance performance and accuracy.

A clear example of systems that have integrated recommender system in platforms which are Netflix, Disney+, YouTube and so on. Those platforms have provided users with an easier way to find the movie that best matches user preferences and watch movies at the same time, but the recommendation might not be accurate. As a result, this review will focus on the hybrid-based application within the movie recommender system domain.

Therefore, this paper explores various recommender system techniques that have been widely used such as CB, CF, hybrid-based filtering techniques and so on that have been widely used. All the techniques will be discussed briefly in this paper to help comprehend their concept and how they work by reviewing the related previous research paper. By doing this, potential improvement can be identified.

Several research questions and objectives have been established as reference in this review:

- What are the current available recommender system techniques available on the Internet?
  Section 2 will briefly explain the topic to have a better understanding.

- What are the commonly used recommender system techniques in movie recommender system?
  Section 3 will show some of the techniques that have been used.

- What are the outstanding research gaps and trends that can be found?
  Section 4 will provide a comprehensive analysis of current trends and gaps.

2. BACKGROUND

2.1 Overview of Recommender System

According to [1], a recommender system is a system that will suggest a user product based on the user's app activity. It has been a prevalent system seen in any online platform and apps that have been used in our daily life. Many sectors have adopted recommended systems such as social media, e-commerce, streaming services, travel and hospitality, and so on. This proves that the recommender system is a very powerful tool that has been used to provide personalized experience for each user, which has led to a better experience.

According to [2], the definition of a better experience is that it can recommend user content that matches user's lifestyle and interest. With the aid of a recommender system, the user's experience will be significantly enhanced, which results in the importance of implementing the system into daily life. The recommender system works by collecting user's previous activity data and uses the recommender system technique to perform recommendations for the user by analysing the data. Therefore, the recommendation is more personalized compared to the normal recommendations.

Recommender systems can be classified into broad categories of traditional and modern techniques. The traditional techniques that CB and CF are the two most popular approaches that CB to develop movie recommendation systems.

Modern approaches incorporate a wide range of methodologies. For example, hybrid-based, Large Language Models (LLMs), generative-AI based, multimodal technique and so on. However, this paper targets three central techniques: hybrid-based, semantic-based, and generative AI-based recommender systems. Of the mentioned approaches, the most prevalent in this literature is the hybrid-based approach due methodology that combines different techniques to increase recommendation accuracy and system robustness. A significant advantage of hybrid recommender systems is their ability to reduce shortcomings inherent to individual methods. For example, while CB is heavily reliant on item metadata, CF has several problems like the cold-start problem of data sparsity scalability issue and synonymy. By combining these methods, hybrid models can capitalize on their strengths while rectifying weaknesses inherent within them for better effectiveness and reliability in recommendations.

The evaluation of the performance of a recommender system is also necessary to verify that it operates effectively in producing relevant and significance recommendations. Many types of evaluation metrics are used to measure different aspects of recommendation quality. The traditional accuracy-based metrics, which include precision, recall, and F1-

score, assess the correctness of the recommendations whereas error-based metrics include MAE and RMSE, which indicate the deviation of predictions [3]. Besides relevance, rank-based evaluation measures such as Mean Reciprocal Rank (MRR) and Normalized Discounted Cumulative Gain (NDCG) provide an assessment of the relevance of ranked recommendations [4]. Metrics for coverage, diversity, and novelty measure the system's capability in offering a diverse set of recommendations as well as unexpected ones to avoid over-specialization and filter bubbles. Lastly, measures for scalability and latency ensure that the system is also geometrically efficient in computing at large-scale deployments. Such a comprehensive framework of evaluation incorporating these metrics will be useful in the optimization of recommender systems. Appropriate selection of the evaluation criteria will empower researchers and practitioners to achieve higher quality recommendations, better user engagement, and system performance closer to user expectations.

Recommender systems are part of most aspects of daily activity and continue to influence the ways people interact with various technologies. The increasing reliance on automated technological solutions has in turn created a demand for increasingly sophisticated recommendation models that will improve the user experience. Movie recommendation systems, as one of the major applications, play an important role in personalizing content delivery through recommendations for films that suit individual preferences. A movie recommendation system is created to give movie suggestions that are personalized to the viewer based on various components that may include genre preferences, viewing history and behaviour of the user. The study of movie recommendation systems remains an active and rapidly evolving field, driven by continuous advancements in ML and Artificial Intelligence (AI). As digital entertainment platforms expand and user preferences become more dynamic, researchers have focused on enhancing recommendation accuracy, scalability, and user personalization. Over the past five years, numerous studies have introduced novel hybrid models, integrating various filtering techniques and deep learning approaches to address existing limitations and improve recommendation performance.

For instance, in 2020, [5] proposed a dynamic weighted hybrid recommender system to optimize the balance between content-based and CF methods. In 2021, [6] introduced a graph-based hybrid model that leveraged co-rated movie relationships, genre similarities, and closed caption features to improve recommendation quality. This was followed by a 2022 study [7] that enhanced hybrid recommendation strategies by integrating graph-based techniques with CF to better capture complex user-item interactions. Recent developments in the field have explored multimodal data sources and advanced user profiling techniques. In 2023, [8] proposed a demographic and facial expression-based hybrid recommender system, incorporating emotional analysis to personalize recommendations. In 2024, [9] advanced this further by integrating sentiment analysis of movie reviews into hybrid filtering techniques, demonstrating the growing importance of Natural Language Processing (NLP) in recommender systems. Looking ahead, the 2025 study by [10] introduced user partitioning and log-likelihood content comparison, highlighting the shift toward more adaptive and probabilistic recommendation models. These recent studies underscore the ongoing relevance of movie recommendation systems in both academia and industry. With the increasing volume of multimedia content and the demand for highly personalized user experiences, research in this domain remains crucial. Future directions are expected to focus on deep learning-based hybrid models, reinforcement learning for adaptive recommendations, and explainable AI (XAI) to enhance user trust and transparency in recommender systems. This paper focuses on reviewing various movie recommendation techniques, with an emphasis on hybrid-based ML approaches. It explores their effectiveness, advantages, and limitations, while evaluating their performance based on metrics such as MAE, RMSE and so on.

