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Survey and Analysis of Movie recommendation systems and Filtering Algorithms

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Abstract:

This paper highlights an overview of recommender systems and describes the generation of recommendation methods. Recommender Systems are systems that help users find relevant items or products of interest from the large collection of information on the Internet. it helps users that have no enough competence to evaluate the overwhelming number of alternatives by recommending the most suitable items based on their history, preferences and constraints. Collaborative Filtering is the most popular approach used in building a recommender system due to its superior performance. There are several collaborative filtering methods developed. However, they all have an inherent problem of cold start and data sparsity. Recommender systems are a subset of information filtering systems and are software tools and techniques providing suggestions to the user according to their need. Many popular electronic commerce sites widely use Recommender systems to recommend news, music, research articles, books, and product items. This paper attempts to describe various limitations of recommendation methods and their advantages. The major problems of the existing area are reviewed and presented from different perspectives. However, solutions to these issues are rarely discussed in previous works. In this study, current trends and possible solutions to all the problems are discussed.

Keywords: Collaborative Filtering, Content-based Filtering, Hybrid filtering, Recommender System.

1.0 INTRODUCTION

The explosive growth of information in an online environment has made the case of information search and selection very serious; users are overloaded by options to consider, and they may need more time or knowledge to evaluate these options personally. Recommender systems have proven to be a key way for users to cope with information overload and have become one of the most powerful and popular tools that help users discover items or products of interest from the large collection of information. Several recommender systems to suggest relevant objects to users were developed (Agrawal & Jain, 2017; Chakrabarti et al., n.d.; Eyjolfsdottir et al., n.d.; Hande et al., n.d.; Institute of Electrical and Electronics Engineers & Hindusthan Institute of Technology, n.d.; Kumar et al., 2015), classified into three major categories: Collaborative filtering, Content-based, and Hybrid recommendation systems.

Collaborative Filtering bases its prediction on the belief that people who have a similar test or agreed in the past will also blend in the future and will settle or like similar kinds of an item as they liked in the past. Collaborative Filtering is the automatic filtering of analyzing items by gathering the opinions of others (Ekstrand et al., 2010). Content-based Filtering uses the comparison between objects and the past preferences of a particular user. It works with the user's data explicitly or implicitly to generate a user profile, which is then used to make suggestions to the user. A hybrid approach combines two or more

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techniques, like collaborative Filtering and content-based Filtering, to complement each other. Most recent recommender systems today use a hybrid-based method to overcome some of the problems in recommender systems, such as cold start and data sparsity.

2.0 Types of Filtering Algorithms:

2.1 Collaborative Filtering:

Collaborative filtering (CF) is a popular recommendation algorithm that bases its predictions and recommendations on the ratings or behavior of other users in the system. The fundamental assumption behind this method is that different users' opinions can be selected and aggregated to provide a reasonable prediction of the active user's preference. Intuitively, they assume that if users agree about the quality or relevance of some items, they will likely agree about other items.(Ekstrand et al., 2010) Collaborative filtering (CF) has only been alive for more than a decade; CF takes its geneses from something humans have been doing for centuries sharing opinions and interests with others (Dhawan et al., n.d.).

The collaborative filtering algorithm is divided into two sub-categories, which are generally called memory-based and model-based approaches. Memory-based approaches directly work with values of recorded interactions. Model-based approaches use an implicit "generative" model that elaborates the user-item interactions and tries to discover them to make new predictions.

Collaborative filtering systems are more widely researched because they can recommend different items to users, such as; Books, Music, Movies, etc. Movies are part and parcel of our life. As a result, several Collaborative filtering Recommender Systems were developed [2], [7], [8]. For example, the study [1] proposed a MovieGen Recommender system that asks users some question and act on the answers given by the users to recommend movies to them. However, the system takes little time since it asks users too many questions. [2] developed a collaborative movie recommender system (MOVREG) that recommends movies to users based on information they provided to the system. It also helps them to find movies of their choice and save time based on the experience of other users. However, the system has no right and wrong answers. Also, the study [7], [8] developed a collaborative product recommender system for online social networks that recommend products to a cluster of users based on their connection to social media sites because nowadays, people are connected through the likes of Facebook, Twitter, and so on.

2.1.1 Advantages of collaborative filtering technique:

- Implementation of RS using a Memory-Based Collaborative filtering technique is easy.
- Additional new data incrementally is easy in Memory-Based Collaborative filtering.
- Improved prediction performance by a Model-Based Collaborative filtering technique.

