# Movie Recommendation System: A Review Report

**Pooja**
*M.Tech Scholar*
*Department of Mechanical Engineering*
*Geeta Engineering College, Naultha, Panipat, India*

**Mr. Bhupender Sharma**
*Assistant Professor*
*Department of Mechanical Engineering*
*Geeta Engineering College, Naultha, Panipat, India*

## Abstract

Recommendation system plays important role in Internet world and used in many applications. It has created the collection of many application, created global village and growth for numerous information. This paper represents the overview of Approaches and techniques generated in recommendation system. Recommendation system is categorized in three classes: Collaborative Filtering, Content based and hybrid based Approach. This paper classifies collaborative filtering in two types: Memory based and Model based Recommendation .The paper elaborates these approaches and their techniques with their limitations. The result of our system provides much better recommendations to users because it enables the users to understand the relation between their emotional states and the recommended movies.

**Keywords:** **Matlab, Optimization, Particle Swarm Optimization, Movie Recommendation System**

## I. INTRODUCTION

In the year 1992, David Goldberg, David Nichols, Brian M. Oki and Douglas Terry developed 'Tapestry system' for filtering mails which were relying on collaborative filtering. Here, the term collaborative filtering means people are getting together to share their views about particular items and checking out each other's reviews on the basis of whatever reading material they are having at that time. Moreover, annotations were a major part of recording reviews of people as during the time of 'Tapestry system' mails were annotated and recorded so that further filtering can be made possible. Furthermore, implicit and explicit feedback was also a major part of the process because for rating based recommendations they provided an explicit feedback. Likewise, to the systems that would later on use ratings (yet not limited to) to recommend products, like on Amazon.com. Global characteristics of the mail were also used. It has been vividly seen that recommendation systems has been a major part of consumerism as majority of people relate recommendation systems as a apart of e-commerce sites and shopping destinations. Therefore, recommendation systems find numerous applications when it comes to purchasing or surfing information about any particular product .To substantiate my view, internet sites, shopping websites, electronics etc. are visited by people on daily basis foe meeting their needs. In addition to this, recommendation systems are conspicuously used in guiding people about variety of products that they enquire or they are interested in buying. The category of the idea is based upon some general issues that may include previous buying behavior of the customer and demographics of persons. Paul Resnick and Hal R. Varian, in the year 1997 introduced the term Recommender System'. There were basically two prominent reasons behind finding this particular name as the first and foremost was recommenders could not work properly as the users were unaware of each other's identity, apart from that the other reason was their recommendation also included the interest of the user. Implicit feedback for recommendations was also being provided in combination with the aggregation techniques [2]. To exemplify, collaborative filtering of internet news was done by a system called Group lens, it worked on two strategies first one was implicit feedback through reading time and explicit feedback through ratings. Furthermore, taking into consideration the privacy concerns of users a new strategy was also recommended and it was pseudonyms and to combine various recommendations weighted voting was used. Not only the efficiency but the cost was also given attention and it was found that maintenance and progress of these systems was hefty and it was important to identify whether the merits outweigh the demerits.

## II. RELATED WORK

In the field of recommendation system and further considered the various parameters for analyzing the efficiency of a recommendation system such as robustness, quality, accuracy and scalability. She also analyzed that by knowing about these parameters further advancements can be done easily in future research work. Furthermore, she mentioned the system and user's perspective for evaluation which includes particularly robustness, confidence, sparsity, scalability, trust, and privacy and user preference [1]. In a systematic manner the approach has been explained and outputs were shown. Comparison of already prevailing approaches is done with it and consequently analyze the results is performed. It is also compared with existing approaches, and the results have been analyzed and interpreted. Evaluation metrics such as mean absolute error (MAE), standard deviation (SD), root mean square error (RMSE) and t-value for the movie recommender system delivers better results as our approach offers lesser value of the mean absolute error, standard deviation, and root mean square error [2]. This paper presents