2.2 Overview of Recommender system

2.2.1 Traditional Recommender System

The CB approach [11] is a recommending technique that allows users to specify the items they want to be recommended by entering the name or description of the item. For this purpose, it employs Vector Space Models, particularly Probabilistic and Term Frequency Inverse Document Frequency (TF-IDF) [12], thus linking documents to corpus and offering recommendations based on statistical analysis or ML methods. This gives the possibility of recommending even new items without user ratings, maintains accuracy, and is highly responsive to changes in user preferences. The drawback is that its efficiency depends on the metadata about the item being recommended.

CF is a technique used to create a user-item matrix that contains information about the preferences and interests of users [12]. This is done by determining similarities between profiles and making recommendations based on that.

Users with similar preferences are clustered into neighbourhoods, and recommendations are generated by suggesting items highly rated by their neighbours within the same group. The first type of technique is memory-based methods [13], which combine the preferences of a user and his neighbours to derive recommendations, and the second type is item-based methods [14] that compute similarities between products. Techniques for improvement in efficiency include model-based approaches [15] that are designed using techniques of ML or data mining to create a predictive model based on historical ratings. The models created are therefore like those derived from neighbourhood-based approaches and may yield surprising recommendations still relevant to user preferences. However, CF has limitations such as cold-start problems, data sparsity problems, scalability, and synonymy.

2.2.2 Modern Recommender Systems

A. Hybrid-based

This work introduces a hybrid recommender model designed to resolve the weaknesses and boost the performance of individual recommender models, the CF and the CB models [16]. This technique can be categorized into seven types as depicted in Figure 1 while Table 1 describes the hybrid-based model and its main usage.

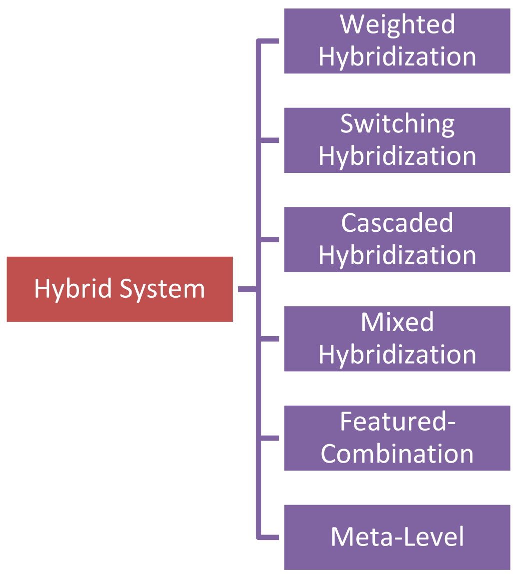

Figure 1: Type of Hybrid-based Techniques

B. Semantic-based Filtering Techniques

According to [17], this technique is a method for defining machine comprehensible resources. This keyword-based technique processes natural language in a human-like manner. It has been employed to identify similarities in learner concept maps, recommend resources based on tags and popularity, and match training materials to user preferences by analysing their attributes. In this paper [18], they have implemented semantic based filtering techniques into their e-learning system.

C. Generative AI Techniques

According to [19], these models can generate new content, producing high-quality novel data that can enhance recommender systems by expanding their learning base. Specifically, Generative Adversarial Networks (GANs) and Variational Autoencoders (VAEs) are known for their content generation abilities, and along with Transformer-based and Autoregressive models, are utilized within recommender systems.

Table 1: List of Hybrid-Based Techniques and Explanation of the Techniques

Hybrid Method	Description
Weighted Hybridization	The system iteratively refines weights based on user feedback regarding the accuracy of its predictions.
Switching Hybridization	Changes how a recommendation model is being used based on the situation.
Cascade Hybridization	Combine the data processed by the previous model with another model to generate a product that will most suit the user's preferences.
Mixed Hybridization	The system recommends products to users based on their complete historical data.
Feature-Combination	Combination of both features of the CF model and CB; the CF acts as featured data while CB acts as augmented data.
Feature-Augmentation	The model classifies an item's preference score, and this output is then integrated as input for the subsequent model.
Meta-level	Using one entire model as input data for another system. By compressing and representing data using Meta-Level, collaborative mechanisms become easier to implement compared to using raw data.

The research paper of [20] mentioned that the traditional recommender system is lack diversity, which cannot provide users with a more precise recommendation and has a cold-start issue. The research paper states that integrating Generative AI into the recommender system will increase the user experience.

This paper introduces the Boltzmann Machine (BM) [21], a stochastic RNN with an energy-based structure. The BM consists of two primary layers: a visible layer for input data and a hidden layer that functions as a feature detector. However, the dense interconnectivity of neurons in the visible layer poses challenges when processing large datasets. Conversely, the BM offers the advantage of efficiently reducing training time.

The second technique in the research paper is well known, has been widely used, and is variant of BM. This technique is the Restricted Boltzmann Machine (RBM) [22]. It has the same amount of layer as BM, but there is no connection between the layers. This technique is applied in unsupervised learning [23]task. For example, dimensionality reduction, feature learning, CF, and so on. The research paper stated that the deployment of BM into the field is impossible therefore, this technique has been proposed.

