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A comprehensive analysis on movie recommendation system employing collaborative filtering

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Abstract
Collaborative Filtering (CF) is one of the most extensively used technologies for Recommender Systems (RS), it shows an improved intelligent searching mechanism for recommending personalized items. It effectively makes use of the information retained by the application to find similarities between the sections of the application. Apart from RS, other applications of CF making use of the sensing and monitoring of data are environmental sensing, mineral study, financial services, marketing, and many more. Different industries like Tourism, Television, E-Learning, etc. make use of this technology, software such as Customer Relationship Management also make use of this technology. This paper discusses the prowess CF algorithm and its applications for Movie Recommendation System (MRS). It gives a brief overview of collaborative filtering consisting of two major approaches: user-based approach and Item-based approaches. Further, in model-based filtering methodology, it is discussed how machine learning algorithms can be implemented for movie recommendation purposes and also to predict the ratings of the unrated movies and bifurcate or sort movies as per the user preference. Followed by, it throws some light on the methodologies used in the late past and some of the basic approaches that are taken into consideration to incorporate it into MSR. Additionally, this paper anatomized many of the recent past studies in depth to draw out the essence of the researches and studies, its crucial steps, results, future scope and methodologies, followed and suggested by multiple researchers. Finally, we have discussed various challenges in MRS and probable future developments in this field. It is to be noted that various challenges in the field of CF recommendation systems like cold start, data sparsity, scalability issues, etc. were raised and many approaches tried to tackle these challenges in innovative and novel ways. Conclusively CF algorithm is a highly efficacious technique for the application of MRS and its integration with other techniques will lead students, researchers and enthusiasts to more cogent approaches for MRS.

Keywords Collaborative filtering · Recommender systems · Movie recommendation system

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1 Introduction

In the era of Information overload RS play a very crucial role in connecting the users to the content of their interest. RS frameworks utilize the assessments of a network of users to help individuals in that network all the more adequately distinguish items of their interest from a pool of numerous choices available [45, 90]. The recommendation systems have key applications in various fields like e-commerce websites like Amazon, eBay and Flipkart, social media platforms like Facebook, online music and video streaming platforms, e-learning portals and many others [17, 70, 72, 102]. RS utilizes the information available about the past behaviour and preferences of the user, identifies the user's liking based on it, and suggests recommendations based on his or her interest [16]. One of the most widely used technologies for RS is CF and over the period, many metaheuristic algorithms have been developed based on it and also some of them have been successful in giving convincingly positive results [45], moreover, researches are in ongoing phase to enhance the robustness of such algorithms and thereby improving the results. The recommendation systems have helped e-commerce sites improve the profitability of their business-like, Data released by Amazon the recommender algorithm implemented by them accounts for approximately 30% of the revenues, also YouTube revealed statistics that the engagements of user have increased greatly: credit to the implementation of highly efficient recommender algorithms [72]. Also, it can be said that RS has enabled companies to provide personalized services to the user likability.

In 1992 Dave Goldberg and his teammates proposed the idea of CF. CF is a widely used technique for RS [91], in this filtering technique the user rates all of the movies of his/her choice and then based on this user's rating profile and other similar users having similar tastes are found, also often CF can be used along with content-based filtering to give more optimized results [45]. CF helps to get to the crux of information relevant to the user and filter out the irrelevant information for them [46, 60, 89, 96, 100]. One of the key problems to be addressed in this field is the scalability of the algorithms and also its computational speeds [96]. Furthermore, CF can be divided into:

a. Memory-based techniques, It includes the user based and item based techniques whereas,
b. Model-based techniques technique employs clustering, matrix factorization, etc. models.

The similarity between the available content and the user's taste can be calculated by various methods namely, Jaccard similarity, Cosine similarity, Pearson similarity [8] etc., but the most promising turns out to be the Pearson similarity method since it indicates the similarity between users likings and the available items. Popular streaming websites like Netflix have known to use CF for their recommendation system [95].

Collaborative filtering, being a very traditional technique in the field of RS holds the same importance even today, as many techniques which have been developed for RS based on CF dominate even today. Amidst CF has found applications in various fields [25, 71, 88, 124, 130] like, [109] proposed a 3-tier model based on CF to provide valuable insights on bidding prices for both consumers and sellers typically in the electricity markets. [126] Proposed a distinctive algorithm for news RS based on CF which anticipates which news article the user would read next. One of the very novel applications of CF was proposed by [9] was geo-tagging the tweets i.e. messages on Twitter employing a multi-stage CF approach. Thus it has been witnessed that CF has found applications in quite diversifying fields. Movie recommender engine is essential for all movies streaming platforms like Netflix [38], Amazon Prime

Video, Hotstar, Hulu, HBO, and Disney Plus [118]. With the growing amount of information available on the internet it becomes increasingly difficult to find what particular set of content might interest an individual, the conventional approach would be to search on the search engines but they are not able to suggest the movies that closely matches an individual's tastes. Therefore it is necessary to implement recommender systems that study the user behaviour and can give more apt suggestions [22, 31]. The MRS is often plagued by the cold start problem in which if a new item gets added to the platform it fails to garner attention because it is not reviewed and rated enough [27]. The ratings can be derived either explicitly from the user or implicitly by observing their usage patterns [95]. The commonly used are content-based filtering, recommendation systems via Collaborative filtering include memory-based filtering and model-based filtering (Fig. 1) [5, 23].

Moreover, it is significant to note that such algorithms have aided in enhancing the quality of engagement of consumers on movie streaming platforms, also have led to an increase in customer involvement time on the movie streaming platforms and help websites provide personalized services to the user. It is also worthy to note that RS plays a crucial role in this era of information overload. Highly efficacious approaches like memory-based filtering, model-based filtering, and content-based filtering have been proposed by various authors for developing an MRS based on CF. However, the CF-based algorithms are continuously evolving to solve the issues persisting in the state-of-art techniques.

This paper targets to provide a meticulous overview of Collaborative Filtering, majorly covering its aspects like Model Based filtering Approaches and Memory-based approaches and comprehensively analyzing the role of it (Collaborative Filtering) in Movie Recommendation Systems along with a concise tabular summary covering significant work of the recent literature in this field. Followed by detailed analysis of the past studies to spectate and gain

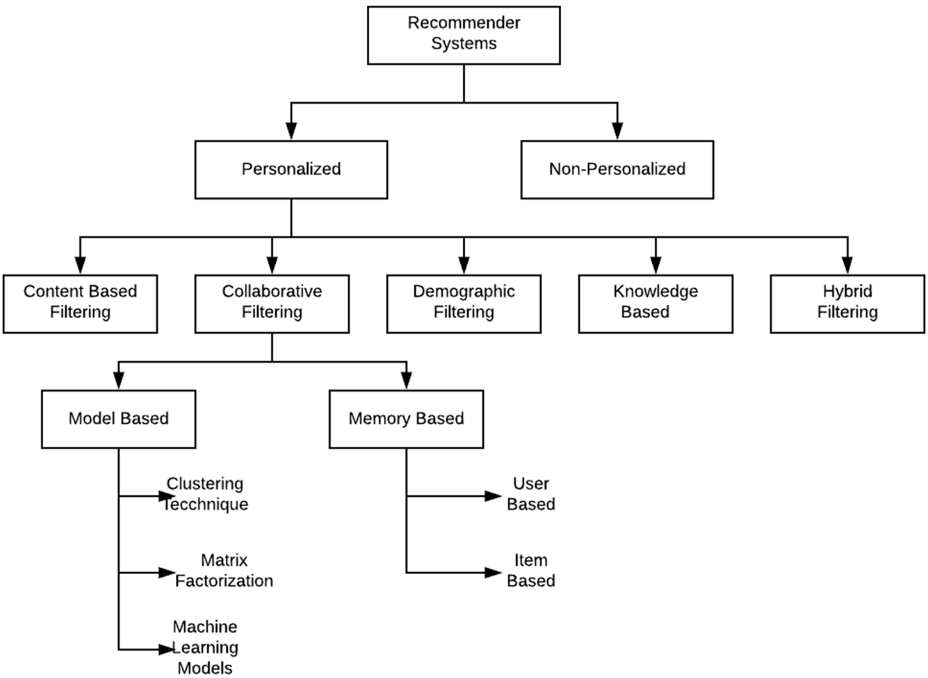

Fig. 1 Various Approaches for RS

useful information in the growth of the CF field over the years and to analyze improvement and future work as suggested by other researchers.

2 An overview of collaborative filtering

In this section valuable insights about CF has been discussed. RS has been employed using various approaches (Fig. 1), like Content-Based Filtering, Collaborative filtering [97], Demographic Filtering, Knowledge-Based, and Hybrid Filtering. Among all Collaborative filtering has been one of the pioneering and most prominently used approaches for RS [103]. It is a technique in which we predict the interest of a user based on other user's choice history, the psychological idea behind this is, the people who think similarly tend to make similar choices. Collaborative Filtering termed coin in 1992 and has been in application for around 30 years. [15, 78] Suggested that CF can further be divided into Memory-Based Approaches and Model-Based techniques in general as visualized in Fig. 1.

The main idea behind working of CF is that an individual tends to value review of those people more who have similar likings, rather than those with having a different opinion. Thus CF has been developed in a similar way that it uses various metaheuristic approaches to calculate the similarity between entities, incorporates the ratings and feedback given by users, and gives recommendations based on the findings of similar results [107]. Thus CF enables the e-portals to give personalized recommendations to the user based on the user's personality, likings, interests, etc. [33, 50, 63]Traditional CF had limitations like data sparsity, cold start problem, gray ship problem, scalability [24, 48, 70, 96]. But over the period hybrid Collaborative filtering techniques [127] have been developed to tackle the shortcomings of typical CF algorithms such developments make the applicability of CF significant even in the twenty-first century [2, 75].

2.1 Memory based approaches

The central idea of Memory-based CF is to recommend user items based on past ratings and reviews given by the user. The theme of this approach is to remember the user's likings and dislikings and based on it model gives personalized recommendations [128]. The main advantage of memory-based CF are elementary implementation, high efficiency, can easily adjust new data in the system [125]. Although this approach has issues like high computation time, new user cold-start problem, scalability but researchers have been successful up to a great extent to overcome them [3, 32, 125]. Memory-based approaches can be classified further into the following categories: User-based Approach and Item-based Approach (Fig. 2).

