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Updates on Movie Recommendation System

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ABSTRACT
In recent years, there is a huge number of movies on the internet. Users have different desires for a movie to watch as there are different cultures, languages, and genres to choose from in a movie domain. As a result, a recommendation system approach is used to suggest the best movies to users according to their preferences. Several different algorithms and strategies have been proposed to effectively capture users' interest and provide an accurate recommendation of movies. Memory-Based Collaborative Filtering Recommender Systems existed for the best part of the last two decades. It is an advanced technology, implemented in various commercial applications which because of its effectiveness has been the predominantly used technique to date in recommendation system. Memory-based collaborative filtering approach is popularly and extensively used in practice but yet faces some key challenges in providing high-quality recommendations due to the daily increase of items and visitors of different websites. This paper presents a review of different techniques and similarity measures used in the movie recommendation system and also proposed a model that can be used to build robust, accurate and scalable movie recommendation to users.

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INTRODUCTION

The movie recommendation system is extensively used in several media platforms online, which aim to help users access their preferred movies efficiently from a vast movie library [21]. At the moment, there is a tremendous number of movies available on the internet as the source of entertainment has been increasing rapidly, due to the revolution in the entertainment industry. Users have to choose their favourite movie from a large number of available options which can be tedious and overwhelming to any user. As a consequence, building an automated system having different approaches to recommend the most suitable movie products to users can be of great significance. Due to an explosive growth of internet data in the recent time, recommendation systems have become increasingly popular and widely used in areas such as movies, news, e-commerce, books, and other utilities [2]. A recommendation system is an information filtering model that predicts and suggests the most relevant item(s) such as movies, news, books, music and places to users based on their preferences [3,4]. These systems have several benefits, [4] the most important

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being customer satisfaction and generating revenue for e-commerce companies. There are three main types of approaches to develop a recommendation system [5,6] namely: (i) content-based filtering, (ii) collaborative filtering, (iii) hybrid system method.

The Content-based filtering method [4][27] considers the descriptions and features of customer's interested items to provide suggestions. A content-based recommendation system works with data that the user provides either implicitly (e.g user's personal information) or explicitly (e.g movie rating) [5-7]. Based on that, a profile of the user is constructed which is then used to provide recommendations. The system becomes more accurate as the user provides more inputs or takes more actions on the recommendations [4][24]. This technique doesn't require other user's data to provide recommendations thus, it has no cold start or sparsity problems [7][30]. A Content-based approach can also recommend items that are new and unpopular to users [8]. Nevertheless, content-based filtering has some drawbacks. In [5][6][28] it recommends only items within the spectrum of previously liked items as it is incapable to exploit the quality judgment of other users. Also finding an appropriate feature or description of an item is often difficult in this technique.

In a collaborative filtering technique, recommendations are provided not based on the context but by analyzing the behaviour of different users and their preferences [21]. It analyses how similar the taste of one user is to another user and makes recommendations based on that [1][25][6]. In this case, movies ratings are collected from different users and then suggest the most relevant movie to customers based on neighbouring users with similar choice and interest in the past [1]. Nowadays, collaborative filtering is the most efficient approach used by movie recommendation systems, which is based on the idea of the nearest-neighbour mechanism [1]. This method assumes that users with similar history rating patterns may likely have the same preference in the future [1][5]. The Collaborative filtering technique has a very interesting property of being able to do future learning on its own, which means it can start to learn for its self what features to use [22-25]. However, collaborative filtering method always suffers from many issues such as 'sparsity' due to insufficiency in user's history rating data, 'scalability' because of the rapid increase in the number of users/items and 'cold start problems' due to a new user or product in the system [1][5-8]. The hybrid recommendation system is the combination of the result obtained from the content-based filtering and collaborative filtering method to provide better recommendations [29]. It takes advantage of both the approaches to build a more efficient recommendation system [6-8]. Figure 1 illustrates a framework of the different techniques used in the recommendation system.