The third technique will be Deep Belief Network (DBN) [24], an advanced deep learning algorithm to overcome problems that deep neural networks have faced through a hierarchical feature learning strategy. It is a powerful model that can learn features by using layer-by-layer learning strategies. Using that technique can improve the model's training efficiency and generalization ability. In addition, combining these networks with multiple Restricted BM (RBM) and implementing greedy methods for learning and approximate inference. By using high dimensional input data will improve the generalization ability if DBN.

The fourth technique will be Deep BM (DBM) [25], an RBM consisting of multiple layers of hidden units. A DBM will connect the first visible layer to multiple hidden layers using a deep architecture network. The DBM is known for its ability to get self-representations that grow more complex from time to time, and the study of this method is believed to be a great way of solving speech or object recognition problems.

Using this approach, the recommender system can provide more personalized preferences, more diversity and closer to user choices.

D. LLMs

According to [26], it says that is a model that is enriched with knowledge which can help perform tons of NLP tasks remarkably excellence. The research on LLMs is continuing until today to increase the performance of the model based on existing knowledge. Even though the model is full of knowledge, the capability of processing and understanding the large amount of information has remained constrained. Nowadays, LLM has been used widely in various programs. For instance, LLMs like GPT-4 [27], PaLM 2[28], LLaMA [29], DeepSeek [30] and so on. From that, we can know that LLMs can perform tasks like NLP, common sense reasoning [31], [32] and mathematical problem solving [33], [34] with remarkable proficiency.

According to [35], it says that LLMs is an AI tool that is created using multi-layers of recurrent neural networks (RNNs) which have been trained by using tons of data to generate output that is like humanity. As compared to traditional language models, it is quite different as traditional models are programmed to predict the upcoming word that can be used into a sentence by using statistical techniques.

E. Multimodal Recommender System

According to [36], it says that they use Cornac [37] which is Python framework that is designed to develop multimodal recommender systems. They mentioned that Cornac contains various recommender modules that work well with different data types. For instance, text, graph, image and so on. It also has a standardized workflow in handling all the modalities. In addition, Cornac is also very convenient when it comes to handling auxiliary data. The expanding application of current models is a key part of this standardization which can lead to application across multi-modality which is called cross-modality.

In text modality, there are many approaches that can be used in text modality. For instance, Term Vector, Matrix Factorization (MF), Topic Model, Auto-Encoder, Convolutional Neural Network (CNN), RNN and so on.

- Term Vector
  This is the simplest way to represent a text. This is a way to encode text where the importance of each word is numerically represented.

- MF
  When compared to Term Vector that is dimensionality of vocabulary size, MF can model a lower dimensionality representation using MF on document-term matrix.

- Topic Model
  One of the popular techniques in topic model is Latent Dirichlet Allocation (LDA) [38], it offers semantic understanding of a text corpus by assigning each document a probability distribution across latent topics, and each topic a probability distribution over the vocabulary.

- Auto-Encoder
  Neural topic models leverage the architecture of autoencoders. In precise, AutoSVD++ uses contractive auto-encoders, while Collaborative Deep Learning (CDL) [39] and Collaborative Deep Ranking (CDR) [40] are applied together to act as denoising auto-encoders, and Collaborative Variational Autoencoder (CVAE) [41] is built upon variational auto-encoders.

- CNN
  When compared to topic models, topic models will not remain the sequence of words in text. By using CNN, it can be solved. For instance, Convolutional Matrix Factorization (ConvMF) [42] which uses CNN to extract features from text reviews. In addition, Deep Cooperative Neural Network (DeepCoNN) [43] also implements CNN on items and user’s review.
- RNN
  In some cases, we will need to generate sequential text by using RNN or its variants. For instance, (NRT) [44] and Multimodal Review Generation (MRG) [45] are combined with Long Short-Term Memory (LSTM) for generating text and multi-layer perceptron (MLP) for predicted ratings.

When it comes to image modality, the two most used techniques are Pre-trained Embedding and CNNs.

- Pre-trained Embedding
  Pre-trained neural networks are used to generate dense, high dimensional embedding image which is then reduced to a lower dimension which is often through learned projections so that it can be compatible with bilinear MF framework. Models like Visual-aware MF (VMF) [46] (for ratings) and Visual Content Enhanced POI (VPOI) [47] (for check-ins) exemplify this approach. Similarly, Attentive Collaborative Filtering (ACF) [48] (for images and videos) uses Bayesian Personalized Ranking (BPR) [49] for preference ranking, and Neural Personalized Ranking (NPR) [50] enhances visual preference with spatial and topical metadata.

- CNN
  Moving beyond the use of pre-trained embeddings, this group of models employs a CNN module to learn visual features directly from the pixel data. (DVBPR) [51] represents a direct continuation of VBPR in this direction. Comparative Deep Learning (CDL) [52], while also learning visual features with a CNN, further incorporates a MLP [53] to create a more comprehensive understanding of users by utilizing additional information like tags. In contrast, Collaborative Knowledge Base Embedding (CKE) [54] and Joint Representation Learning (JRL) [55] adopt a multi-view learning strategy, considering visual data as just one of several perspectives for learning user and item representations

On the other hand, the three most commonly graph modality used techniques are Feature-based, Regularization-based and Architecture-based.

- Feature-based
  Just as with text and images, low-dimensional representations of users and items can be extracted from graph data and used to enhance preference models. A variety of models, including (Sorec) [56], Matrix Co-Factorization (MCF) [46], Probabilistic Collaborative Representation Learning (PCRL) [57], Conditional/Joint VAEs [58], and GraphRec [59], employ this approach. They differ in their underlying assumptions and the specific methods they use to integrate graph information into the preference learning process.