In user-based CF technique, user profiling is done on the basis rating and feedback given or collected from the user and based on this profile, users having similar tastes are selected, and then they are given recommendations based on the similar users [112]. These similar users are called neighbours and the scalability of these neighbours is a major issue for CF algorithms. This can be mend by improvisation in the user-based CF algorithms on the grounds of neighbour selection for instance, [12] used graph partitioning for selecting the neighbouring users, and [61] used fuzzy clustering to find potential neighbours. Whereas, in item-based CF filtering technique. The new item can be suggested based on previous ratings given by a user using a user-item similarity matrix [85], also the ratings for the similar products can be computed using various algorithms. Besides the use of machine learning algorithms like kNN for finding similar items, [53] suggested a new up-scaling item-based CF algorithm implemented on MapReduce in Hadoop [37].

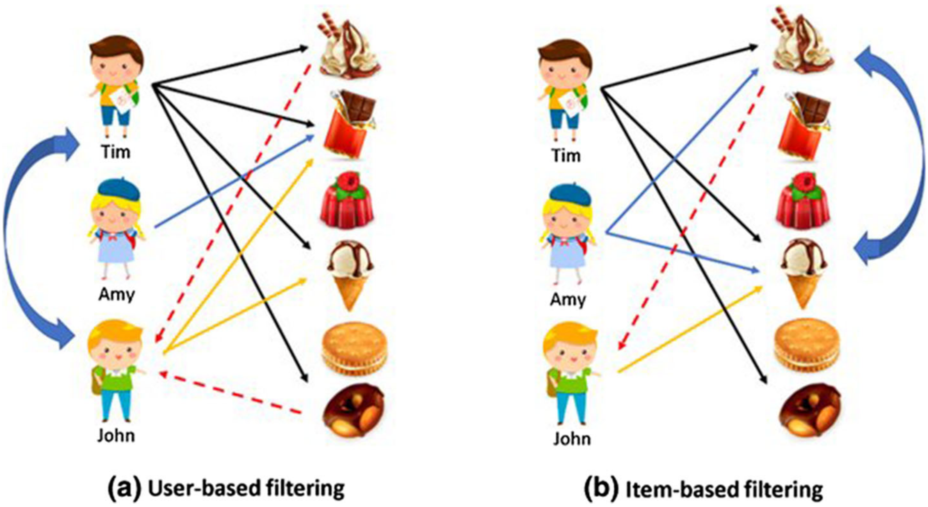

Fig. 2 User-based Filtering v/s Item-based filtering [18]

Moreover, item-based CF stands the relevance with time whereas the user based patterns may change over time but the kind of items persists. Other approaches like [116] also suggest a hybrid approach by combining user based and item based techniques. Some of the formulas used in calculating similarity are as follows: Here, u and u' are two users between whom the similarity is to be calculated, I is the set of all the items rated by both the users, $r_{u,i}$represents the ratings given by user u to item i and $r_{u',i}$represents the ratings given by user u' to item i and r_{-} is the average ratings given by the respective user.

- Pearson Correlation Coefficient formula:

$$pcc\left(u,u'\right) = \frac{\sum_{i\in I}\left(r_{u,i}-r_{-}\right)\left(r_{u',i}-r_{-u'}\right)}{\sqrt{\sum_{i\in I}\left(r_{u,i}-r_{-u}\right)^2}\sqrt{\sum_{i\in I}\left(r_{u,i}-r_{-u}\right)^2}}$$

- Cosine Similarity formula:

$$cos\left(u,u'\right) = \frac{\sum_{i\in I} r_{ui} r_{u'i}}{\sqrt{\sum_{i\in I}\left(r_{ui}\right)^2\sqrt{\sum_{i\in I}\left(r_{u'i}\right)^2}}}$$

- Mean Square Difference formula [101]:

$$MSD\left(u,u'\right) = \frac{\sum_{i\in I}\left(r_{u,i}-r_{u',i}\right)^2}{I}$$

2.2 Model based filtering approaches

In the model-based approach various machine learning algorithms like SVM classifier and SVM regression [41] can be used for recommendation purposes and also to predict the ratings of an unrated item. This approach provides relief from a large memory overhead that is present in the memory-based approach [29]. Some of the most frequently used algorithms are Clustering, Matrix factorization and Deep learning approaches. Clustering technique recruits K-means clustering approach, the clustering may be done based on the Expectation Maximisation algorithm, and they also apply repeated clustering to prevent the data from spreading out [110]. The matrix factorization approach can be visualized in Fig. 3 in which it characterizes both users and movies using two axes ranging from —male-female versus serious-escapist. Matrix Factorization technique makes the recommendation to the user based on the pattern recognized in the correlation matrix generated, which helps in simulating actual scenarios [62].

In the deep learning approach, the feature learning can be done by Stacked Denoising Autoencoders [76] architecture using the item descriptions given on the web and then these features can be exploited to be used in a CF model [114, 120]. Model-based CF approaches are useful for tackling large databases of information that are more prevalent today and also helps in dealing with sparse matrices [29].CF performs formation of groups of similar users and giving the user recommendations based on the group which they belong to.

3 Approaches for movie recommender system

In this era, when their number of choices are available to a user, web-sites need to give personalized services to each user for boosting the customer satisfaction and quality of customer's time engagement. It has been observed that users typically are indecisive in nature thus when so much choice is available they either end up choosing none or making poor

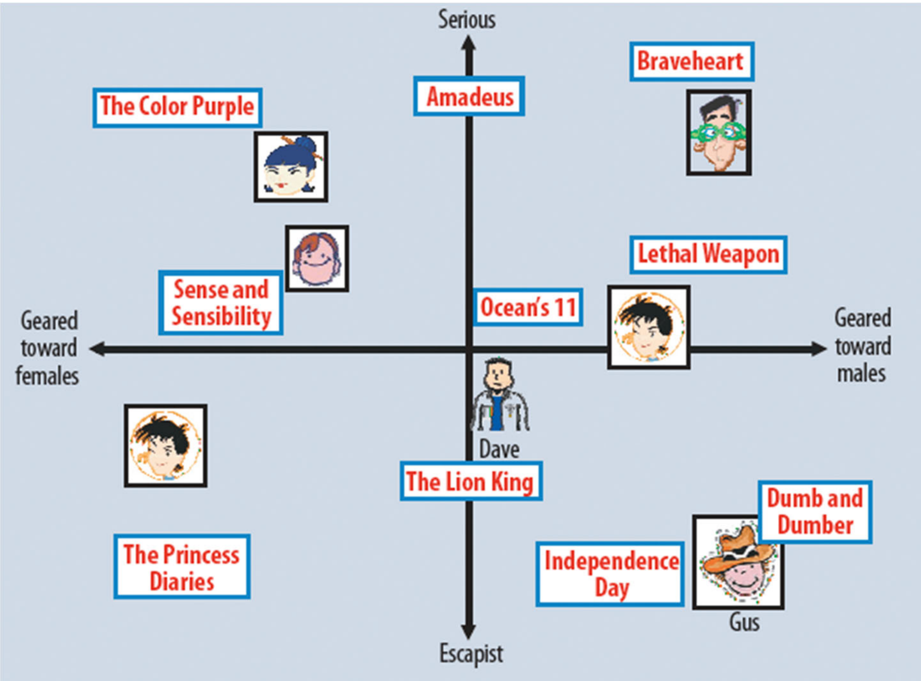

Fig. 3 A simplified depiction of the matrix factorization based approach [62]

decisions [98]. A survey conducted indicated that a typical user on movie streaming platforms like Netflix loses his interest after 60 to 90 s of analyzing up to 20 titles if this happens, it leads to customer dissatisfaction, in turn, losing the customer itself [38]. Thus, it is very important to develop an efficient recommender system that highly assists users in decision making. Over the period of the time evolution of recommendation, systems have been witnessed, they have been developed using distinctive approaches and overall employing such approaches have bolstered the e-portals increase their business [64].

The recommendations given by the portal enhances the chances of the user trusting them. Figure 4 depicts the user-interfaces of two very popular streaming platforms namely Amazon Prime Video and Netflix, describing how they display the results of recommendations generated for the user.

[92] Used one of the oldest types of Recommender Systems, the technique of "User modeling via stereotypes". The basic ideology behind stereotyping is to predict the user behaviour with the limited information available about the user. [10] Suggested issues with stereotyping are, one-fits-all is too extensive as an approach which would underperform for heretic users and they typecast users for an example if the majority of Indians like watching Sacred Games it is not mandatory that it holds true for all Indian users. This fact limits the applicability of such systems [11]. Whereas, [119] promoted such methodology because of

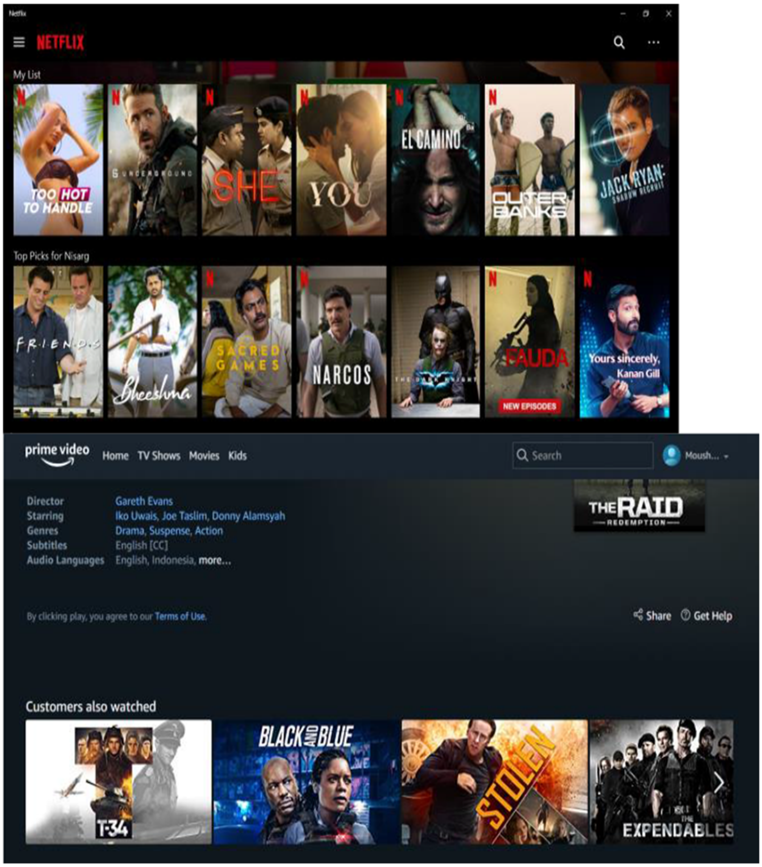

Fig. 4 Snapshot of various Movie Streaming platform depicting their MRS results for a typical user

their low computation cost and stated scenario in which such an approach works quite well. In Fig. 5, shows steps that, how some of the MRS steps are undertaken to employ various approaches and how they affect the users and the streaming platforms.