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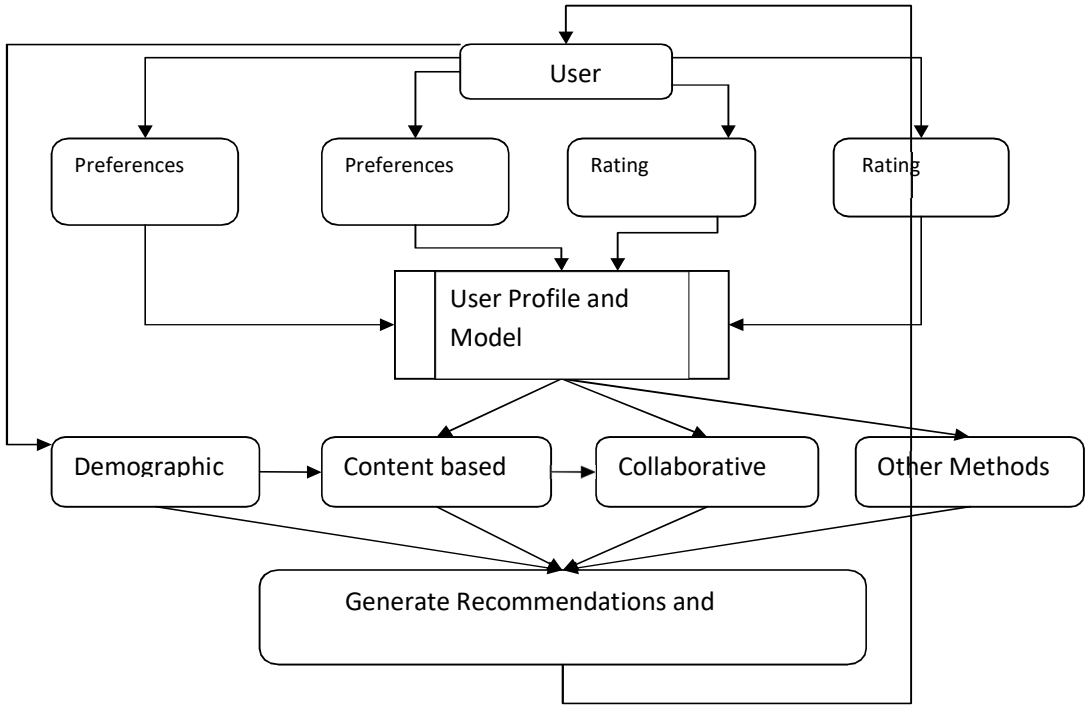


Figure 1: General Framework of Recommender System

RELATED WORKS

Kumar et al [6] have presented a movie recommendation system using a collaborative filtering approach which considered user's rating to provide recommendations. The proposed system uses the K-means algorithm to sort movies. W. Chen et al [9] proposed a fully content-based recommendation system technique to recommend movies. In the proposed system, a neural network is used to obtain features of movies and learn similarities between them. The method provides recommendations of movies based on that similarity.

Table 1: Advantage(s) and Disadvantage(s) of existing recommendation system methods

SN	Paper title	Approach used	Advantages	Disadvantages
1	A Movie recommender system: MOVREC [6]	Collaborative filtering approach.	Improve prediction quality.	Cold Start problem.
2	Fully content-based movie recommender system with feature extraction using neural network [9]	Content-based filtering approach.	Improve prediction quality.	Over specialized and computationally costly.
3	A collaborative filtering recommendation engine in a distributed environment [16]	Collaborative filtering approach	More robust to sparse data (Less sparsity)	Scalability problem.