- Regularization-based
  These approaches use the graph structure to regularize the latent space of the preference model. This regularization typically works by encouraging users or items that are connected in the graph to have similar representations in the learned latent space [60], [61].

- Architecture-based
  In this category of models, graph information is directly incorporated into the architecture of the preference model itself. Examples models are Social Poisson Factorization (SPF) [62], SocialRBM [63], Collaborative Context Poisson Factorization (C^2PF) [64], and Knowledge Graph Attention Network (KGAT) [65].

These are among the various diverse ser of modalities that relate to multimodal recommenders. After going through the three types of modalities, we can notice that there is potential to come up with cross-modality in some cases. Cross-modality is that combination of modality and modality to come up with a better modality. By leveraging cross-modality techniques, we might unlock a broader selection of algorithms applicable to a specific data type [66].

2.3 Review Methodology

This paper utilizes a technical review approach to integrate and contrast significant advances in hybrid recommender systems within the movie domain. Instead of a formal systematic review, this work has developed conceptual organization, evaluation, and discussion around representative methods, models, and trends extracted from pivotal literature.

To keep the content relevant and up to date, we searched for research articles, review papers and technical reports published between 2018 and early 2025 that are based on peer-reviewed journals and high-impact conference proceedings. The foundational sources of literature are as follows.

- IEEE Xplore
- ACM Digital Library
- ScienceDirect
- SpringerLink
- Google Scholar

The literature search was conducted using keyword combination of "hybrid movie recommender system", "movie recommender system", "Generative AI movie recommender system", "Content-based movie recommender system", "Collaborative filtering movie recommender system", "collaborative filtering + content-based filtering movie recommender system" and so on.

We prioritized studies that:

- Describe possible hybrid recommender system architectures, with emphasis on the movie domain.
- Report empirical results on standard datasets, like MovieLens, and use evaluation metrics such as MAE, RMSE, Precision and so on.

This review does not pretend to be exhaustive but highlights significant developments, compares technological contributions, and points out new trends that may be of interest to researchers and practitioners.

3. HYBRID-BASED MOVIE RECOMMENDATION SYSTEMS

[67] proposed an item-based CF based system. In their proposed methodology, they utilize the k-Nearest Neighbors (KNN) algorithm with cosine similarity to determine the distance between a target movie and all other movies in the MovieLens dataset (28M ratings, 1M+ tags, 60k movies). The system then ranks movies by their top k nearest neighbours. Performance was evaluated using precision, recall, F1-score, and MAE. Comparing their method to CB, model-based CF, user-user CF, and item-item CF, they found their approach yielded the lowest MAE score (0.248), outperforming CB (0.269), model-based CF (0.265), and user-user CF (0.258). They also say that more features can be used and a combination of both CB and CF can be implemented to improve performance, which results in a hybrid approach.

[68] proposed an efficient deep learning approach CF recommender system (DLCRS). They implemented deep learning neural network to act as MF. The dataset that has been selected to perform testing are MovieLens 100k and MovieLens 1M. The performance of the proposed methodology is then evaluated using RMSE. The proposed methodology is then compared with User Avg, Movie Avg, Movie-User Avg users-based cosine similarity, item-based cosine similarity, SVD and MF. The DLCRS model has the lowest RMSE score when using both datasets. The RMSE of MovieLens 100k is 0.917 while RMSE of MovieLens 1M is 0.903. From the result, the DLCRS does outperformed other technique.

On a separate work, [69] proposed a hybrid deep learning-based recommender system (DNNRec). They integrated user and item embeddings with user and item side information to create a combined feature set. The deep neural network layer is set to three hidden layers, but it can be increased based on computational power. They have tested the system with multiple datasets. The dataset that has been used to perform testing are from Book-Crossing, MovieLens100k, MovieLens1M and FilmTrust. They also address cold-start problems that arise from traditional holdout and cross-validation methods. The system is then evaluate using RMSE, MAE, Mean Squared Error (MSE) and R-squared value (R^2). When it comes to comparing performance with other techniques on all the four datasets, the proposed methodology outperformed all the other techniques that have been used to perform comparison. The methods used for comparison are global average, user average, item average and so on. The DNNRec has the lowest MSE 0.874, RMSE 0.935, MAE 0.746 and R-squared value 0.364 when comparison done using MovieLens 100k dataset. They suggest that future research could expand beyond ratings prediction to include ranking and streaming scenarios.

[70] proposed a monolithic hybrid system which is connected to an expert system. A web system, Predictory, was developed to fully implement the proposed methodology. Predictory comprises several modules: a user interface, a recommender module, an expert system, and an information collector. The recommender module is consisting of CF system and CB system. The dataset they selected is from MovieLens, which contains 100,836 ratings from 0.5 to 5, and was done by 610 users based on 9724 movies. The methodology has been measured with the help of precision,

recall, and F1-measure. The proposed method's evaluation result is Precision 81%, Recall 83%, and F1 Measure 82%. The better aspect of this recommender system is that it offers better recommendations than another model accessible on the internet. Models available online include MovieGeek. [71] and Elastic Graph Recommender [72]. The authors says that there is a lot of future work that can be done. The first improvement addresses dynamic genre preferences. Initially, if a user marks a genre as unpopular, the system avoids recommendations from it. However, if the user's ratings indicate a shift in preference, the system updates the genre's status to favourite. Therefore, the system can perform recommendations based on user-preferred genres.