[3] a new regression model based on the support vector machine (SVM) classification and an improved PSO (IPSO) for the development of an electronic movie PRS. The implementation process is defined in steps. Firstly, establishment of SVM classification model to attain a list of movie recommendations for ratings of movie which is based on regression model of SVM .At last, the proposed method helped in combining the user demographic information and behavior to understand the user preferences. This paper [4] proposed the use of collaborative Filtering (CF) with personalized recommendation system (PRS) and support vector machine (SVM) classification. However, they also used improved PSO (IPSO) in their research work. Moreover, they considered two major factors or parameters users' demographic and behavioral information. Furthermore, their research worked on two principles namely pre-classification and personalized recommendation. Additionally, the result included an improved PSO algorithm and aggregation degree factor (IPSO) .They also used movie lens data set and compared five recommendation methods. This paper [5] presented a novel model for movie recommendations using additional visual features extracted from pictorial data like posters and still frames, to better understand movies. This paper investigated both low-level and high-level visual features from the movie posters and still frames for further improvement of recommendation methods. Extensive experiments on real world datasets show that our approach leads to significant improvement over several state-of-the-art methods. In this [6], proposed a movie recommender system Movie Mender. The objective of Movie Mender is to provide accurate movie recommendations to users. Usually the basic recommender systems consider one of the following factors for generating recommendations; the preference of user i.e. content based filtering) or the preference of similar users (i.e. collaborative filtering). To build a stable and accurate recommender system a hybrid of content based filtering as well as collaborative filtering will be used. It [7] compared User-based and Item-based Collaborative Filtering Algorithms with many different similarity indexes with their accuracy and performance. We provide an approach to determine the best algorithm, which give the most accurate recommendation by using statistical accuracy metrics. The results are compared the User-based and Item-based algorithms with movie recommendation data set. This paper [8] worked on K-Means based crowd-aware recommender system which considered the nearest crowd of a specified user then further located preferences of those which can be suggested to the user at that point of time. In a particular dataset, to make a cluster of spots among the set of spots a K-means clustering algorithm is used. This paper [9] discussed the cold start problem which arises due to data irregularity. In search of similar set movie labels are used for improving the user recommended rate of the new movie in cold start problem. In the testing with movie lens dataset, this particular method of optimization outweighs the original algorithm. It [10] presented a new set of benchmark tasks designed to evaluate end-to-end dialog systems. The movie dialog dataset measures how well such models can perform at both goal driven dialog, of both objective and subjective goals thanks to evaluation metrics on question answering and recommendation tasks, and at less goal driven chit-chat.

In this paper [11] implemented the recommendation system based on collaborative filtering using Mahout. Mahout is such a data mining framework that normally runs coupled with the Hadoop infrastructure at its background to manage huge volumes of data. Movie Recommendation systems store user preferences over movies and find the relation between users and movies based on properties of movies like director, actor, actress, singer or producer etc. This paper [12] presented a new factor termed as human emotions while using recommendation systems along with Content Based Filtering (CBF), Collaborative Filtering (CF), emotions detection algorithm and their own algorithm, which is represented by matrix. In addition to this, the advantage lies in the fact that there is a relation between people’s emotional states and the recommended movies. In this paper [13] studied various classes of recommendation system namely Collaborative Filtering, Content based and hybrid Approach. Her paper classifies collaborative filtering in two types particularly memory based and model based Recommendation .The paper elaborates these approaches and their techniques with their demerits. This paper shows the survey in which various hybrid approaches also lack some kind of accuracy levels because of information explosion, in terms of quality and secrecy new methods should be developed and this particular area should be searched. Majority of the time the unfair rating problem is not considered by the movie recommendation systems [14]. This type of unfair rating is correctly examined by him an corrected also. Moreover, he suggested analyze of user‘s emotions and reviews from twitter should be considered. Consequently, it becomes possible to suggest the movie in which the candidate has interest in a timely Movie lens data was used in his approach. A [15] recommendation system based on collaborative filtering called MOVREC. Therefore, two parameters were taken into consideration which includes K- means algorithm and ratings given by users. The platform used by them was PHP using Dreamweaver 6.0 and Apache Server 2.0.They suggested having a larger data set that will enable more meaningful results using their system. Additionally, they planned for using incorporates different machine learning and clustering algorithms. Finally, they proposed to implementation of a web based user interface that has a user database, and has the learning model associated to each user. In this paper [17] understood the need of implementing a recommendation system because there is myriad number of data available on internet, to make it easy for user to access right data. However selection of neighbors has become harder in present time. Therefore he represented a hybrid model-based movie recommendation system which utilizes the improved K-means clustering along with genetic algorithms (GA). It [18] studied the role of internet in making the recommendation system a crucial one in people’s life as there are various factors on which the selection of a user depends and it may include location, history and interest of users. It [19] demonstrated a hybrid approach of implementing recommendation systems using content based methods as well as collaboration methods. They did experimentations on a movie data to show optimum levels of accuracy. Moreover, they increased the accuracy level in comparison to matrix factorization approach. Additionally, it was proposed that demographic information of the users along with the genre information of the users can further help in inclining the accuracy levels. In this paper [20] applied collaborative filtering approach to make a movie recommendation system. They applied expectation Maximization Algorithm.