The other class of Recommendation systems are Content-Based Recommendation System, in this method content of the movies are analyzed like Cast, Genre, director of the movie, etc. are taken into consideration, such method is employed in MRS because there may be people who like the movies in which *X* actor/actress has acted or somebody may be interested in movies directed by *Y*. The concept behind content-based filtering is that if a user liked movie 'A' in the past he will probably also like movie 'B' which is similar to movie 'A' [1]. [16] Had proposed a content-based movie recommender system which was user-centric and considered the content of the movie, another such method was also developed in which they trained a neural network based model, Word2Vec CBOW with content-based details [21] which was a hybrid approach based on content-based filtering but this methodology has a drawback as it doesn't take consideration of user's feedbacks for the items making it difficult for the user at the initial phase of the recommendation [73].

CF is an extensively used approach in Recommender Systems in general and also in the niche segment of MRS. CF incorporates the ratings given by the user and gives personalized recommendations based on the past rating history of the user and thus it is said that CF is one of the most powerful and highly used techniques which is employed in Recommender Systems [30, 39]. The crucial part of the CF-based recommender system is its tenacity to predict the most similar users and items with the limited amount of data available to it [14, 94]. CF has shown some great results for MRS as it incorporates the feedback of users also analyses the movie's relevancy for the user and there have been various developments to CF which have

Fig. 5 Overview and implications of MRS by various Techniques

enhanced results produced by CF [20]considering some other hybrid models that have been developed to overcome the limitation of simple CF [28, 117].In the next section, the paper targets the vast employability of CF in MRS.

4 Analysis of various approaches for MRS employing CF

The CF approach for movie recommendations is one of the most extensively used approaches, with growing amounts of data it has become inevitable to address the problems of data sparsity, data dimensionality and other problems like cold start, coverage and many more [74]. Many innovations have come up in the field of MRS and in particular, CF approaches like data mining can be incorporated with CF [34], K-means and Genetic Algorithm based (model-based CF) movie recommenders [118], clustering-based CF approach [49] among many others. Moreover, content-based and CF-based hybrid approaches have also shown plausible results in MRS as noticed in [36].CF based approaches have evolved to overcome the traditional shortcomings and owing to the increased computational power they have found real-world applications.

[40]stated how a cerebral model has been developed for decision making in various fields varying from economics, sociology, game theory and more. Here the author conducted an experiment for which they designed a game, in which the included 3 and then 2 players at a time, the main task of the game was to reach the goal with minimal spending (or exchanging with other players before the game beings) of their utilities. With this experiment, the authors successfully establish a new generalized utility-based methodology to examine the cooperation and fairness in multiplayer (where players are more than 2) interactions. Whereas in the two-player system they were unable to be decisive about it and was impossible for the model to detect the difference between fairness and cooperation in the decisions of a candidate. Due to which they were able to study in-depth about the group interaction in a game set in turn explaining the social motivation of an individual. Similarly, this model can be implemented for MRS, where depending upon the interaction of the user with the service providing platform can be monitored to suggest future content recommendations.

[80]discussed how with the rapid development of E-commerce data overloading it has become a cumbersome task to sort out and make use of crucial information for the users. Even though multiple recommender systems are available in the market but these methods are restricted by the linear model of matrix factorization [44]. Here authors suggested a novel methodology in which the model takes care of the continuously generated data, unlike other past methodologies. They considered to continuous train the model with user feedbacks to revel the essential feedback, which further will be re-trained to learn user's preferences. But the major issue was regarding the noise in the continuous information that was being fetched as it could heavily impact the model's accuracy. Therefore, they proposed a new Enhanced Collaborative Autoencoder (ECAE) to generate useful data with the technique of knowledge distillation. The authors broke down the overall methodology in three steps: firstly they incorporated generation and retraining stages into a unified framework so that the nose can be reduced as it propagates via retraining. Secondly, as the noise level is yet different for the data they passed it via distillation layer to balance the impact of the noise, and finally, they consider both the predict results of generation and retraining network to provide user-specific recommendations. On comparing their studies with other existing methodologies (like NCF (Neural Collaborative Filtering)) they observed an overall improvement in the accuracy of about 0.59% to 4.625% for a recommendation system.

Whereas later [81]focused more on the behavioural pattern of the users, They stated that with significant growth in the social media in the recent past years has provided a vast amount of data to research and a great opportunity to analyse the behavioural pattern of the users and thereby inculcating user preference in several applications and fields. In the past studies, authors observed that there was a compulsive need for robustly training the data on deep learning model but the major issue was regarding the data of user ratings and social network being highly sporadic. Therefore authors came up with a proposed model of correlative denoising autoencoder (CoDAE), which get trained by the compact and the robust representations from rating and trust data. They bifurcated a user with different riles namely: raters, truster and trustee. Their model contains three layers of 'Denoising Auto-encoder' (Input layer, Middle layer and Hidden layer). Where in the Input layer each input of the users as a truster or trustee is considered as a unique user. In the middle layer, the output of each user (truster or trustee) depicted a user's preferences in a different aspect. And in the hidden layer, they incorporate the function of exchanging the information between user features with multiple mentioned roles. On testing of the proposed model, the authors observed a range of accuracy improvement from 0.37% to 2.81% compared to TDAE (a novel deep learning-based social recommendation method) which is quite significant. This can further be implemented in the field of MSR for a robust recommendation system in an initial phase of content recommending as conventionally most of the models faced the problem of cold start due to less availability of the data in the early phase.

As [82] saw the rise in the area of social media data and its influence of the people views on the recommendation system, based on the influence of the peers in the past studies. But most of the past studies focused only on the interaction between two users but neglected the major chunk i.e. social influence on each other. Authors here target to focus on the social influences, so they developed a model (Social-aware Collaborative Deep Learning (SocialCDL)), a deep autoencoder to adapt and learn from social representations for recommending system, they even considered the low-level and high-level social information features based on multi-layer neural networks and matrix factorization technique. Hence they developed a novel methodology Sparse Stacked Denoising Autoencoder (SSDAE), to grasp over the lacking aspects of the previous models, which were data sparsity and imbalance social network problems. Further, they also integrated learnt representations with matrix factorization and BPR model for the rating prediction task. When compared their model SocailCDL implemented with SSDAE they observed that they could notably improve the performance of the recommendation system based on the social information, feedbacks and reviews.

In MRS it is not only important to recommend movies that the user might like but rather recommend the movies which the user is probably going to like the most. [108] Developed a personalized MRS based on CF in which they suggested enhancement to the existing approach. For calculating the users with similar likings, the authors used Euclidean distance technique. They adopted a continual learning approach which could incorporate the changes in likings of users over the period and to accomplish this they altered the Euclidean distance conventional technique with the weighted framework of Euclidean distance technique in which the distance factor is multiplied with a distinctive factor based on the timestamp. As the model integrates the timestamp factor for users it can capture the dynamic behaviour of users over a while and considering the same could render superior quality movie recommendations. Recommendations for movies are rendered based on the nearest neighbour's movie and the time factor. The MovieLens dataset aggregated by the University of Minnesota was used to assess the model's performance. On assessment they observed an average precision of the model was 96.1%, the recall was 95.1% and F-measure was 95.6% for the same [7, 13, 93, 96, 108]. The approach developed showed motivating results though to give even more personalized recommendations for movies it is suggested to use the social media profile of the user and develop a hybrid approach combining various frameworks.

CF has been widely employed in recommender systems and because of its predictive prowess have been used in tangled tasks like MRS. [104] proposed a novel approach combining the user based and item based clustering approach for recommending movies to active users. Their objective was to enhance the traditional clustering algorithm thereby enhancing the quality of recommendations rendered to users. They used a k-means algorithm for user clustering and for calculating similarity they inculcated Pearson correlation formula to know the correlation between the features, users rating history, watch history in their CF model. They used Euclidean distance for finding out adjacency between the users in the K-means algorithm, followed by predicting the ratings for various movies for the user and by employing this technique they were able to give the most probable movie recommendations which the user might like and have not watched. They tested their algorithm on the Movie lens dataset using the WEKA software to employ the algorithm. The major attributes of the dataset are userid, movieid and rating, the missing entries in the dataset were replaced with mean/mode of the parameter. The results showed a 2438.9141 sum of squared errors and it was analyzed that the accuracy was quite reasonable which could be enhanced by employing meta-heuristic algorithms for clustering like the FCM.Further, this study can be used in finding out the most influential features and the correlation between them to enhance the result for the movie recommendation system.

Although CF has a great ability to predict users interests based on the user's history, there are issues like the sparseness of data and the cold start problem. To overcome such limitations of traditional CF, [72] suggested a CF algorithm embedded with Doc2Vec for movie recommendation. They employed deep learning techniques to analyze the synopsis and extract the feature vector for the same, which is used in the CF recommendation algorithm. The Doc2Vec model helps infer the similarity of the movie with other movies based on analyzing the synopsis of the movie. The model is based on the word order of the sentence, semantics and grammar builds a fixed dimension vector and the similarity of the vector is examined and employed in the CF algorithm. Here also the MovieLens dataset was used for the evaluation of the model and the crawler tool was used to collect movie profile data (i.e. synopsis). Similarity-based on the users rating is combined with the similarity formulated between the vectors using Pearson correlation formula. The updated aggregate similarity is used in the CF algorithm. The accuracy of this approach was comparatively low 33.51% and the recall value of 10.23% but the algorithm showed a significant improvement over the traditional CF algorithm in terms of accuracy and recall value. It can be noted that analyzing more data about movies like movie posters, videos of movies, cast, related book, feedbacks etc. would enhance the accuracy of the model and quite probable that as a result render better recommendations to the users.

Matrix Factorization is an important technique for CF, in this field many developments happened due to the success of probabilistic matrix factorization algorithm and as a result algorithms like Singular Value decomposition (SVD), SVD++ have been developed which have been proven highly efficient in Recommender Systems. [49] Presented a novel model filiations derived from matrix factorization, called Markovian Factorization of Matrix Process (MFMP) for MRS. The aim of employing MFMP was to enhance the prediction of movie ratings for users utilizing the time-stamped rating data. As the MFMP model incorporates the time data as well so it can also capture the momentary dynamics more accurately and thus help proffer more apt movie recommendations to users. The 2 variants of MFMP model were evaluated on MovieLens data set and the results were compared with a conventional tensor factorization and a timeSVD++ model. Root Mean Squared Error (RMSE) and precision parameters were used for analyzing the performance of models. The RMSE for the 1st order MFMP model was 0.885 and the same for 2nd order MFMP model was 0.875 when time slot size was kept 30 days which was quite better than the 1.1 RMSE of timeSVD++ model. Also, the Precision@10 value for 2nd order MFMP was 0.66 which outweighed the precision of timeSVD++ model which was 0.4. It is worthy to note that the MFMP models have substantial potential for a movie recommendation and to make it more efficient in nature, one could include a mechanism to maintain and eliminate the noise information.