[73] proposed a hybrid-based recommender system. This study proposes a methodology that combines Cosine Similarity for movie and user similarity calculation with Singular Value Decomposition (SVD)++ for recommendations. Using the MovieLens 100k dataset (100,000 ratings, 1,682 movies, 943 users), the authors compared their approach to other CF techniques: KNN, SVD, and Co-Clustering. Performance was evaluated using RMSE and MAE. The proposed method achieved the lowest RMSE (0.9201) and MAE (0.7219), demonstrating superior performance. The authors assert that their methodology effectively addresses cold-start and data sparsity challenges.

proposed a methodology using k-means clustering within a CF approach. Their architecture comprises four modules: movie feature extraction, k-means clustering, user profiling, and recommendation. The system utilizes the MovieLens dataset, containing movie titles, IDs, and 19 genre attributes (represented as binary '1' for present and '0' for absent). Principal Component Analysis (PCA) was employed to reduce the genre attributes from 19 to 10. The researchers compared the performance of the original dataset with the PCA-reduced dataset using k-means and a combined CF approach, evaluating results with RMSE. The PCA-reduced dataset demonstrated lower mean error and thus superior performance. Subsequently, they applied their methodology to the MovieLens 100k dataset, which includes 100,000 ratings (1-5 scale) from 943 users on 1,682 movies, with each user rating at least 20 movies. User demographic information (age, gender, occupation, zip code) was also included. The evaluation metrics used were precision, recall, and F-measure. They assessed the models by providing movie recommendations to all users and comparing the mean F-measure. The authors claim this methodology consistently delivers strong results compared to other recommendation approaches. However, they acknowledge a limitation: the potential for improvement by incorporating advanced ML and deep learning models.

[75] proposed a modern hybrid recommendation model consisting of four components: CF, CB, SOM CF and Hybrid filtering. The hybrid system utilizes feature augmentation and weighted methods. After obtaining results from the CF and CB models, their scores are combined using a linear combination. The resulting list is then classified, and the top 200 recommended items are selected. Subsequently, these selected items are re-classified based on SOM CF scores (feature augmentation), ranked from best to worst, and the top N items are presented as recommendations. The MovieLens 100k dataset, containing 100,000 ratings, was used, partitioned into a training set (90,570 ratings) and a test set (9,430 ratings). The model's performance was evaluated using RMSE and Precision-Recall. Lower RMSE scores indicate better performance, while higher Precision-Recall scores also signify improved performance. This method demonstrated significant improvements in precision and accuracy. However, a limitation is its increased computational time compared to other models.

[76] proposed an improved hybrid and knowledge-based recommender system consisting of improved CB and CF. The improvement of CB is achieved by integrating fuzzy clustering, while the progress of CF is achieved by incorporating probabilistic classifiers. They utilized the MovieLens dataset, comprising 100,000 ratings from 600 users on 9,000 movies. The system's performance was evaluated using varying training and testing set splits. The testing sets consisted of 30%, 25%, 20%, 15%, and 10% of the total records, with the remaining data allocated to the training sets. The evaluation metrics adopted are Accuracy, MAE and (RMSE). The proposed system has reached the minimum average RMSE rate of 0.1987 and a maximum average accuracy of 75.79%. The proposed approach is more effective than the existing models based on a lower RMSE rate and higher accuracy compared to the existing model. Yet, improvement can be made by using more advanced methods of supervised and unsupervised learning to optimize the system's performance.

[77] proposed a hybrid recommendation system that combines CF and CB. The system uses movie genres as a reliable source of content information. This method addresses cold-start, data sparsity, and cross-language recommendation challenges through Genre-Average Hybrid Filtering (GAHF) and Genre-Similarity Hybrid Filtering (GSHF). GAHF calculates predictions based on a user's average ratings for specific genres tagged in movies, while GSHF employs a genre-genre similarity matrix to predict ratings even when users have not interacted with certain genres. This system was evaluated on the MovieLens-100k and MovieLens-25M datasets, employing metrics such as MAE and Mean

Square Error (MSE). Results demonstrated that GSHF consistently outperformed traditional CF approaches, particularly in cold-start scenarios. Advantages of the method include its ability to expand user preferences across diverse genres and languages, its reliability due to expert-curated genre labels, and its resilience to sparse data. However, limitations include scalability concerns for large datasets, potential biases in genre diversity, and the need for additional content like user demographics to enhance predictions further. This work highlights the robustness of hybrid filtering for improving recommendation systems and provides a foundation for further exploration in domains beyond movies.

[78] proposed a hybrid-based recommender system named Social Recommender Deep Autoencoder Network (SRDNET). Their methodology utilizes a deep autoencoder network to mitigate data sparsity. They employed the MovieTweetings and Open Movie Database (OMDB) datasets. User-based CF was used to determine user similarities and provide recommendations based on shared interests. Item-based content-based (CB) filtering was also incorporated to generate recommendations by analysing movie features. The authors hypothesized that combining these techniques would enhance accuracy and reduce cold-start and data sparsity issues. The model's performance was evaluated using MAE and RMSE. They also perform performance comparison with MRS-RBM, A-COFILS, AutoRec, PP-CF, VB-CF, MV-DNN, MML-CB and FCMR [79-86]. The SRDNet seems to be outperforming all the other techniques that have been used to perform comparison. The RMSE score for SRDNet is 1.41 and MAE score is 0.73. Both scores are the lowest among other techniques.