2.1.2 Disadvantages of the collaborative filtering technique:

- Cold Start Problem: In the case of the new user, the system either doesn't know what to recommend or performs poorly.
- Scalability: The CF technique generates recommendations over billions of users and products, which require a significantly huge amount of computational power.
- Sparsity: Only small subsets of the items are rated by the users from the available dataset of items. Hence, very few ratings are available to generate a

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recommendation, leading to poor performance.

2.2 Content-based filtering:

Content-Based Filtering (CBF): Another familiar approach in Recommender System is content-based filtering. The CBF methods are based on a profile of the user's preference and a description of the item. Shortly, this algorithm tries to recommend things related to those a user liked in the past. However, most researchers on this filtering algorithm do not consider time as a factor in their design. Practically, time is a factor that can change users' preferences. In a movie recommendation system, if a user has been watching most horror movies for some time, that user will be recommended horror movies mostly as his preference by the system based on his previous history. However, if the user switches to comedies, his current choice changes from horror to comedy. Nevertheless, due to the omission of time as a factor in filtering recommendations, the system will continue to recommend the user horror movies because horror movies make up most of their past preferences.

2.2.1 Advantages of Content-based filtering:

- Content-based recommender system provides user independence through exclusive ratings, which users use to build their profile.
- Provides transparency to the active user by explaining the working of the Content-Based filtering.
- Content-Based filtering is good for recommending items not yet rated or viewed by any user.

2.2.2 Disadvantages of Content-based filtering:

- In CB Filters, it isn't easy to generate the characteristics of an item.
- CB Filters suffer from an over-specialization problem because it advocates the same types of items.
- It is more difficult to get feedback from users in CBF because users normally do not sort the items (as in CF). Therefore, it is not possible to determine if the recommendation is correct.(Shah et al., 2018)

2.3 Hybrid approach:

A hybrid approach combines collaborative filtering, content-based filtering, and any other techniques. Most recent recommender systems today use a hybrid-based method. The hybrid filtering algorithm can be implemented in many ways; by conducting content-based and collaborative-based predictions differently and then joining them together by putting the content-based filtering capabilities to the collaborative-based approach (and vice versa) or by unifying the processes into one model. Several studies that empirically evaluate the performance of the hybrid system with the pure collaborative and content-based methods demonstrated that the hybrid methods could provide more accurate recommendations than pure approaches. These methods can also overcome common problems in recommender systems, such as cold start and the sparsity problem.

2.4 Demographic Filtering:

This filtering algorithm categorises users or items based on their attributes and makes a recommendation based on demographic categorisations. In other words, in the filtering based on demographic information, users are classified by their features, and recommendations are given to the class of demographic information.**(Biswas & Packirisamy, 1982)**

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Demographic information filtering creates categories of users with similar demographic characteristics, and then users' cumulative buying behaviour or preferences within these categories are tracked. For a new user, recommendations are made by first finding which category he falls in and then the cumulative buying and preferences of previous users are applied to that category to which he belongs. Like collaborative techniques, demographic techniques also form "people-to-people." correlations but use dissimilar data. A collaborative and the content-based method requires a history of user ratings which is of a different kind than the Demographic approach.**(Ryngksai & Chameikho, 2014)**

3.0 Related Works

Eyrun, Gaurangi, and Nan (Eyjolfsdottir et al., n.d.) designed the MovieGen Recommender system using machine learning (SVM) and cluster analysis based on a hybrid recommendation approach. They used an SVM algorithm to predict movies preference for a user based on their information, which incorporates the collaborative approach (i.e., it indicates the user choice based on the choice of other similar users) and content-based approach by taking into consideration the user choice not based on the user past but rather based on the answers he gives to the question asked by the system. The k-means clustering algorithm was used to make a recommendation from the datasets by choosing a cluster with a maximum number of movies once genres and periods have been predicted using the user preferences based on his personal information. However, the system asks a series of questions from users, which takes a lot of time to predict the user's choice because the user has to input what the system asks from him manually before the system gives a recommendation.

Manoj *et al.* (Kumar et al., 2015)developed a collaborative filtering movie recommender system (MOVREC) that recommends movies to users based on the users' information. The user is given options to choose from some attributes which include Director, Actor, Genre, Year, and Ratings, then predict the user's choices based on the preferences of previously visited history of users. The system collects the actions and feedback of users and stores it in a customized database, which may be used for generating new recommendations in the next user-system interaction. When any user enters the system, he is given a couple of options: search for a particular movie, see the upcoming movies list, or go to the recommendation page. On the recommendation page, he is given a choice to select/input values for different attributes; on this basis, the system will prepare an array of suitable movies that match the user input or value given. However, the system solely depends on the feedback or weight given by users before it recommends movies; hence, it is very difficult to evaluate the system's performance since there is no right or wrong recommendation; it is just a matter of opinion.