## III. Phases of Recommendation Process

### A. Explicit Feedback

The system normally activates the person via the device interface to provide rating for items to construct and enhance his version. The accuracy of recommendation relies upon on the amount of ratings supplied via the person. The only shortcoming of this method is, it requires effort from the customers and additionally, customers aren't constantly ready to supply sufficient facts. Despite the fact that specific feedback needs more effort from consumer, it's far still seen as presenting extra dependable information, since it does now not involve extracting options from moves, and it additionally provides transparency into the recommendation system that effects in a slightly better perceived recommendation great and greater confidence inside the recommendations [3].

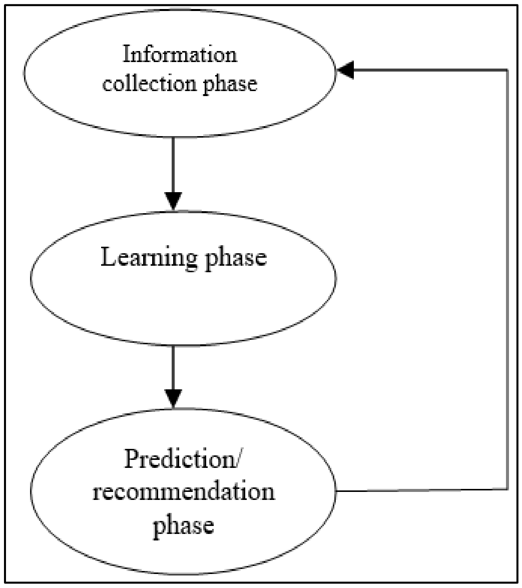


Fig. 1: Recommendation Phases

## IV. Recommendation Filtering Techniques

The use of efficient and accurate recommendation techniques is very important for a system that will provide good and useful recommendation to its individual users. This explains the importance of understanding the features and potentials of different recommendation techniques. Figure 2 shows the anatomy of different recommendation filtering techniques.

### A. Content-Based Filtering

Content-based technique is a domain-dependent algorithm and it emphasizes more on the analysis of the attributes of items in order to generate predictions. When documents such as web pages, publications and news are to be recommended, content-based filtering technique is the most successful. In content-based filtering technique, recommendation is made based on the user profiles using features extracted from the content of the items the user has evaluated in the past. Items that are mostly related to the positively rated items are recommended to the user. CBF uses different types of models to find similarity between documents in order to generate meaningful recommendations. It could use Vector Space Model such as Term Frequency Inverse Document Frequency (TF/IDF) or Probabilistic models such as Decision Trees [23]. Neural Networks to model the relationship between different documents within a corpus. These techniques make recommendations by learning the underlying model with either statistical analysis or machine learning techniques. Content-based filtering technique does not need the profile of other users since they do not influence recommendation. Also, if the user profile changes, CBF technique still has the potential to adjust its recommendations within a very short period of time. The major disadvantage of this technique is the need to have an in-depth knowledge and description of the features of the items in the profile.