[87] proposed a hybrid system that uses SVD for dimensionality reduction in CF, which later combines with CB and a popularity model based on user preferences. Their proposed methodology uses two sets of datasets. They utilized two datasets: MovieLens, containing 27,753,444 ratings from 283,228 users on 58,098 movies (rated 1-5 stars) and including genre information; and IMDB, comprising 10,000 movies with features such as ID, release date, and language. They employed the RMSE and MAE for evaluation. The performance of the proposed methodology has outperformed both the combined model and the KNN baseline approach. The RMSE result is 0.85906, while MAE is 0.64235, which is lower than the other approaches. The advantage of this approach is that it can provide a more accurate movie recommendation. The research paper also suggested some possible improvements. They recommend using other techniques, such as MF algorithms or localized MF. It also suggested incorporating deep learning and reinforcement learning approaches into the system to produce more personalized recommendations to the user.

[88] proposed a methodology which is a hybrid approach. Utilizing the MovieLens dataset (100,000 ratings, 1-5 stars, from 943 users on 1,682 films, including genre information), which contains user IDs, movie IDs, ratings, and timestamps, the system employs a three-stage approach. First, CB recommends movies based on user preferences, analysing movie content such as genre, actors, directors, and narrative. Cosine Similarity is used, combining ratings.csv and movies.csv to create a user-movie ratings pivot table. Movie genres are extracted using Count Vectorizer, and a cosine similarity matrix is generated. Second, CF recommends movies based on similar user preferences and high ratings. Library- and user-based CF methods are implemented, combining movie and user rating datasets to create a user-similarity matrix. Finally, sentiment analysis is incorporated to analyse emotional content from movies, enabling recommendations based on user feelings, even for genres they might typically avoid. The system was evaluated using Accuracy, Precision, Recall, F1 Score, RMSE, Coverage, and F-Measure. The proposed methodology achieved Precision of 0.875, Recall of 0.0435, F1 Score of 0.0828, Accuracy of 0.9889, RMSE of 0.0435, and F-Measure of 0.1813, outperforming systems using only CB or CF. The authors claim that sentiment analysis provides more accurate and personalized recommendations than systems relying solely on ratings. They suggest future improvements could include incorporating audio and visual characteristics for sentiment analysis, using advanced deep learning for sentiment analysis, and expanding the dataset for better generalization.

[89] proposed a hybrid recommender system that combines CF and CB. They used the MovieLens dataset, which includes 100,000 ratings (0.5 to 5 stars) from 943 users on 1,682 movies. The system's performance was evaluated using Recall, Precision, MAE, F1-Score, and RMSE. For the hybrid model, F1-scores ranged from 0.5035 to 0.5124, Recall values from 0.3443 to 0.3536, and Precision values from 0.9301 to 0.9366. The best thing about this technique is that it enhances the accuracy in predictions. Some possible future improvements are advanced methods such as deep learning and neural network can be implemented to enhance the system. Other features can still be explored, such as scalability, real-time performance, meta-learning, cross-domain applicability, and ethical considerations. The solution to the user cold start problem can also increase the user experience. In addition, this system can work with multi-modal data for richer recommendations and refine user-centric personalization techniques to improve the system's overall effectiveness and fairness.

More recently, [90] proposed the Hybrid Knowledge-Infused Collaborative Filtering (KECF) model, which can improve movie recommendation systems by integrating knowledge-based data into CF. This approach aims to mitigate the challenges of traditional CF, including cold-start, data sparsity, and scalability. The KECF model operates in three stages: latent feature extraction, clustering, and recommendation generation. The authors selected the MovieLens-25M dataset, which includes 25 million ratings that is collected from over 162,000 users for more than 62,000 movies. The dataset contains extensive metadata, encompassing user demographics and detailed movie information such as genres and release years. This comprehensive dataset allowed the authors to benchmark their model under varying sparsity levels (95% to 99%), ensuring robustness in data-scarce environments. Evaluation metrics included MAE and RMSE, with results demonstrating that KECF consistently outperforms traditional CF models and neural and MF-based baselines. The KECF model offers notable advantages, notably its ability to mitigate cold-start problems using plot and genre data, ensuring accurate recommendations for new users and movies. It also promotes diverse recommendations, preventing filter bubbles and encouraging exploration of new genres and actors. The hybrid similarity metric also balances user preferences and movie attributes, delivering highly personalized recommendations. Scalability tests also highlighted the model's ability to maintain superior performance across high sparsity levels, making it suitable for large-scale recommendation tasks. Despite its strengths, the model has limitations. Future research will focus on incorporating real-time user interactions and feedback to improve the system's adaptability. The reliance on movie plot and genre metadata may pose challenges for deployment in domains lacking structured data. Moreover, while the enhanced K-Means++ algorithm improves clustering, further exploring alternative clustering methods may yield additional benefits. These limitations provide avenues for expanding and refining the model to address broader applications in recommendation systems.

[91] proposed a hybrid recommender system that consists of CB and CF. They utilized the MovieLens 1M dataset, which includes 1,000,209 anonymous ratings from 6,040 users on 3,900 movies. The ratings file contains user IDs, movie IDs, ratings, and timestamps, while the movies file includes movie IDs, titles, and genres. The system's performance was evaluated using RMSE and MAE. Comparing their hybrid model with a CF model, they found that the hybrid model achieved lower RMSE and MAE, indicating higher accuracy. The authors highlighted that their methodology generates more accurate and personalized recommendations and offers visualization aids to help users identify preferred movie genres. They suggested incorporating user demographic information to further enhance accuracy and provide additional insights into user interests. Additionally, they noted that other aspects could be considered to improve similarity assessment.

Table 2 shows the summary of the studies reviewed earlier, highlighting their core approaches, techniques used, datasets applied, evaluation metrics, and practical strengths and limitations. This review captures the shift from earlier hybrid models incorporating components like CF and CB using KNN to more recent frameworks that use deep learning, sentiment analysis, expert systems, and knowledge based. This comparison will establish the status of recent developments and steer the forthcoming investigation in the field of hybrid recommender systems.