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SN	Paper title	Approach used	Advantages	Disadvantages
4	An SVM based collaborative filtering approach for top –n web service recommendation [11]	Collaborative filtering approach.	Improve prediction quality and scalability problem.	Gray sheep problem.
5	A hybrid recommendation algorithm based on Hadoop [15]	Hybrid approach	Improve speed and achieve better performance.	Less scalable and fails for large data sets.
6	An Improved content-based collaborative filtering algorithm for movie recommendations [13].	Content and collaborative filtering approach.	Better efficiency and scalability.	Cold start problem.
7	Improving the Effectiveness of Collaborative Filtering on Anonymous Web Usage Data [18].	Collaborative Filtering approach	Fast results show because of clustering, Scalability problem solved.	Gray Sheep problem and cold star problems
8	A Hybrid Recommender System for Dynamic Web Users, International Journal Multimedia [19]	The content-based filtering approach	Improve prediction quality	Gray Sheep problem

Antonio et al [10] described a peculiar method of predicting user's preferences in recommendation systems. It makes use of a non-negative matrix factorization collaborative filtering which is based on the Bayesian probabilistic model. L. Ren and W. Wang [11] described a collaborative filtering method to provide desired services by the use of support vector machine (SVM) to filter out the services which are preferred by the users. A. Ali et al [12] proposed a content-based recommendation system method to recommend music. The method represents music as a vector to find similar songs using a deep learning approach. With this technique, the issue of the cold start problem is overcome. A. pal et al [13] proposed a movie recommendation system using an improved content-based collaborative filtering algorithm, by finding similarities of genres and tags between the content of one movie and other which are preferred by the user. The method used two deep learning networks to rank and generate candidates. Sasmita et al [14] have presented a way to enhance the issues of sparsity and scalability based on machine learning methods. The proposed work come up with a hybrid based recommendation approach by combining clustering method and dimensionality reduction to improve the efficiency of traditional collaborative filtering technique. Kunhui et al [15] have introduced a recommendation algorithm to ensure scalability and minimize time consumption of the complex process. The algorithm is implemented by the use of the Map-Reduce programming paradigm. The hybrid algorithm has 3 main steps which are: constructing the user-item matrix, using a k-means algorithm to form user cluster and predicting the target item ratings to recommend top-n items to a user by the use of slope one algorithm. Table 1 depicts a comparison of some

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existing recommendation system approaches related to this study each with respective advantage(s) and disadvantage(s).

Table 2: Different Similarity Measures

Serial No	Name	Definition	Formula
1.	Pearson Correlation	This similarity metric has a value between -1 and +1 where a positive high value suggests a high correlation, a negative high value suggest contrariwise high correlation (when one say True the other says False), and lastly, a zero correlation indicates uncorrelated samples. It is used to figure out the linear relationship between items such that a change in one item results in a proportional change in the other item.	$R(j,k)=\frac{\sum_{u\in U}(R_{(u,j)}-\bar{R}_j)(R_{(u,k)}-\bar{R}_k)}{\sqrt{\sum_{u\in U}(R_{(u,j)}-\bar{R}_j)^2}\sqrt{\sum_{u\in U}(R_{(u,k)}-\bar{R}_k)^2}}$ Where $R_{(u,j)}$ indicates the rating of user u on item j, while $R_{(u,k)}$ indicates the rating of item k given by the same user u. $\bar{R}_j$ and $\bar{R}_k$ indicates the average ratings of the *i*-th and *j*-th items respectively.
2.	Cosine Similarity	The Cosine Distance similarity function looks at two samples to compare and studies the cosine of the angle between them to measure the similarity. In this case, two items are thought of as two vectors in the *m* dimensional user-space.	$Cos\left(\vec{i},\vec{j}\right)=\frac{\left(\vec{i}.\vec{j}\right)}{\left\|\vec{i}\right\|_2 * \left\|\vec{j}\right\|_2}$ Where i and j represent the respective vectors.
3.	Adjusted Cosine Similarity	Unlike in the case of Pearson Correlation similarity computation that considers the average rating of user u for the co-rated items, the Adjusted cosine similarity computation is done by subtracting the average rating of the corresponding user u from each co-rated pair (i.e. all the items rated by user u).	$A(j,k)=\frac{\sum_{u\in U}(R_{(u,j)}-\bar{R}_u)(R_{(u,k)}-\bar{R}_u)}{\sqrt{\sum_{u\in U}(R_{(u,j)}-\bar{R}_u)^2}\sqrt{\sum_{u\in U}(R_{(u,k)}-\bar{R}_u)^2}}$ Where $R_{(u,j)}$ and $R_{(u,k)}$ indicates the ratings given by user u to item j and item k respectively. $\bar{R}_u$ is a vector indicating the average rating given by user u to a different item in the matrix of Item-User
4.	Euclidean Distance	This is the most common use of a distance; it examines the root of the square difference between coordinates pair of items/users respectively.	$S(u,v)=\sqrt{\frac{\sum_{i\in I_{uv}}\left(R_{ui}-R_{vi}\right)^2}{\left\|I_{uv}\right\|}}$ Where *S*(*u, v*) represents the similarity of users *u* and *v*, across all items commonly rated.
5.	Mean Squared Distance	Mean squared distance is a measure of the average of the squares of the errors that is, the average squared difference between the estimated values and the actual value. it is always non-negative, and values closer to zero are better.	$S(i,j)=\frac{\sum_{i\in U_{ij}}\left(R_{iu}-R_{ju}\right)^2}{\left\|U_{ij}\right\|}$ Where *S*(*i, j*) represents the similarity of items *i* and *j*, across all users that rated such items.