 

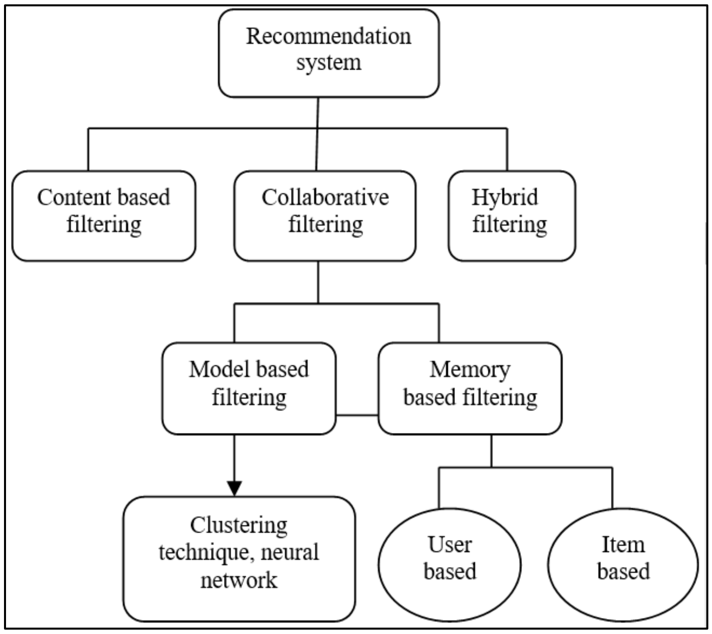

Fig. 2: Recommendation Techniques

### *B. Collaborative Filtering*

Collaborative filtering is a domain-independent prediction technique for content that cannot easily and adequately be described by metadata such as movies and music. Collaborative filtering technique works by building a database (user-item matrix) of preferences for items by users. It then matches users with relevant interest and preferences by calculating similarities between their profiles to make recommendations [14]. Such users build a group called neighborhood. A user gets recommendations to those items that he has not rated before but that were already positively rated by users in his neighborhood. Recommendations that are produced by CF can be of either prediction or recommendation. Prediction is a numerical value, Rij, expressing the predicted score of item j for the user i, while Recommendation is a list of top N items that the user will like the most as shown in figure 3. The technique of collaborative filtering can be divided into two categories: memory-based and model-based [15,16].

*1) Model-Based Techniques*

This technique employs the previous ratings to learn a model in order to improve the performance of Collaborative filtering Technique. The model building process can be done using machine learning or data mining techniques. These techniques can quickly recommend a set of items for the fact that they use pre-computed model and they have proved to produce recommendation results that are similar to neighborhood-based recommender techniques. Examples of these techniques include Dimensionality Reduction technique such as Singular Value Decomposition (SVD), Matrix Completion Technique, Latent Semantic methods, and Regression and Clustering. Model-based techniques analyze the user-item matrix to identify relations between items; they use these relations to compare the list of top-N recommendations. Model based techniques resolve the sparsity problems associated with recommendation systems.

*2) Memory Based Techniques*

The items that were already rated by the user before play a relevant role in searching for a neighbor that shares appreciation with him [17]. Once a neighbor of a user is found, different algorithms can be used to combine the preferences of neighbors to generate recommendations. Due to the effectiveness of these techniques, they have achieved widespread success in real life applications. Memory-based CF can be achieved in two ways through user-based and item-based techniques. User based collaborative filtering technique calculates similarity between users by comparing their ratings on the same item, and it then computes the predicted rating for an item by the active user as a weighted average of the ratings of the item by users similar to the active user where weights are the similarities of these users with the target item. Item-based filtering techniques compute predictions using the similarity between items and not the similarity between users. It builds a model of item similarities by retrieving all items rated by an active user from the user-item matrix, it determines how similar the retrieved items are to the target item, then it selects the k most similar items and their corresponding similarities are also determined. Prediction is made by taking a weighted average of the active users rating on the similar items k.