4. CASE STUDIES

4.1 Netflix Personalized Recommender Engine

Netflix uses a complex hybrid recommendation system of CF and CB filtering. The system evaluates both explicit and implicit user interactions watch history, search behaviour, and content ratings. Using a MF-based CF approach, Netflix discovers patterns in user behaviour and suggests personalized movies to the users.

To further enhance the quality of the recommendations, Netflix uses CB that involves analysing metadata including genres, cast, and director. The hybrid approach helps Netflix get around the cold-start problem since even new users are likely to get relevant recommendations. ML models continuously refine suggestions by adapting to changes in user preferences. The impact of a hybrid recommender system is significant in driving increased engagement with the service and higher retention rates.

4.2 Amazon Prime Video's Hybrid Recommendation Approach

Amazon Prime Video uses a hybrid recommendation system of CF, CB, and deep learning models. The collaborative component employs user-based and item-based approaches to find similarities in viewing patterns. Through the analysis of user behaviours, purchase history, and watch habits, Amazon Prime Video can generate personalized recommendations that enhance the discovery of content through supplementation.

The CB filtering aspect uses metadata like movie descriptions, genres, and customer reviews to connect users with appropriate content. Additionally, Amazon employs deep learning techniques such as RNNs and transformers to interpret sequential user interactions. This hybrid method enables Amazon Prime Video to fine-tune the recommendation accuracy while keeping the diversity of movies suggested according to each user's preference.

Table 2: Comparative Analysis of Hybrid-based Movie Recommender Systems

Study	Hybrid Approach	Key Techniques	Dataset(s) Used	Performance Metrics	Strengths	Limitations
[67]	CF + CB (Weighted)	KNN + Cosine Similarity	MovieLens (28M)	MAE = 0.248	Simple, effective baseline	Limited feature scope
[69]	Deep Hybrid (DNNRec)	DNN + User/item embeddings	ML-100k, 1M, FilmTrust, Book-Crossing	RMSE = 0.935, MAE = 0.746	Handles cold-start, diverse datasets	Computationally expensive
[70]	Monolithic Hybrid + Expert System	CF + CB + Rule-based system	MovieLens-100k	Precision = 81%, F1 = 82%	Expert module integration	High complexity
[73]	Hybrid (SVD++ + Cosine)	SVD++, CF, Cosine Sim.	MovieLens-100k	RMSE = 0.9201, MAE = 0.7219	Good accuracy, cold-start mitigation	Narrow scope (single dataset)
[77]	Genre-aware Hybrid	Genre-average + Genre-similarity	MovieLens-100k, 25M	MAE, MSE (not specified)	Cross-language + cold-start	Bias in genre distribution
[78]	Deep Hybrid (SRDNet)	Autoencoder + CB + CF	MovieTweetings + OMDB	MAE = 0.73, RMSE = 1.41	Reduces data sparsity	Lower RMSE than others
[88]	CB + CF + Sentiment	Cosine + CF + Sentiment Analysis	MovieLens-100k	Precision = 0.875, Accuracy = 0.9889	Emotion-aware, personalized	Sentiment analysis may be noisy
[90]	Knowledge-Infused Hybrid	KECF: CF + clustering + plot/genre	MovieLens-25M	MAE, RMSE (outperforms baselines)	Scalable, diverse & cold-start aware	Needs structured metadata
[91]	CB + CF (Simple Hybrid)	Genre-based filtering + User-item CF	MovieLens 1M	RMSE, MAE (values not specified)	Accurate, genre-visualization, user-friendly	Lacks use of demographics and multimodal features

4.3 Disney+ and the Use of Context-Aware Hybrid Recommendations

Disney+ uses a hybrid recommendation system that combines CF with context-aware algorithms. Besides, Disney+ goes beyond the basic user likes to include contextual factors such as geo location, time of day and type of device.

The system adapts dynamically recommendations for example to seasonal trends, upcoming movie releases and regional viewing habits.

Disney+ utilizes reinforcement learning techniques to fine-tune the recommendation process as it unfolds. For instance, during the holidays, the system emphasizes family-friendly content; late-night recommendations may focus more on adult-oriented programming. Thus, ensuring a personalized viewing experience that evolves with user behaviour and external parameters.

4.4 YouTube's Video Recommendation Algorithm for Movies

YouTube uses a powerful hybrid recommendation system of CF, CB, and deep learning models. The CF component studies user interactions like likes, watch time, and subscriptions to predict movie preferences. Moreover, in determining the preferences of its users, YouTube's algorithm also incorporates CB by analysing the metadata of videos.

Deep learning models of YouTube include neural collaborative filtering (NCF) which also uses the transformer architecture). The system ranks the recommendations based on several factors, such as user engagement with the content and relevance to the context. This hybrid model allows YouTube to offer personalized movie recommendations that change according to one's viewing habits.

As a summary, Netflix, YouTube, Disney+, and Amazon Prime Video use hybrid recommender systems that combine CF with CB to make more accurate recommendations. These platforms share a notable trend in the application of deep learning technologies, which include neural networks, transformers, and reinforcement learning that help in the real-time fine-tuning of user preferences. Moreover, these platforms focus on personalization as well as engagement optimization so that the recommendations change according to user interactions and contextual parameters. However, each service has something different to offer. Netflix's A/B testing-driven recommendation refinement constantly experiments with new models to improve ranking and engagement. YouTube focuses on long-term user intent prediction and deep learning, optimizing recommendations based on watch history and real-time interactions. Disney+ offers context-aware recommendations adjusting suggestions based to seasonal trends and regional preferences. Amazon Prime Video combines the purchase behaviour data with voice search interactions that create a seamless cross-platform recommendation experience. Table 3 summarizes the features of these systems.