Schafer et. al. [20] summarizes some of the significant questions in which a Collaborative Filtering algorithm tries to assist. They are: Help me find new items I might like, advise me on a particular item, help me find a user (or some users) I might like, help our group find something new that we might like, help me find a

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mixture of "new" and "old" items, help me with tasks that are specific to this domain. To be successful at this task, a Collaborative Filtering algorithm has to tackle two issues: identify similar users or items to the target one, and average their (potentially weighted) ratings, to predict unrated items, so that the ones with the highest score can be recommended to the user.

PROPOSED SYSTEM

The major step in the technique of collaborative item-based filtering is to compute item similarity and then choose the top items with high similarity among. The key concept used in computing item similarity between two items is to first isolate the users who have rated both of these items in the form of a weighted matrix and then apply the method of similarity computation to find the similarity weight value which is then used to make predictions. In our work, we proposed two different ways to compute such similarity weights between items and make a comparison between the different approaches.

Cosine Distance Similarity

The Cosine Distance similarity function looks at two samples to compare and studies the cosine of the angle between them to measure the similarity. In this case, two items are thought of as two vectors in the *m* dimensional user-space. The similarity between them is measured by computing the cosine of the angle between these two vectors. In vector form, the Cosine Distance similarity is defined as:

$$Cos\left(\vec{i},\vec{j}\right) = \frac{\left(\vec{i}\,.\,\vec{j}\right)}{\left\|\vec{i}\right\|_2 * \left\|\vec{j}\right\|_2} \quad (1)$$

Where i and j are the respective vectors.

Adjusted Cosine Similarity

Adjusted cosine similarity computation is done by subtracting the average rating of the corresponding user u from each co-rated pair (i.e. all the items rated by user u). This method reduces the number of big error predictions and hence improve the accuracy of predictions in the recommendation system. The Adjusted Cosine Distance was proposed as a way to compensate for the fact that users rate items differently. The similarity weight AC(j,k) between items j and k is calculated using the formula below.

$$AC(j,k) = \frac{\sum_{u\in U}(R_{(u,j)} - \bar{R}_u)(R_{(u,k)} - \bar{R}_u)}{\sqrt{\sum_{u\in U}(R_{(u,j)} - \bar{R}_u)^2}\sqrt{\sum_{u\in U}(R_{(u,k)} - \bar{R}_u)^2}} \quad (2)$$

Here $R_{(u,j)}$ and $R_{(u,k)}$ indicates the ratings given by user u to item j and item k respectively. $\bar{R}_u$ is a vector indicating the average rating given by user u to a different item in the matrix of Item-User.