[54] Presented a distinctive CF approach which integrated implicit and explicit feedback. In traditional CF methods, implicit feedback has been neglected. But in the proposed method they combined multiple implicit feedbacks named RMIF into Matrix Factorization architecture. The positive mindset of users, rating history of users, user similarities are predominantly considered as implicit feedback. Holistically digging into users' actions and taking into consideration various implicit feedbacks jointly aid enhancing the robustness and efficacy of the algorithm. The Matrix Factorization technique is used to predict unknown ratings. Integrating the implicit and explicit feedback the aim is to enhance the MRS to provide qualitative recommendations to the users. The model's performance was analyzed on the MovieLens-100 k (ML-100 k) dataset published by GroupLens lab. The Mean Absolute Error (MAE) for the presented RMIF model was 0.703 and Root Mean Squared Error (RMSE) for the same was 0.898, the MAE value for ICF was 0.827 and RMSE value was 1.035 and for SVD++ the values were 0.724 and 0.928 respectively. The results indicated that the presented model is better than other models like SVD++, biased MF, ICF and other conventional approaches for the Movie Recommendation endeavor and as it incorporates implicit feedback it can model the users well leading to generating efficient movie recommendations for the users. Moreover, the proposed algorithm showed significant enhancements for the cold start problem. On further analyzing the model it was deduced that among the implicit feedbacks, a positive attitude plays a leading role in the movie CF to magnify the effectiveness of the presented model steps like noise removal can be employed to aid in improving the stability of the model.

Conventional CF had certain limitations like with the increase in the number of users and items, handling the large data, i.e. scalability and another limitation was data sparsity [6, 51, 55, 56, 65, 99, 115, 118]. To overcome the limitations of heretic CF [6] proposed a hybrid model for movie recommendation based on CF embedded with Particle Swarm Optimization (PSO). They applied a type division method to decrease the dense intricate data area. They analyzed various methods for clustering to get superior results than K-Means and found Fuzzy c-means (FCM) as a solution. FCM was better as it doesn't restrict a user to a single cluster rather it allows a user node to belong to more than one cluster. PSO was used to enhance the results in place of using Genetic Algorithm (GA) which suffers from the unguided mutation issue. K-means enable PSO with initial parameters to enhance its performance. The model was trained in two phases i.e. offline and online to reduce the computational time of the model. The presented K-Means-PSO-FCM (PSOKM-FCM) model is evaluated on the MovieLens dataset which consists of 100,000 ratings given by 943 users for distinct 1682 movies. The Mean Average Error for the suggested model is 0.7547 and the same for other heretic approaches like GA-KM clustering was 0.8040, for PCA-KM was 0.8412. Thus it could be deduced that PSOKM-FCM is a hybrid approach sought to have better movie recommendation efficacy than other conventional CF algorithms for movie recommendation. It was significant from the study that not only the parameter related to movie matter but also parameter related to the users also play a vital role in MRS.

Alternating Least Squares (ALS) is one of the critical techniques for Matrix Factorization based CF. Examining the ALS model choosing varying features can aid in developing a coherent MRS. [67]Evaluated a MRS employing Apache Spark build using the ALS algorithm. It is suggested that choosing features of ALS affects the performance of MRS thus it's crucial to choose apt features for developing an efficient MRS. They tried to optimize the values for users' matrix keeping the movie matrix unchanged. Moreover, the minimum error principle was used for movies/users pair as the criterion for choosing the pair of matrices. ALS succeeds in doing this as it randomly fills the user's matrix with the estimates optimizing the value of movies was used for the same reason. Apache Spark is a vivid cluster computing system that presents aristocratic Application Programming Interfaces (API) employing various programming frameworks such as R, Java, and Python. The MovieLens dataset which contained approximately 24 million ratings was used to gauge the performance of the model. The model was tested for 2 combinations of parameters. For the first combination, the observed RMSE was 1.07422; the computation time for the same was 1.41323 s. The observed RMSE for the second combination was 0.9167 and computation time for the same was 1.463743 s. Thus it was deduced that parameter selection is important for the suggested MRS algorithm and in this study, the second combination was better as it gave superior accuracy without significant changes in computation time. Thus it can be said that the ALS algorithm employing Apache spark is an effective approach for developing MRS though it is worth noting that even more metaheuristic loss functions could be designed which could aid in enhancing the accuracy of the suggested model.

[66]Proposed a neoteric approach for movie recommendation to overcome the limitations of traditional CF recommendation algorithms. Their objective was to resolve issues like the poor performance of the CF algorithm in case of data sparsity and challenges with modelling changes as per user interest. They suggested a neoteric hybrid movie recommendation algorithm which unifies the movie parameters and user interest. The user interest and movie feature vectors are collectively updated regularly and then the matrix of user similarity is developed based on the user interest vector. Moreover, short-term interest and long-term interests are taken into consideration while modelling user interest vectors, which aims to make the system integrate the dynamics of user interest. For building the user interest vector, a weighted average is used which adjusts short and long term interests of the user. This approach helps to model the dynamic nature of user interest and thus help to render better movie recommendations for the user. Also, the movie feature and user interest both are aggregately considered in the algorithm. The MovieLens dataset was used to evaluate the efficacy of the model. The MAE was used to analyze the performance. It was deduced from the empirical analysis that the MAE for the proposed algorithm was 0.825 which showed on an average about 7% improvement in MAE compared to other heretic CF algorithms like user-based CF, TPNS algorithm [72, 79, 116]. To enhance the accuracy of the present approach, more social context information can be inculcated to further improve the MRS.

One of the main problems faced while making movie recommenders is the data sparsity, and due to the information overload nowadays it becomes necessary to address this problem, [79] aimed at using a content fostered technique to improve web-based movie recommendations, consequently, they suggested to combine the previously successful methods like local and global user similarity and effective missing data prediction, the system is called

ReMovender. While calculating the item-based similarity of the movies their actual content is also taken into consideration. Under sparsity, the less number of ratings makes it difficult to find similar users based on one person's ratings. The local and global user similarity (LU&GU) factor helps us to find the connect similar users amidst the data sparsity and the effective missing data prediction (EMDP) makes data forecasts by using the item, user similarity or both. Moreover, a significant weighting factor is also added to the Pearson Correlation Coefficient (PCC) formula to hinder the decrease in accuracy of similarity calculations. The main components of this ReMovender system include an information extractor which extracts the metadata of the movies from the IMDB dataset using the IMDbPY python package, each movie has a set of dimensions whose information is extracted from IMDb, it also includes a user interface where the administrator can look over the user viewings and update the knowledge base of the system and lastly the recommender model makes a prediction considering the user ratings and the content gathered it also makes the use of the significance weighted PCC method for similarity calculation. The Content boosted CF Recommendation system was tested on the MovieLens dataset the Mean Absolute Error (MAE) was calculated to compare this system too, item-based PCC, similarity fusion, EMDP, LU & GU, Content boosted CF Recommendation system (only CF-based recommender) and user-based PCC, the CBCFReM reported the lowest MAE of 0.7541 with 20 ratings and 100 users. Thus this method outperformed others and in future, the researchers are looking forward to integrating the content information more naturally and also the user and item relationship integrated methods can be explored [105] proposed a two-phase approach for movie recommendations with the first phase being CF approach and the second phase being the sentiment classification. This sentiment incorporated CF recommendation was done as an alternative approach to the traditional content similarity computation. The classification of the movies is done in two categories namely, positive and negative, the movies that are recommended in the first CF phase and labelled positive by the sentiment classifier are finally recommended to the user. The sentiment classification is done using a semantic oriented way by using part of speech tags and the other method used by Naive Bayes classification. The semantic classification is allocated by getting the difference between the point-wise mutual information of a word carrying positive connotation and a word carrying a negative connotation and later a latent semantic analysis is done. The dataset of MovieLens was used and on top of that for sentiment analysis review data was also collected from the critics (one review per movie). This method provides more focused results and therefore providing a better than CF approach.

[68] proposed a novel method of item-based CF for movie recommendations which can help in alleviating the cold start problem suffered by new items in the system. Their approach aims at making better recommendations by extracting item features that account for a user's past behaviour, this helps in the recommendation of new items. The mixed similarity is calculated between user items and then feature similarity is also calculated. The accuracy indicators of CF recommender systems are decision support indicators and the statistical accuracy indicators [35, 58] mean absolute error (MAE) is one such statistical indicator used in this paper. The dataset used was the MovieLens dataset and the new item based approach was compared to the classic item-based approach and their MAE was compared. For 90 nearest neighbours, the new item based approach had MAE of 7.20 whereas the traditional item-based approach had MAE of 0.739 therefore since this new method had a lesser MAE, it outperforms the traditional item-based approach. This shows that drawbacks in the traditional item-based CF approach particularly, the cold start problem can be alleviated by using a user's past viewing history.

The CF approach seems to match users on the bases of their similarity in viewings and ratings so [75] developed an innovative approach by introducing semantics to CF, they aim at extracting the underlying meaning behind why a user views a movie and about his/her particular interests. Introducing semantics is done as a memory-based CF modification, they also propose a unified approach that takes into account both user and item similarity to address the data sparsity problem. Their approach was to compute the semantic space of the following factors: the genre, the actors, and the director; this information was extracted from the IMDb website, then the semantic distance and the ratings are combined with the help of kernel multiplication and a linear combination of prediction methods, of which the former seemed to produce better results than the later. The MovieLens dataset was used and the evaluation metrics were MAE and Mean Squared Error (MSE), for high sparsity values the model proposed by the authors had MAE and MSE of 0.929, 1.495 respectively compared to the only rating model having MAE and MSE of 0.947, 1.538 respectively, hence this model outperforms the ratings only model when the data sparsity is high. The researchers aim at extracting more semantic information to further strengthen the recommendations.