Table 3. Features of Movies Platform

Platform	Hybrid Model Used	Deep Learning Usage	Key Innovations
Netflix	MF + CB	Neural networks for ranking & personalization	Personalized ranking, A/B testing, contextual recommendations
YouTube	CF + CB + Deep learning	Transformers, NCF	User intent prediction, long-term engagement optimization
Disney+	CF + Context-aware recommendations	Reinforcement learning & deep neural networks	Seasonal & event-based content personalization
Amazon Prime Video	User-item & item-item CF + CB	RNNs, Transformers	Purchase history integration, voice search-based recommendations

5. DISCUSSIONS

Despite the rapid advancement of recommender systems, several existing challenges impact the precision, scalability, and user experience of these systems. One significant challenge is the cold-start problem, which occurs when a system has insufficient data on new users or new items and thus cannot provide personalized recommendations. While hybrid models lessen this problem by combining collaborative and CB, they still struggle with entirely new content where no user interaction has been recorded.

Another significant limitation is the data sparsity being witnessed especially in systems that are based on CF wherein a great percentage of the user-item matrix is left unfilled. The outcome of which is ineffective recommendations as there is lack of sufficient interaction data. Scalability is another burning problem as for now the real-time recommendations need to be provided over huge datasets in a timely manner. This fact that current streaming services, e-commerce platforms and social media networks are growing fast causes a lot of computational work to be done by recommendation algorithms. Although deep learning models enhance accuracy, they are computationally expensive and require high processing power which might limit their wide deployment.

Moreover, recommender systems are often non-informative and cannot say why a particular item was recommended to the user. The issue is especially critical in sensitive applications like healthcare or finance, where transparency is necessary. Besides that, ethical issues such as filter bubbles and biased recommendations remain unresolved since algorithms mostly reinforce what the user likes instead of promoting diverse content.

The future of recommended systems might be improved with the enhancement of the personalization level and interpretability. A rising field of research, XAI, will make recommendations more transparent and understandable. In addition, reinforcement learning is expected to improve recommendation accuracy along with deeper uncovering of relationships between users and items through graph neural networks (GNNs). All these multimodal data, including text, images, and user emotions, will lead to more context-aware and emotionally intelligent recommendations. With privacy concerns growing, federated learning will become increasingly important so that recommendation models can learn from decently distributed data without compromising user privacy.

Figure 2 depicts the word cloud on the terms that appear most often and are most relevant within the context of recommender systems, highlighting important concepts, approaches taken, and challenges faced. The size of each word in the cloud represents its frequency or relevance in the area.

- Dominant Keywords - The keywords “collaborative filtering”, “content-based filtering”, “hybrid approach”, “deep learning”, and “personalization” are most prominently found, signifying the fundamental techniques used in contemporary recommendation systems.
- GNNs, transformer models, autoencoders and reinforcement learning are some examples of the new wave technologies which are considered as a next step in this domain.
- Challenges and Evaluation - Terms like “cold-start”, “data sparsity”, “scalability”, “bias”, “explainability”, and “interpretability” are indicative of the challenges that still exist in research and development.
- Future Trends: The terms “federated learning”, “explainable AI (XAI)”, “privacy-preserving”, and “multi-modal learning” reflect the emerging trends likely to influence the future of recommendation systems.

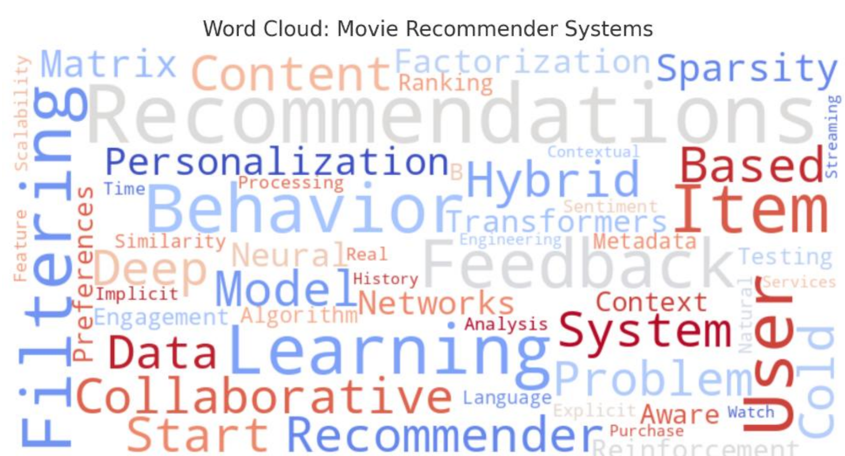

Figure 2. Word Cloud on Recommender Systems

6. CONCLUSION

Recommender systems have witnessed tremendous evolution in the last few decades with hybrid models, deep learning, and graph-based approaches contributing significantly to enhanced personalization and user experience. The challenges that remain include the cold-start problem, data sparsity, scalability, and interpretability. But the new trends in XAI, reinforcement learning, multimodal learning, and federated learning will play an important role in enhancing transparency, flexibility, and privacy. As these technologies mature, future recommender systems will become increasingly effective, efficient, and ethically responsible in their use across various applications including the movie domain.

In the future, LLMs can be implemented into a movie recommender system which can provide deeper contextual understanding of user preferences by processing the comments, description of the movie, and so on. We believe that by implementing it into a movie recommender system, the system will be able to enhance user experience, accuracy and generate more personalized recommendations.

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CONFLICT OF INTERESTS

No conflict of interests were disclosed.

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Our publication ethics follow The Committee of Publication Ethics (COPE) guideline. https://publicationethics.org/

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