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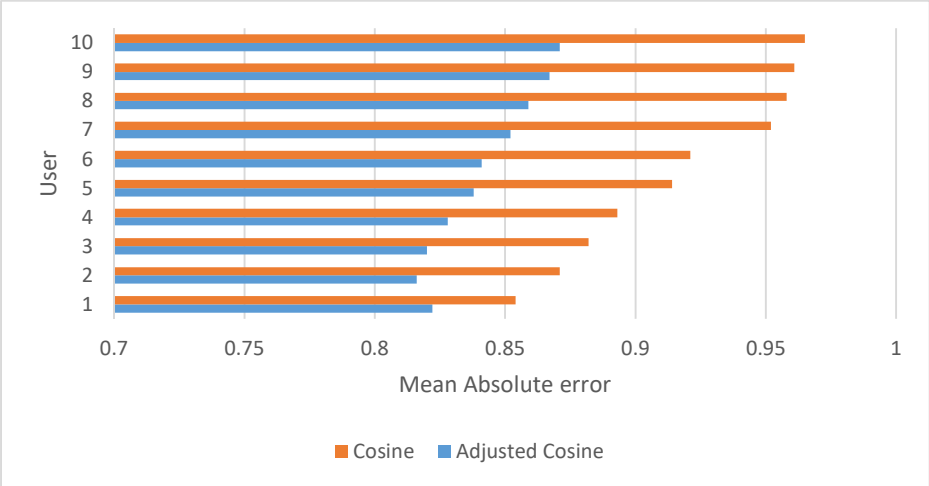


Figure 2: MAE of Adjusted Cosine and Cosine similarity measures Using Collaborative Filtering Recommendation System.

In our experiment we made a relative comparison of root mean square error (RMSE) and mean absolute error (MAE) in each of the two approaches (Adjusted cosine and Cosine similarity) we proposed in building an effective collaborative filtering recommender system. We firstly choose the top-recommended movies in each scenario for 10 different users and calculate the root mean square error (RMSE) and mean absolute error (MAE) respectively in each case for comparison. As can be seen in figure 2 and figure 3 for 10 different users, adjusted cosine has an overall relatively lower (RMSE) and MAE over Cosine similarity measure and therefore better accuracy.

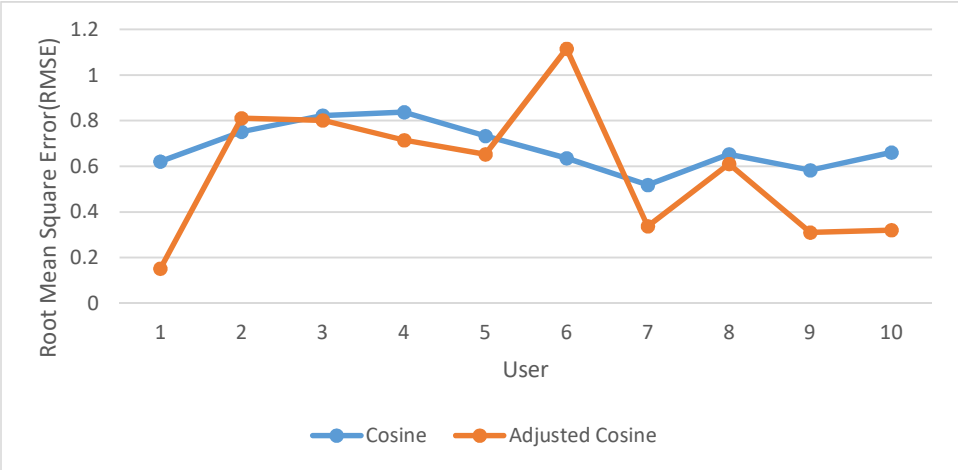


Figure 3: RMSE of Adjusted Cosine and Cosine similarity measures Using Collaborative Filtering Recommendation System.

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CONCLUSION

Recently, a large number of recommendation filtering techniques have been proposed and implemented using either content-based filtering, collaborative filtering method or a combination of both to create a hybrid system recommendation method. In this paper, we have studied and analyzed the existing systems, the approaches and the similarity measures used in recommendation system techniques. As shown in figure 3 and figure 4, offsetting the average rating of the user from all the items rated by the user himself in the case of adjusted cosine is better in minimizing prediction error as the value of mean absolute error (MAE) and root means square error (RMSE) respectively is considerably lower. Hence in building an effective recommender system we proposed to use the adjusted cosine in finding the similarity weight value to improve the recommendation accuracy.

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