[42] proposed a hybrid approach by combining content-based filtering and CF, the CF is also model-based and fuzzy clustering is applied for similarity calculation. This was done to alleviate problems like sparsity, the cold start of new items and overspecialization. At first, the CF is done on matrix with pseudo ratings (which use the pure content-based filtering) and the neighbours are selected based on neighborhood size and similarity threshold, then the CF and the pseudo ratings are amalgamated and ultimately, the fuzzy clustering is performed to get more accurate clusters. They use the MovieLens dataset and the evaluation metrics used were MAE and Receiver Operating Characteristic the content-based collaborative filtering model outperform Pure Content-Based and Pure Collaborative Filtering based models with MAE and ROC-4 of 0.845 and 0.6094 respectively. Also, the CBCF with fuzzy clustering outperformed the only CBCF and the online CBCF without clustering and the online CBCF as it was able to drastically reduce the online recommendation time. Thus this hybrid approach effectively recommend movies with shorter computation time.

[74] Proposed a Hellinger Coefficient Based Collaborative Filtering (HCBCF) technique, it was introduced in light of the data overload faced these days and it becomes arduous for the systems to observe each item and user and their ratings and it takes up a lot of time to recommenders to process this information. The flow of their approach is that firstly, the Hellinger coefficient is found for items vectors and their similarity is calculated, then the nearest neighbours are fetched and then followed by ranking and evaluating them and finally, the recommendation is made. Moreover, the KNN data model is also used for clustering similar users based on their Hellinger coefficient, this helps in forming more accurate clusters of similar items. The datasets used in this paper are MovieLens and the Netflix data, the main objective of the HCBCF approach was faster recommendations. The result of HCBCF-KNN was compared to KNN-Cosine similarity, KNN-Pearson correlation, kNN Jaccard similarity and KNN Tanimoto and the evaluation metrics used were MAE, RMSE and accuracy percentage, the proposed model outperformed the rest of the models on both datasets. Moreover, the proposed model also had less elapsed time for evaluation than the other models on both the datasets. Hence it is evident that the HCBCF-KNN approach has helped to reduce the time invested for evaluation of the recommender system and at the same time providing more efficient results.

[69] have proposed a model-based CF approach using neural networks. They built upon [121] model (Integration of content-based approach and hybrid collaborative filtering) and

suggested that if there is enough historical data the model-based approach can be applied and if there is not sufficient historical data then the similarity is to be done with the content of the movie and the user and therefore in this case where there is not sufficient information the neural networks can be used to predict the ratings of the movie. The MovieLens dataset was used and the features used for the neural networks are user ID, user gender, user age, user occupation, movie ID, and movie category, the activation functions used were ReLu and TanH. Moreover, their performance was evaluated on Scikit learn and TensorFlow modules, the TensorFlow module, with a MAE of 0.76 outperformed the Scikit learn module and also had a faster processing time. Also, the CF similarity matrix approach using historical data had a higher MAE (0.88) than the neural network approach, therefore; the neural networks provide a good model-based CF approach towards movie recommendations.

In this section, the paper discussed various approaches employed for movie recommendation based on CF. We have discussed various models like SVD, SVD++, RMIF, Doc2Vec, MFMP, PSOKM-FCM, UPCC, IBCF, collaborative encoders and ephemerally discussed their findings. CF has been predominantly used in MRS and till date, it is an integral portion of the modern-day movie recommender systems. The conventional CF algorithm had limitations like cold start problem, data sparsity, modelling the changing nature of user's interest, scalability issues, etc. Over the period, there have been metaheuristic developments which have helped resolve the issues up to a great extent. Though research is ongoing to develop an algorithm which is robust, reliable and generalizable for all environments for the MRS. Researchers have suggested various mathematical formulas for similarity prediction and other hybrid formulas which promise to improve the efficiency of the MRS. Albeit to the prowess of CF for movie recommendation, there has been escalating interest among the researchers to further revamp the models and to build more efficient models for the same. Anatomizing various research works may surmise that CF was, is and will be an integral part of MRS. Further, more studies are covered in Table 1 with several implemented technologies over the past years to get the gist about more movie recommendation system.

5 Challenges and future scope

MRS employing variants of CF algorithms have given significant results on suppositious grounds but the veritable efficacy of the system could only be evaluated after it is deployed in a real-world scenario. The recommendations rendered by MRS are quite peculiar and thus building a system which can generalize it for a group of users is a very demanding task [52, 129]. CF approach for MRS tends to underperform for cases like cold start problem, data sparsity, and shriller attacks for new users [86, 122] and though there have been improvements for them the solutions are not quintessential, the scope of improvement is always there. There are yet many undiscovered corners in the studies or rather challenges or exceptional case where these robust model fail to give suitable results, like, in scenarios when the same user account is shared among various users the recommender system may be unable to render recommendations which will be suitable for all users using that account. Perfection in the model dynamicity is yet to be achieved and is very strenuous task [106]. Also, movie recommendations are very subjective in nature so its effectiveness may vary in different environments. Erroneous inputs may dwindle system in rendering plausible recommendations for the user, tackling such issues is a critical task. MRS has evolved over the period and still, research is underway to develop a stellar and robust MRS.

Table 1 Anatomizing various approaches employed for MRS based on CF

Authors and Studies	Dataset Used	Methodology	Accuracy	Advantages	Limitation
[123]	MovieLens 100 K	Combining item-based and user-based to enhance CF algorithm for MRS	50 Nearest neighbors threshold by the user. MAE 0.8448	Suggested methodology of collaborative filtering algorithm based on users was rapid and accurate	Data Sparsity and Scalability of system are the hurdles to efficacy of the suggested MRS.
[85]	IMDb and MovieLens combined	Novel approach of Analyzing similarity between movies using information like director and genre of movie.	For CIS model RMSE 0.86 MAE 0.8	Usage of similarity measure (user's ratings) to overcome the sparsity and cold start problem.	Robustness of the algorithm is questionable when employed in real time application.
[20]	MovieLens 100 K	Integrating Artificial Immune Systems with CF	Approach MAE User-based 0.7066 Item-based 0.7237	The affinity between an antigen and an antibody and the affinity of an antigen to an immune network implemented for MRS is at par with other state of the art techniques	The proposed system has cold start problem and data scalability issues.
[131]	Aggregated by Local movie streaming platform	Taking users age and gender into consideration to calculate the similarity between users in order to enhance traditional user based CF algorithm	Ratio of α/β RMSE 1 1.1335 5 1.1334 10 1.145	Included more influential factor to increase the user similarity pool thereby improving the MRS.	The algorithm needs to be tested for more general dataset for assuring the reliability of the approach.
[47]	IMDb	K-means algorithm was employed for movie clustering with a weighted formula used for correlating users.	RMSE 2.65 MSE 7.04 MAE 2.16	Used correlation of user data, user activity and movie preferences, hence gives more user oriented recommendations.	Dynamics of change in user interest is not taken into consideration.
[57]	Movielens 100 K	CF embedded with Cuckoo Search	For k = 64 clusters RMSE 1.23639 SD 0.10944 MAE 0.68422	With the help of initial preference list they avoided the problem of cold start.	If initial division of clusters is not appropriate than model may underperform.
[26]	Movie Rating Dataset published on Twitter	A customized MRS based on CF integrating analysis of the twitter profile user.	The movies rendered as recommendation were quite relevant for users.	Social media dependent MRS will avoid the problem of user data sparsity and cold start.	The algorithm will not work well for users who are not there or are not active on Twitter.

Table 1 (continued)

Authors and Studies	Dataset Used	Methodology	Accuracy		Advantages	Limitation
[59]	MovieLens	A item based CF approach for MRS which is dynamic and adapts based on the positive feedback	Accuracy RMSE	79.7% 1.01	Optimal and faster compared to other models, dynamic and real-time in nature.	The accuracy is quite low compared to the pre-existing state of art models.
[111]	MovieLens 100 K	The model employs the relationship of user feature-scores inferred from user-item association through ratings	MCF using five UIIR RMSE	 1.1672	Suggested model improved the accuracy by 8.36% for prevention of cold start with maximum of 5 user.	The Generalizability of MRS for various datasets is contentious.
[86]	Netflix user item rating dataset	Implementing item based CF, analyze the user item score matrix and formulate relationships across items and render recommendations	K-value 10 20 30	RMSE 0.941 0.938 0.95	Easy to implement, Reliable and Justifiable (when user are far greater than items).	Issues like cold start problem, shriller attacks for new users prevail in the presented approach
[84]	MovieLens 1 M	Presented a method to replace the missing values with mean value of similar users and employing Euclidean distance measure for K-NN cluster formation before implementing SVD	SVD Euclidean Mean For K =10 model Parameter TPR FPR	 Value 0.165 0.010	SVD assists in finding latent patterns in the user rating.	The computational complexity of the model is quite high
[31]	MovieLens	Implementing user-based CF and item based CF for various values of nearest neighbour value.	Approach User based NN= 30 Item based NN= 30	MAE 0.804 0.800	number of nearest neighbors used for User-based CF and Item-based CF has minute difference in the accuracy	The reliability of algorithm and efficacy in real life scenarios is suspicious
[19]	Self-made Dataset	MRS which employs Singular value Decomposition (SVD) and Pearson Correlation Coefficient (PCC) to calculate similarity is proposed	SVD+PCC Average MAE Standard Deviation	 0.8960 0.2931	Inclusion of models like UCF, SVD cosine similarity, and Pearson correlation. Works efficiently for small scale movies.	The model needs to be evaluated for general large datasets to validate its reliability

Table 1 (continued)

Authors and Studies	Dataset Used	Methodology	Accuracy	Advantages	Limitation
[27]	MovieLens 20 M	A efficacious hybrid technique canonical correlation analysis (CCA) to exploit complementing information across modalities	Best results obtained employing CCA fusion Model MAP AVF+Genre (V+EM) 0.0097 AVF+Deep (A+V) 0.0097	Multiple aspects like audio and video were also considered for recommendation system analysis.	The algorithm will poorly perform when item features are too few and when user-item interac-tions are less.
[77]	MovieLens 100 K	Integrating CF and tag based filtering where genre, actor of movies are used as input tags	RMSE 1.4892 Standard Deviation 0.0395	Clubbing based on similar items resulted in elimination of cold start problem.	The RMSE value is inferior compared to the RMSE achieved by other metaheuristic CF approaches.

To overcome the limitations of CF algorithm many researchers took forth different methods to overcome the problems and thereby providing efficient MRS. [4, 104] suggested that a MRS based on CF algorithm comprising more intricate pre-processing steps should be developed which might improve the coherence of the MRS. More steps like embedding the key information of the movie, DSPCFA, cloud computing, employing Autoencoder, FMC, metaheuristic algorithms [43, 83, 87, 113, 132] has been incorporated by many researchers to enhance the MRS. Further for future work researcher, student or enthusiasts can study the influence of other parameters like the impact of spoilers, releasing of some other movie during that interval, user's gender, age and sentiment specific can be taken into consideration to bolster the MRS.