Harpreet, Maninder, and Amritpal (Virk et al., n.d.) proposed a hybrid online movie recommender system. The system provides movie recommendations based on Content-based and collaborative filtering for better offers. They used a user profile created at the beginning in the content-based aspect. The profile has information such as age, gender, taste, etc. Taste is based on how the User rates the items. To make a recommendation to the User, the system compares items that were rated by the User with items that the User does not rate to calculate similarities. Those items similar to rated objects will be recommended to the User. In collaborative filtering, the system focused on the relationship between the User and items, where similarities of items are determined by the similarity of ratings of those items by the User who has rated both of them. The goal of

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the system is to help users by providing relevant movie recommendations based on user feedback using simple GUI and help users to deal with information overload by giving them better recommendations. However, the system relies on user ratings (feedback) given to the movies watched by the User before a recommendation is made, whereas movies that any user has not rated will not be recommended.

Rupali *et al.* (Hande et al., n.d.) proposed a hybrid movie recommendation system known as a content-based collaborative filtering system (MOVIEMENDER); owing to the various demerits of pure content-based and pure Collaborative Filtering based systems, the system takes advantage of both the representation of the content as well as the similarities among users. The intuition behind this technique is to use a content-based predictor to fill the user-rating matrix that is sparsely distributed. The system used a mixed approach of content-based and collaborative filtering such that both algorithms complement each other, thereby improving the system's performance and accuracy. It analyses and itemizes some advantages and disadvantages of both content-based and collaborative filtering to overcome the drawbacks of each algorithm and improve the system's performance. The purpose of the system is to recommend movies to its users based on their viewing history and the ratings that they provide to the system. However, despite using the hybrid algorithm of a Content-based filtering system and a Collaborative filtering system, the Cold-start issue is still unsolved, since new users/new items suffered in the system.

Prerana and Shabnam (*Effective Hybrid Recommender Approach Using Improved K-Means And Similarity*, n.d.) Effective Hybrid Recommender Approach Using K-means and Similarity, proposed a hybrid approach using clustering and similarity to recommend things (movies, songs, books) to users. In the model, the dataset is split into two parts: Training and testing. K-means Clustering algorithm was used to make user cluster, and Spearman's rank correlation was used to calculate similarities; this reduced the RMSE and time complexity of the existing basic K-mean algorithm in which the quality of final clusters highly depends on the selection of initial centroids. They experimented on the most popular MovieLens dataset to demonstrate their system's effectiveness. The experiment is performed on MovieLens 1M dataset using MATLAB tool for matrix manipulations, plotting functions and data, implementation of algorithms, creation of user-friendly interfaces, and interfacing with programs written in other languages, including C, C++, Java, Fortran, and Python. However, the RMSE and Time complexity can still be reduced by combining various Clustering algorithms with different similarity metrics.

Ponnam *et al.* (Ponnam et al., 2016) presented Movie Recommender System Using Item Based Collaborative Filtering Technique; they proposed item-based collaborative filtering to examine the User-item rating matrix and identify the relationships among various items, then used these relationships to compute the recommendations for the User. The system uses both item-based and user-based collaborative filtering. In the item-based Recommendation process, the procedure generally looks at ratings given to similar items, in contrast with the User-based Collaborative filtering approach, which looks for the most similar users. The item-based collaborative filtering approach uses things that are most similar to the target item, for which it will predict the rating by using the item similarity weights and the K most similar items and the unknown rating. Then recommend the top N items having the highest predicted rating as recommendations to the User. A Stable

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benchmark dataset was used on the Netflix Dataset, consisting of around One million ratings from 6040 users on 4000 movies. They used adjusted cosine similarity to calculate the similarities between the items, then calculated these similarity weights to calculate the predicted rating of the movies, and then gave the top N number of recommendations to the users. However, the system prediction accuracy needs to be improved by employing some other methods; as a result shown in the paper based on Precision and recall is not encouraging; also, it relies on user feedback provided to make predictions and recommendations to users without which the system cannot make a recommendation.