*3) Problems of Collaborative Filtering Techniques*

Collaborative Filtering has some major advantages over CBF in that it can perform in domains where there is not much con-tent associated with items and where content is difficult for a computer system to analyze (such as opinions and ideal). Also, CF technique has the ability to provide serendipitous recommendations, which means that it can recommend items that are relevant to the user even without the content being in the user's profile [18]. Despite the success of CF techniques, their widespread use has revealed some potential problems such as follows.

*a) Cold-Start Problem*

This refers to a situation where a recommender does not have adequate information about a user or an item in order to make relevant predictions. This is one of the major problems that reduce the performance of recommendation system. The profile of such new user or item will be empty since he has not rated any item; hence, his taste is not known to the system [19].

*b) Data Sparsity Problem*

This is the problem that is occur as a result of lack of enough information, that is, when only a few of the total number of items available in a database are rated by users [20]. This always leads to a sparse user-item matrix, inability to locate successful neighbors and finally, the generation of weak recommendations. Also, data sparsity always leads to coverage problems, which is the percentage of items in the system that recommendations can be made for [8].

*c) Scalability*

This is another problem associated with Recommendation algorithms because computation normally grows linearly with the number of users and items [6].A recommendation technique that is efficient when the number of dataset is limited may be unable to generate satisfactory number of recommendations when the volume of dataset is increased. Thus, it is crucial to apply recommendation techniques which are capable of scaling up in a successful manner as the number of dataset in a database increases. Methods used for solving scalability problem and speeding up recommendation generation are based on Dimensionality reduction techniques, such as Singular Value Decomposition (SVD) method, which has the ability to produce reliable and efficient recommendations.

*d) Examples of Collaborative Systems:*

Ringo [15] is a user-based CF system which makes recommendations of music albums and artists. In Ringo, when a user initially enters the system, a list of 125 artists is given to the user to rate according to how much he likes listening to them. The list is made up of two different sections. The first session consists of the most often rated artists, and this affords the active user opportunity to rate artists which others have equally rated, so that there is a level of similarities between different users' profiles. The second session is generated upon a random selection of items from the entire user-item matrix, so that all artists and albums are eventually rated at some point in the initial rating phases.

Group Lens [7] is a CF system that is based on client/server architecture; the system recommends Usenet news which is a high volume discussion list service on the Internet. The short lifetime of Netnews, and the underlying sparsity of the rating matrices are the two main challenges addressed by this system. Users and Netnews are clustered based on the existing news groups in the system, and the implicit ratings are computed by measuring the time the users spend reading Netnews.

Amazon.com [5] is an example of e-commerce recommendation engine that uses scalable item-to-item collaborative filtering techniques to recommend online products for different users. The computational algorithm scales independently of the number of users and items within the database. Amazon.com uses an explicit information collection technique to obtain information from users. The interface is made up of the following sections, your browsing history, rate these items, and improve your recommendations and your profile. The sys-tem predicts users interest based on the items he/she has rated.

### *C. Hybrid Filtering*

Hybrid filtering technique combines different recommendation techniques in order to gain better system optimization to avoid some limitations and problems of pure recommendation systems [14,15].The idea behind hybrid techniques is that a combination of algorithms will provide more accurate and effective recommendations than a single algorithm as the disadvantages of one algorithm can be overcome by another algorithm [16]. Using multiple recommendation techniques can suppress the weaknesses of an individual technique in a combined model. The combination of approaches can be done in any of the following ways: separate implementation of algorithms and combining the result, utilizing some content-based filtering in collaborative approach, utilizing some collaborative filtering in content-based approach, creating a unified recommendation system that brings together both approaches.

### *D. Switching Hybridization*

The system swaps to one of the recommendation techniques according to a heuristic reflecting the recommender ability to produce a good rating. The switching hybrid has the ability to avoid problems specific to one method e.g. the new user problem of content-based recommender, by switching to a collaborative recommendation system. The benefit of this strategy is that the system is sensitive to the strengths and weaknesses of its constituent recommenders. The main disadvantage of switching hybrids is that it usually introduces more complexity to recommendation process because the switching criterion, which normally increases the number of parameters to the recommendation system, has to be determined [20].

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