6 Conclusion

In this paper, we have comprehensively discussed different CF approaches applied for MRS. In this aeon with overloading of data on systems; it becomes quite difficult to sift through all this information. Traditional ways of plain searching might render ineffective in these situations, hence the CF system is adopted to intelligently filter through the data and find similarities based on more relevant factors. This method has both memory and model-based approaches, a particular advantage of the model-based approach is that they don't have to store the historical data; they can be trained for predictions. Hybrid models combining content and CF have shown promising improvements for personalized recommender systems, mitigating the problem of data sparsity can be overcome by innovative CF embedded with PSO approach and sentiment analysis. Moreover, deep learning approaches when combined with CF help to alleviate the cold start problem, as synopsis can be analysed, collaborated and correlated with the user data in turn suggesting the most influential parameters for MRS, thereby overcoming the problem of not getting relevant recommendations due to the lack of data. Further similarity measure based algorithms, SDV to find the latent pattern in user rating and the amalgamation of social media data with MSR were implemented to overcome the problems of data sparsity and cold start. Multiple studies on the recommender system have also been performed like Enhanced Collaborative Autoencoder (ECAE), correlative denoising autoencoder (CoDAE) to enhance the working of recommending systems.Although there have been several potent advancements in this field, there is still room for a better approach which can tackle all the challenges like real-time recommendations, generating more robust systems to prevent the cold start and simultaneously provide the most optimized and personalized recommendations to the user.

Abbreviations *Acronym,* Explanation; *CF,* Collaborative Filtering.; *RS,* Recommender Systems.; *MRS,* Movie Recommendation System.; *MFMP,* Markovian Factorization of Matrix Process.; *SVD,* Singular Value decomposition.; *RMSE,* Root Mean Squared Error.; *MAE,* Mean Absolute Error.; *PSO,* Particle Swarm Optimization.; *FCM,* Fuzzy c-means.; *ALS,* Alternating Least Squares.; *GA,* Genetic Algorithm.; *API,* Application Programming Interfaces.; *EMDP,* Effective Missing Data Prediction.; *PCC,* Pearson Correlation Coefficient.; *MSE,* Mean Squared Error.; *PCB,* Pure Content Based.; *HCBCF,* Hellinger Coefficient Based Collaborative Filtering.; *SD,* Standard Deviation.; *MAP,* Mean Average Precision.; *AVF,* Aesthetic Visual Features.; *A,* Audio Information.; *V,* Visual Information.; *EM,* Editorial Metadata.; *CIS-GD,* Combination of correlation-based item similarity approach and Similarity calculation based on the genre and director movies.; *MCF,* Modified Collaborative Filtering Algorithm.; *UIIR,* User-Item Interaction Records.; *NN,* Number of neighbours.; *K-NN,* K-Nearest Neighbour.; *SVD,* Singular Value Decomposition.; *TPR,* True Positive Ratio.; *FPR,* False Positive Ratio.

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Data availability All relevant data and material are presented in the main paper.

Declarations

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References

1. Aggarwal CC, Aggarwal CC (2016) Content-based recommender systems. Recomm Syst 139–166. https://doi.org/10.1007/978-3-319-29659-3_4
2. Ahn HJ A new similarity measure for collaborative filtering to alleviate the new user cold-starting problem. https://doi.org/10.1016/j.ins.2007.07.024
3. Al-Bashiri H, Abdulgabber MA, Romli A, Kahtan H (2018) An improved memory-based collaborative filtering method based on the TOPSIS technique PLoS One 13:. https://doi.org/10.1371/journal.pone.0204434
4. Alhijawi B (2019) Improving collaborative filtering recommender system results using optimization technique. ACM Int Conf proceeding Ser 183–187. https://doi.org/10.1145/3369114.3369126
5. Aljunid MF, Manjaiah DH (2019) Data management, analytics and innovation, advances in intelligent systems and Computing. Springer, Singapore
6. Aljunid MF, Manjaiah DH (2019) Movie recommender system based on collaborative filtering using apache spark. Springer, Singapore
7. Avery C (1997) Recom System 40:88–89
8. Aygün S, Okyay S (2015) Improving the Pearson similarity equation for recommender systems by age parameter. 2015 IEEE 3rd Workshop on Advances in Information. Electronic and Electrical Engineering (AIEEE) 2015:1–6. https://doi.org/10.1109/AIEEE.2015.7367282
9. Banweer K, Graham A, Ripberger J, Cesare N, Nsoesie E, Grant C (2018) Multi-stage collaborative filtering for tweet geolocation. In: Proceedings of the 2nd ACM SIGSPATIAL Workshop on Recommendations for Location-based Services and Social Networks (LocalRec'18), vol 4. Association for Computing Machinery, New York, NY, USA, pp 1–4. https://doi.org/10.1145/3282825.3282831
10. Barla M (2011) Towards social-based user modeling and personalization. Inf Sci Technol Bull ACM Slovakia 3:52–60
11. Beel J, Gipp B, Langer S, Breitinger C (2016) Research-paper recommender systems: a literature survey. Int J Digit Libr 17:305–338. https://doi.org/10.1007/s00799-015-0156-0
12. Bellogín A, Parapar J Using Graph Partitioning Techniques for Neighbour Selection in User-Based Collaborative Filtering
13. Billsus D, Billsus D, Pazzani MJ, Pazzani MJ (1998) Learning collaborative information filters. Proc Fifteenth Int Conf Mach Learn 54:47
14. Bobadilla J, Ortega F, Hernando A (2012) A collaborative filtering similarity measure based on singularities. Inf Process Manag 48:204–217. https://doi.org/10.1016/j.ipm.2011.03.007
15. Breese JS, Heckerman D, Kadie C (2013) Empirical analysis of predictive algorithms for collaborative filtering. 43–52
16. Cami BR, Hassanpour H, Mashayekhi H (2018) A content-based movie recommender system based on temporal user preferences. Proc - 3rd Iran Conf Signal Process Intell Syst ICSPIS 2017 2017-Decem:121–125. https://doi.org/10.1109/ICSPIS.2017.8311601

17. Campos PG, Díez F, Cantador I (2014) Time-aware recommender systems: a comprehensive survey and analysis of existing evaluation protocols. User Model User-adapt Interact 24:67–119. https://doi.org/10.1007/s11257-012-9136-x
18. Chen YC, Hui L, Thaipisutikul T (2020) A collaborative filtering recommendation system with dynamic time decay. J Supercomput 77:244–262. https://doi.org/10.1007/s11227-020-03266-2
19. Chen VX, Tang TY (2019) Incorporating singular value decomposition in user-based collaborative filtering technique for a movie recommendation system: a comparative study. In: ACM international conference proceeding series. Association for Computing Machinery, New York, pp 12–15
20. Chen MH, Teng CH, Chang PC (2015) Applying artificial immune systems to collaborative filtering for movie recommendation. Adv Eng Inform 29:830–839. https://doi.org/10.1016/j.aei.2015.04.005
21. Chen HW, Wu YL, Hor MK, Tang CY (2017) Fully content-based movie recommender system with feature extraction using neural network. Proc 2017 Int Conf Mach learn Cybern ICMLC 2017 2:504–509. https://doi.org/10.1109/ICMLC.2017.8108968
22. Cho J, Roy S (2004) Impact of search engines on page popularity. Thirteen Int world wide web Conf proceedings, WWW2004 20–29. https://doi.org/10.1145/988672.988676
23. Christakou C, Stafylopatis A (2007) A hybrid movie recommender system based on neural networks 16:771–792
24. Claypool M, Gokhale A, Miranda T, et al (1999) Combing content-based and collaborative filters in an online newspaper
25. Cui G, Luo J, Wang X (2018) Personalized travel route recommendation using collaborative filtering based on GPS trajectories. Int J Digit Earth 11:284–307. https://doi.org/10.1080/17538947.2017.1326535
26. Das D, Chidananda HT, Sahoo L (2018) Personalized movie recommendation system using twitter data. Springer, Singapore, pp 339–347
27. Deldjoo Y, Dacrema MF, Constantin MG, Eghbal-zadeh H, Cereda S, Schedl M, Ionescu B, Cremonesi P (2019) Movie genome: alleviating new item cold start in movie recommendation. User Model User-adapt Interact 29:291–343. https://doi.org/10.1007/s11257-019-09221-y
28. Devooght R, Bersini H (2016) Collaborative filtering with recurrent neural networks
29. Do MPT, Nguyen DV, Nguyen L (2010) Model-based approach for collaborative filtering. In: 6th International Conference on Information Technology for Education, pp 217–228
30. Dou Y, Yang H, Deng X (2017) A Survey of Collaborative Filtering Algorithms for Social Recommender Systems. Proc - 2016 12th Int Conf Semant Knowl grids, SKG 2016 40–46. https://doi.org/10.1109/SKG.2016.014
31. Dwicahya I, Rosa PH, Nugroho R (2019) Movie recommender system comparison of user-based and item-based collaborative filtering systems. https://doi.org/10.4108/eai.19-10-2018.2282541
32. Fernández-Tobías I, Braunhofer M, Elahi M, Ricci F, Cantador I (2016) Alleviating the new user problem in collaborative filtering by exploiting personality information. User Model User-adapt Interact 26:221–255. https://doi.org/10.1007/s11257-016-9172-z
33. Ferwerda B, Schedl M (2016) Personality-based user modeling for music recommender systems. In: Joint European Conference on Machine Learning and Knowledge Discovery in Databases (pp. 254–257). Springer, Cham. https://doi.org/10.1007/978-3-319-46131-1_29
34. Gandhi S, Gandhi M (2018) Hybrid recommendation system with collaborative filtering and association rule mining using big data. 2018 3rd Int Conf Converg Technol I2CT 2018 1–5. https://doi.org/10.1109/I2CT.2018.8529683
35. Gao F, Xing C, Du X, Wang S (2007) Personalized service system based on hybrid filtering for digital library. Tsinghua Sci Technol 12:1–8. https://doi.org/10.1016/S1007-0214(07)70001-9
36. Geetha G, Safa M, Fancy C, Saranya D (2018, April) A hybrid approach using collaborative filtering and content based filtering for recommender system. In Journal of Physics: Conference Series (Vol. 1000, No. 1, p. 012101). IOP Publishing. https://iopscience.iop.org/article/10.1088/1742-6596/1000/1/012101/meta
37. Ghazi MR, Gangodkar D (2015) Hadoop, mapreduce and HDFS: a developers perspective. Procedia Comput Sci 48:45–50. https://doi.org/10.1016/j.procs.2015.04.108
38. Gomez-Uribe CA, Hunt N (2016) The Netflix recommender system: algorithms, business value, and innovation. ACM Trans Manage Inf Syst 6(4):Article 13 (January 2016), 19 pages. https://doi.org/10.1145/2843948
39. Gong S (2010) A collaborative filtering recommendation algorithm based on user clustering and item clustering. J Softw 5:745–752. https://doi.org/10.4304/jsw.5.7.745-752
40. Gorbunov RD, Rauterberg M, Barakova EI (2019) A cognitive model of social preferences in group interactions. Integrated Computer-Aided Engineering 26(2):185–196. https://doi.org/10.3233/ICA-180590
41. Grčar M, Fortuna B, Mladenič D, Grobelnik M (2006) kNN versus SVM in the collaborative filtering framework. Data Sci Classif:251–260. https://doi.org/10.1007/3-540-34416-0_27