Shreya and Pooja (Agrawal & Jain, 2017) proposed an Improved Approach for a Movie Recommendation System to improve the accuracy, quality, and scalability of a movie recommendation system, a Hybrid approach by unifying content-based filtering and collaborative filtering using Support Vector Machine (SVM) as a classifier and genetic algorithm were applied for optimization. The system was implemented on the Movie lens datasets of Movielens 1M dataset, Movie Lens latest small dataset, and Movie lens 10M dataset. The result of the proposed system and comparative results have been shown, which depicts that the proposed approach improves the accuracy, quality, and scalability of the movie recommendation system more than the current approaches. However, the system makes its recommendation based on genre correlation whereby user preference changes with other demographic features, such as age and sex of the user, which can be used to improve recommendation accuracy.

Ching-She, Deepti, and Unnathi (Wu et al., 2019) proposed Movie Recommendation System Using Collaborative Filtering on the Yahoo Research Webscope database to design a movie recommendation system that considers past movie ratings given by various users to provide suggestions to the User. The system uses Apache Mahout Framework and considers movie ratings to provide users with recommendations, using user-based and item-based collaborative filtering separately. For the User-based filtering, User Similarity was computed using Pearson Correlation Coefficient to determine the similarity between users' ratings. The User Neighbourhood is calculated using another machine learning algorithm of distance-based clustering called, Nearest-N-User-Neighbourhood where N is defined. The nearest Neighbour algorithm searches the N nearest data points around each data point to get the most similar data points and group them. In the item-based filtering, the machine learning algorithm Log-Likelihood-Similarity was used to compute the item similarity using the Item Similarity class of Mahout. The item-based recommendation result is loaded to the Hadoop Distributed File System (HDFS) to have scalable and fault-resistant storage. The User-Based recommender results have to be computed every time during a recommendation because, unlike items, users provide ratings. The system rating prediction accuracy is good, as claimed at 100%, where the system recommends ten movies to the User and returns the nearest neighbors who have the most similar taste preference as him. However, the system considers the user ratings to recommend movies to users, whereby a system that works this way always leaves new users/items unconsidered.

Hafed *et al.* (Jordan University of Science & Technology et al., n.d.) proposed a new collaborative filtering recommendation algorithm that benefits from the capabilities provided by the k-means clustering algorithm and Single Value Decomposition (SVD) technique. Firstly, the k-means clustering algorithm was adopted to cluster similar users in the same partition according to their movie preferences. Then the SVD was used in each

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cluster not only as a dimensionality reduction technique but also as a powerful mechanism for similarity computation, which could efficiently help find the most similar users. The proposed system was built in two main phases; the first stage is called offline model creation. In this stage, the recommendation model is created by clustering the users' ratings following their preferences and then using SVD to reduce the data dimensions and calculate user similarities. The k-means algorithm and SVD technique are used in this stage to cluster similar users and reduce dimensionality. The second stage is the online model utilization, wherein the created model produces accurate recommendations for a given active user. Their prediction accuracy is good, as claimed. However, new user/movie suffers in the system since it recommends movies to a cluster of similar users based on a rating from users of the same group.

Muyeed *et al.* (Chakrabarti et al., n.d.)proposed a machine learning-based movie recommender system using clustering and machine learning approaches. The system uses a clustering algorithm to find users with similar tastes in movies and Machine learning approaches to guess what rating a particular user might give to a specific movie so that the information can be used to recommend movies to viewers. The publicly available MovieLens dataset was used; The MovieLens dataset mainly has two files. The first file contains information about movies, such as movie id, movie title, and its list of genres. In contrast, the other file contains information about the users' ratings of a particular movie. These two files have been preprocessed and manipulated to build our system. K-means clustering has been used to separate users with similar tastes in movies. Separate neural networks have been constructed to predict the rating value of movies the new user gives by analyzing their behaviour. They claimed that the system showed 95% accuracy on average in predicting ratings from new user data, which can be used to analyze which movie should be recommended to new users. However, the system solely depends on the user rating of a particular movie before the film is recommended to the network of users in a cluster. Still, the problem is that if a user decides not to rate a movie after watching then, the system will not provide recommendations to users.

Ramin, Hadi, and Mohammad (Nakhli et al., 2019) developed a Movie Recommender System Based on the Percentage of Views using an online movie provider dataset called Namava. The system proposed an Implicit Opinion Measure (IOM) to improve the performance of movie recommender systems on implicit feedback, where the percentage of view is the main metric for the prediction in the system. The system uses a hybrid of collaborative filtering, content-based filtering, and a new method called the residual method. But for the system to work, the correlation between the percentage of views and the explicit feedback (likes and dislikes) must be known, and the validity of using the rate of views should be proved. To recommend movies in the system, the percentage of view of all items in the dataset can be predicted for a query user. The movies with the highest expected views rate will be recommended to the user. Train and test data will not be selected randomly; 80% of the first views for each user are considered the train data for the user, and the remaining as the test data. For the comparison, a random recommender system is regarded as the baseline, and the accuracy of the recommender system will be compared with it. Different methods have been tested in this part, and our best recommender system could work approximately five times better than a random recommender system. However, in a situation where the user has no

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history of view, the system will not make recommendations to him.