42. Gurcan F, Birturk AA (2015) A hybrid movie recommender using dynamic fuzzy clustering. Lect Notes Electr Eng 363:159–169. https://doi.org/10.1007/978-3-319-22635-4_14
43. Hasan M, Tasdikul Hasan M, Selim Reza M, et al (2019) A comprehensive collaborative filtering approach using autoencoder in recommender system. ACM Int Conf proceeding Ser 185–189. https://doi.org/10.1145/3330482.3330518
44. He X, Liao L, Zhang H, et al (2017) Neural collaborative filtering. 26th Int world wide web Conf WWW 2017 173–182. https://doi.org/10.1145/3038912.3052569
45. Herlocker JL, Konstan JA, Riedl J (2000) Explaining collaborative filtering recommendations. Proc ACM Conf Comput Support Coop Work:241–250. https://doi.org/10.1145/358916.358995
46. Hill W, Stead L, Rosenstein M, Furnas G (1995) Recommending and evaluating choices in a virtual community of use. Conf Hum Factors Comput Syst - Proc 1:194–201. https://doi.org/10.1145/223904.223929
47. Himel MT, Uddin MN, Hossain MA, Jang YM (2017) Weight based movie recommendation system using K-means algorithm. In: 2017 international conference on information and communication technology convergence (ICTC). IEEE, pp 1302–1306
48. Hu B, Li Z, Chao W (2012) Data sparsity: A key disadvantage of user-based collaborative filtering? Lect Notes Comput Sci (including Subser Lect Notes Artif Intell Lect Notes Bioinformatics) 7235 LNCS:602–609. https://doi.org/10.1007/978-3-642-29253-8_55
49. Hu Y, Xiong F, Lu D, Wang X, Xiong X, Chen H (2020a) Movie collaborative filtering with multiplex implicit feedbacks. Neurocomputing 398:485–494. https://doi.org/10.1016/j.neucom.2019.03.098
50. Lim KH, Chan J, Leckie C, Karunasekera S (2015a) Personalized tour recommendation based on user interests and points of interest visit durations. In: Twenty-Fourth International Joint Conference on Artificial Intelligence, pp 1–7
51. Jafar O (n.d.) Emerging RS-P of IC on, 2013 undefined A comparative study of hard and fuzzy data clustering algorithms with cluster validity indices
52. Jain KN, Kumar V, Kumar P, Choudhury T (2018) Movie recommendation system: hybrid information filtering system. Adv Intell Syst Comput 673:677–686. https://doi.org/10.1007/978-981-10-7245-1_66
53. Jiang J, Lu J, Zhang G, Long G (2011) Scaling-up item-based collaborative filtering recommendation algorithm based on Hadoop. Proc - 2011 IEEE world Congr Serv Serv 2011 490–497. https://doi.org/10.1109/SERVICES.2011.66
54. Jones MT (2013) Recommender systems , Part 1 : Introduction to approaches and algorithms Learn about the concepts that underlie web recommendation engines. 1–8
55. Kannan R, Ghinea G, Swaminathan S (2015) What do you wish to see? A summarization system for movies based on user preferences. Inf Process Manag 51:286–305. https://doi.org/10.1016/j.ipm.2014.12.001
56. Katarya R, Verma OP (2016) A collaborative recommender system enhanced with particle swarm optimization technique. Multimed Tools Appl 75:9225–9239. https://doi.org/10.1007/s11042-016-3481-4
57. Katarya R, Verma OP (2017) An effective collaborative movie recommender system with cuckoo search. Egypt Inform J 18:105–112. https://doi.org/10.1016/j.eij.2016.10.002
58. Kermarrec AM, Leroy V, Moin A, Thraves C (2010a) Application of random walks to decentralized recommender systems. In: Lu C, Masuzawa T, Mosbah M (eds) Principles of distributed systems. OPODIS 2010. Lecture Notes in Computer Science, vol 6490. Springer, Berlin, Heidelberg. https://doi.org/10.1007/978-3-642-17653-1_4
59. Kharita MK, Kumar A, Singh P (2018a) Item-based collaborative filtering in movie recommendation in real time. In: 2018 First International Conference on Secure Cyber Computing and Communication (ICSCCC), pp 340–342. https://doi.org/10.1109/ICSCCC.2018.8703362
60. Konstan JA, Miller BN, Maltz D, Herlocker JL, Gordon LR, Riedl J (1997a) Grouplens: Applying collaborative filtering to usenet news. Communications of the ACM 40(3):77–87. https://doi.org/10.1145/245108.245126
61. Koohi H, Kiani K (2016) User based collaborative filtering using fuzzy C-means. Meas J Int Meas Confed 91:134–139. https://doi.org/10.1016/j.measurement.2016.05.058
62. Koren Y, Bell R, Volinsky C (2009) COVER feature matrix techniques for. 30–37
63. Kunaver M, Tasic J, Kosir A, et al (2009) Personality based user similarity measure for a collaborative recommender system
64. Lee D, Hosanagar K (2014a) Impact of recommender systems on sales volume and diversity. In: Thirty Fifth International Conference on Information Systems, pp 1–15
65. Lekakos G, Caravelas P (2008a) A hybrid approach for movie recommendation. Multimed Tools Appl 36:55–70. https://doi.org/10.1007/s11042-006-0082-7
66. Leng Y, Liang C, Ding Y, et al Method of neighborhood formation in collaborative filtering

67. Li J, Xu W, Wan W, Sun J (2018) Movie recommendation based on bridging movie feature and user interest. J Comput Sci 26:128–134. https://doi.org/10.1016/j.jocs.2018.03.009
68. Liang T, Wu S, Cao D Applied in Movie Recommender System. 427–432
69. Lin C-H, Chi H (2020) A novel movie recommendation system based on collaborative filtering and neural networks. In: International Conference on Advanced Information Networking and Applications. Springer International Publishing, pp. 895–903
70. Linden G, Smith B, York J (2003) Amazon.com recommendations: item-to-item collaborative filtering. IEEE Internet Comput 7:76–80. https://doi.org/10.1109/MIC.2003.1167344
71. Liu H, Kong X, Bai X, Wang W, Bekele TM, Xia F (2015) Context-based collaborative filtering for citation recommendation. IEEE Access 3:1695–1703. https://doi.org/10.1109/ACCESS.2015.2481320
72. Liu G, Wu X (2019) Using collaborative filtering algorithms combined with Doc2Vec for movie recommendation. Proc 2019 IEEE 3rd Inf Technol networking. Electron Autom Control Conf ITNEC 2019:1461–1464. https://doi.org/10.1109/ITNEC.2019.8729076
73. Lops P, Jannach D, Musto C, Bogers T, Koolen M (2019) Trends in content-based recommendation: preface to the special issue on recommender systems based on rich item descriptions. User Model User-adapt Interact 29:239–249. https://doi.org/10.1007/s11257-019-09231-w
74. Maheswari M, Geetha S, Selva Kumar S (2019) Adaptable and proficient Hellinger coefficient based collaborative filtering for recommendation system. Clust Comput 22:12325–12338. https://doi.org/10.1007/s10586-017-1616-7
75. Moshfeghi Y, Piwowarski B, Jose JM (2011) Handling data sparsity in collaborative filtering using emotion and semantic based features. In: SIGIR'11 - proceedings of the 34th international ACM SIGIR conference on Research and Development in information retrieval. Association for Computing Machinery, New York, pp 625–634
76. Mu R, Zeng X (2020) Auxiliary stacked denoising autoencoder based collaborative filtering recommendation. KSII Trans Internet Inf Syst 14:2310–2332. https://doi.org/10.3837/tiis.2020.06.001
77. Nguyen QN, Duong-Trung N, Le Ha DN et al (2020) Movie recommender systems made through tag interpolation. In: Proceedings of the 4th international conference on machine learning and soft computing. ACM, New York, pp 154–158
78. Nilashi M, Bagherifard K, Ibrahim O et al (2013) Collaborative filtering recommender systems. Res J Appl Sci Eng Technol 5:4168–4182. https://doi.org/10.19026/rjaset.5.4644
79. Özbal G, Karaman H, Alpaslan FN (2011) A content-boosted collaborative filtering approach for movie recommendation based on local and global similarity and missing data prediction. The Computer Journal 54(9):1535–1546. https://doi.org/10.1093/comjnl/bxr001
80. Pan Y, He F, Yu H (2019) A novel enhanced collaborative autoencoder with knowledge distillation for top-N recommender systems. Neurocomputing 332:137–148. https://doi.org/10.1016/j.neucom.2018.12.025
81. Pan Y, He F, Yu H (2020) A correlative denoising autoencoder to model social influence for top-N recommender system. Front Comput Sci 14. https://doi.org/10.1007/s11704-019-8123-3
82. Pan Y, He F, Yu H (2020) Learning social representations with deep autoencoder for recommender system. World Wide Web 23:2259–2279. https://doi.org/10.1007/s11280-020-00793-z
83. Papadakis H, Michalakis N, Fragopoulou P, et al (2017) Movie SCoRe: Personalized movie recommendation on mobile devices ACM Int Conf Proceeding Ser Part F1325: https://doi.org/10.1145/3139367.3139383
84. Patra S, Ganguly B (2019) Improvising singular value decomposition by KNN for use in movie recommender systems. J Oper Strateg Plan 2:22–34. https://doi.org/10.1177/2516600x19848956
85. Pirasteh P, Jung JJ, Hwang D (2014) Item-based collaborative filtering with attribute correlation: A case study on movie recommendation. Lect Notes Comput Sci (including Subser Lect Notes Artif Intell Lect Notes Bioinformatics) 8398 LNAI:245–252. https://doi.org/10.1007/978-3-319-05458-2_26
86. Ponnam LT, Deepak Punyasamudram S, Nallagulla SN, Yellamati S (2016) Movie recommender system using item based collaborative filtering technique. 1st Int Conf Emerg trends Eng Technol Sci ICETETS 2016 - Proc 1–5. https://doi.org/10.1109/ICETETS.2016.7602983
87. Purnomo JE, Endah SN (2019) Rating prediction on movie recommendation system: collaborative filtering algorithm (CFA) vs. Dissymetrical percentage collaborative filtering algorithm (DSPCFA). ICICOS 2019 - 3rd Int Conf informatics Comput Sci Accel informatics Comput res smarter Soc era Ind 40, Proc 1–6. https://doi.org/10.1109/ICICoS48119.2019.8982385
88. Ren X, Dai Y, Ning D, Chen Y (2016) Course selection of students based on collaborative filtering. 594–597. https://doi.org/10.2991/emcs-16.2016.144
89. Resnick P, Iacovou N, Suchak M, et al (1994) GroupLens: an open architecture for collaborative filtering of netnews. Proc 1994 ACM Conf Comput support coop work CSCW 1994 175–186. https://doi.org/10.1145/192844.192905
90. Resnick P, Varian HR, Editors G (1997) Recommender Systems mmende tems. Commun ACM 40:56–58

91. Ricci F, Rokach L, Shapira B (2011) Recommender Systems Handbook
92. Rich E (1979) User modeling via stereotypes. Cogn Sci 3:329–354. https://doi.org/10.1016/S0364-0213(79)80012-9
93. Ruotsalo T, Haav K, Stoyanov A, Roche S, Fani E, Deliai R, Mäkelä E, Kauppinen T, Hyvönen E (2013) SMARTMUSEUM: a mobile recommender system for the web of data. J Web Semant 20:50–67. https://doi.org/10.1016/j.websem.2013.03.001
94. Sanchez JL, Ferradilla S, Martinez E, Bobadilla J (2008) Choice of metrics used in collaborative filtering and their impact on recommender systems. In: 2008 2nd IEEE International Conference on Digital Ecosystems and Technologies, pp 432–436. https://doi.org/10.1109/DEST.2008.4635147
95. Prateek S, Sadhwani Y, Arora P (2017) Movie recommender system. Search Engine Architecture, Spring 2017:1–5
96. Sarwar B, Karypis G, Konstan J, Riedl J (2001) Proceedings of the 10th international conference on World Wide Web, pp 285–295. https://doi.org/10.1145/371920.372071
97. Schafer BJ, Frankowski D, Herlocker J, Sen S (2007) Collaborative filtering recommender systems - CollaborativeFilteringRecommenderSystems.Pdf. Lncs 4321:291–324
98. Schwartz B (2005) The paradox of choice. Why More is Less American Mania . When More is Not Enough. Finance 265
99. Shani G, Gunawardana A (2011) Recommender Systems Handbook
100. Shardanand U, Maes P (1995) Social information filtering: algorithms for automating "word of mouth". Conf Hum Factors Comput Syst - Proc 1:210–217
101. Sheugh L, Alizadeh SH (2015) A note on Pearson correlation coefficient as a metric of similarity in recommender system. 2015 AI robot IRANOPEN 2015 - 5th Conf Artif Intell robot. https://doi.org/10.1109/RIOS.2015.7270736
102. Shi Y, Larson M, Hanjalic A (2014) Collaborative filtering beyond the user-item matrix: a survey of the state of the art and future challenges. ACM Comput Surv 47:1–45. https://doi.org/10.1145/2556270
103. Marko B, Shoham Y (1997) Fab: content-based, collaborative recommendation. Communications of the ACM 40(3):66–72. https://doi.org/10.1145/245108.245124
104. Shristi JAK, Mohanty SN (2018) A collaborative filtering approach for movies recommendation based on user clustering and item clustering. Springer, Singapore
105. Singh VK, Mukherjee M, Mehta GK (2011) Combining collaborative filtering and sentiment classification for improved movie recommendations. In: Sombattheera C, Agarwal A, Udgata SK, Lavangnananda K (eds) Multi-disciplinary Trends in Artificial Intelligence. MIWAI 2011. Lecture Notes in Computer Science, vol 7080. Springer, Berlin, Heidelberg. https://doi.org/10.1007/978-3-642-25725-4_4
106. Stakhiyevich P, Huang Z (2019) An experimental study of building user profiles for movie recommender 898 system. In: In: Proc - 21st IEEE Int Conf high perform Comput Commun 17th IEEE Int Conf Smart City 5th 899 IEEE Int Conf data Sci Syst HPCC/SmartCity/DSS, vol 5, pp 2559–2565. https://doi.org/10.1109/HPCC/900SmartCity/DSS.2019.00358
107. Su X, Khoshgoftaar TM (2009) A survey of collaborative filtering techniques. Adv Artif Intell 2009:1–19. https://doi.org/10.1155/2009/421425
108. Subramaniyaswamy V, Logesh R, Chandrashekhar M, Challa A, Vijayakumar V (2017) A personalised movie recommendation system based on collaborative filtering. Int J High Perform Comput Netw 10:54–63. https://doi.org/10.1504/IJHPCN.2017.083199
109. Tao L, Jiao M, Dai Y, Gao C (2017) A multilayer collaborative filtering recommendation method in electricity market. Proc - 13th web Inf Syst Appl Conf WISA 2016 - conjunction with 1st Symp big data process anal BDPA 2016 1st work Inf Syst Secur ISS 2016 51–55. https://doi.org/10.1109/WISA.2016.20
110. Ungar LH, Foster DP (1998) Clustering methods for collaborative filtering. AAAI Workshop on Recommendation Systems 1:114–129
111. Uyangoda L, Ahangama S, Ranasinghe T (2018) User profile feature-based approach to address the cold start problem in collaborative filtering for personalized movie recommendation. In: 2018 13th Int Conf digit Inf Manag ICDIM, pp 24–28. https://doi.org/10.1109/ICDIM.2018.8847002
112. Uyangoda L, Ahangama S, Ranasinghe T User Profile Feature-Based Approach to Address the Cold Start Problem in Collaborative Filtering for Personalized Movie Recommendation
113. Vimala S V, Vivekanandan K (2019) A Kullback–Leibler divergence-based fuzzy C-means clustering for enhancing the potential of an movie recommendation system SN Appl Sci 1:. https://doi.org/10.1007/s42452-019-0708-9
114. Vincent P, Larochelle H, Lajoie I, Bengio Y, Manzagol P (2010) Stacked denoising autoencoders: Learning useful representations in a deep network with a local denoising criterion. J Mach Learn Res 11:3371–3408
115. Wang L, Meng X, Zhang Y (2011) A heuristic approach to social network-based and context-aware mobile services recommendation. J Converg Inf Technol 6:339–346. https://doi.org/10.4156/jcit.vol6.issue10.43

116. Wang J, Reinders MJT, De Vries AP (2006) Unifying user-based and item-based collaborative filtering approaches by similarity fusion the brain in Duchenne muscular dystrophy view project VITALAS view project unifying user-based and item-based collaborative filtering approaches by similarity fusion. https://doi.org/10.1145/1148170.1148257
117. Wang H, Wang N, Yeung DY (2015) Collaborative deep learning for recommender systems. Proc ACM SIGKDD Int Conf Knowl Discov Data Min 2015-Augus:1235–1244. https://doi.org/10.1145/2783258.2783273
118. Wang Z, Yu X, Feng N, Wang Z (2014) An improved collaborative movie recommendation system using computational intelligence. J Vis Lang Comput 25:667–675. https://doi.org/10.1016/j.jvlc.2014.09.011
119. Weber I, Castillo C (2010) The demographics of web search. SIGIR 2010 Proc - 33rd Annu Int ACM SIGIR Conf res Dev Inf Retr 523–530. https://doi.org/10.1145/1835449.1835537
120. Wei J, He J, Chen K, Zhou Y, Tang Z (2017) Collaborative filtering and deep learning based recommendation system for cold start items. Elsevier. 69:29–39. https://doi.org/10.1016/j.eswa.2016.09.040,
121. Weng S-S, Lee C (2013) Integration of content-based approach and hybrid collaborative filtering for movie recommendation. Int Conf Bus Inf
122. Wu C-SM, Garg D, Bhandary U (2018) Movie recommendation system using collaborative filtering. In: 2018 IEEE 9th international conference on software engineering and service science (ICSESS). IEEE, pp 11–15
123. Xiao P, Shao L, Li X (2013) Improved collaborative filtering algorithm in the research and application of personalized movie recommendations. Proc - 2013 4th Int Conf Intell Syst des Eng Appl ISDEA 2013 349–352. https://doi.org/10.1109/ISDEA.2013.483
124. Yang C, Akimoto Y, Kim DW, Udell M (2019) OBoe: collaborative filtering for automl model selection. Proc ACM SIGKDD Int Conf Knowl Discov Data Min:1173–1183. https://doi.org/10.1145/3292500.3330909
125. Yang Z, Wu B, Zheng K, Wang X, Lei L (2016) A survey of collaborative filtering-based recommender systems for mobile internet applications. IEEE Access 4:3273–3287. https://doi.org/10.1109/ACCESS.2016.2573314
126. Yingyuan X, Pengqiang AI, Hsu C, et al (2015) II. RELATED WORK 2.1 content-based recommendation. 53–62
127. Yu L, Liu L, Li X (2005) A hybrid collaborative filtering method for multiple-interests and multiple-content recommendation in E-commerce. Expert Syst Appl 28:67–77. https://doi.org/10.1016/j.eswa.2004.08.013
128. Yu K, Schwaighofer A, Tresp V et al (2004) Probabilistic Memory-Based Collaborative Filtering 16:56–69
129. Zanitti M, Kosta S, Sørensen J (2018) A user-centric diversity by design recommender system for the movie application domain. Web Conf 2018 - companion world wide web Conf WWW 2018 1381–1389. https://doi.org/10.1145/3184558.3191580
130. Zargany E, Ahmadi A (2015) A new modular neural network approach for exchange rate prediction. Int J Electron Financ 8:97–123. https://doi.org/10.1504/IJEF.2015.070515
131. Zhao D, Xiu J, Zhengqiu Y, Liu C (2017) An improved user-based movie recommendation algorithm. 2016 2nd IEEE Int Conf Comput Commun ICCC 2016 - Proc 874–877. https://doi.org/10.1109/CompComm.2016.7924828
132. Zhou T, Chen L, Shen J (2017) Movie recommendation system employing the user-based CF in cloud computing. Proc - 2017 IEEE Int Conf Comput Sci Eng IEEE/IFIP Int Conf embed ubiquitous Comput CSE EUC 2017 2:46–50. https://doi.org/10.1109/CSE-EUC.2017.194

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