Almu *et. al* (Almu & Ahmad, 2022) Developed a hybrid recommender system that combines content-based filtering and collaborative filtering algorithms using machine learning (KNN) to enable movie predictions to be improved. The system solicits for users' inputs to create user profiles. It then incorporates a set of new features (such as age and genre) to be able to predict user preference changes with time. This enabled it to recommend movies to the users based on their new preferences.

4.0 Datasets

4.1 IMDb

The Internet movie database is an online database of information related to films, Television programs, home videos, internet games, and online streams. It includes cast, production crew, personal biography, plot summaries, user reviews, and ratings. As of October 2018, IMDb has approximately 5.3M Movie titles, episodes, 9.3 Personalities, and 83M registered Users, and it also has a top ranking of 250 Movies by registered users (Kumar et al., 2015).

4.2 Film Trust

This is a small and publicly available dataset extracted from the entire Film Trust site. This dataset has about 35,497 ratings collected from 1,508 users on about 2,071 movies, in which the rating is a multiple of 0.5, ranging from 0.5 to 4. The sparsity of Film Trust is 98.86% (Golbeck & Hendler, 2006).

4.3 Kaggle Dataset

Kaggle, an auxiliary of Google LLC, is an internet community of Data Scientists and machine learning practitioners. It allows users to find and publish datasets, explore and create models in an online data-science working environment, work with other data scientists and machine learning Experts, and enter competitions to solve data science challenges (Rajeev Kumar | Guru Basava | Felicita Furtado, 2020).

4.4 Netflix

This is an open competition for the best collaborative filtering algorithm to foresee user ratings for films based on previous ratings without any information about the user or films. It provides training datasets of 100,480,507 ratings that 480189 users gave to 17,770 movies (Ponnam et al., 2016).

4.5 MovieLens Datasets

This is a Free Dataset of movie ratings gathered from movielens.org; it contains user ratings, movie metadata, and user metadata. The datasets were collected over various periods. Movielens Dataset is of different categories: Movielens 100K Movie rating: this dataset has 100,000 movie ratings from 1000 users on 1700 movies. Movielens 1M has a 1M movie rating from 6000 users on 4000 movies. Movielens 10M dataset has a 10M movie rating from 72000 users on 10,000 movies,

Movielens 25M: it has about 20M movie ratings from 138,000 users on 27,000 movies and Movielens Latest Datasets this is of small and full contains; the small contains 100,000 movie ratings and 3,600 tag applications applied to 9000 movies by 600 users, while the full has 27M movie rating and 1100,000 tag applications applied to 58,000 movies by 280,000 users with 14M relevance scores across 1,100 tags as at 9/2019 (GroupLens, 2021). The Movielens Latest Datasets of 100K and 1M ratings were used in this research.

MovieLens datasets are one of the most used datasets from movielens.org. The datasets have been chosen to be suitable for many types of research because of the following: It is publicly available for download and consists of unnamed ratings of movies gathered by

GroupLens Research. The MovieLens datasets were used in different research (Agrawal & Jain, 2017; Chakrabarti et al., n.d.; *Effective Hybrid Recommender Approach Using Improved K-Means And Similarity*, n.d.; Institute of Electrical and Electronics Engineers & Hindusthan Institute of Technology, n.d.; Jordan University of Science & Technology et al., n.d.; Ponnam et al., 2016), and turn to be efficient in the research outcome.

5. Conclusion:

We studied various research papers, including those mentioned in related work, and the results show that Collaborative Filtering is the most widely used filtering technique. It also has some issues related to sparsity, accuracy, scalability, etc. Most of the research results of many authors show that they focused mainly on Scalability, Cold Start, sparsity and Accuracy. Still, there needs to be more work done on the sparsity issue. Since internet data is growing exponentially, sparsity increases as new records, items, things, music, data, etc., are loaded daily. The hybrid approach is the new dimension of research on recommender systems, where two or more techniques are combined to complement each other. Most recent recommender systems today use a hybrid-based method to overcome some problems in recommender systems, such as cold start and data sparsity.

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