



e-ISSN: 2319-8753 | p-ISSN: 2347-6710

IJIRSET

International Journal of Innovative Research in
SCIENCE | ENGINEERING | TECHNOLOGY

INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN SCIENCE | ENGINEERING | TECHNOLOGY

Volume 12, Issue 7, July 2023

ISSN INTERNATIONAL
STANDARD
SERIAL
NUMBER
INDIA

Impact Factor: 8.423

9940 572 462

6381 907 438

ijirset@gmail.com

www.ijirset.com



Amalgam Flicker admonition System

Er. Pawan Yadav

Associate Professor, Department of Computer Science & Engineering, Eshan College of Engineering, Farah,
Mathura, India

ABSTRACT: Today, recommendation system is used in our daily life. However, they are far from perfect. In this project, we will try to understand various types of recommender systems by comparing their results with other datasets. We will develop a scalable model to perform statistics. We start by developing and comparing different types of prototypes on a smaller dataset of 1000 reviews. Then we try to evaluate the system so that it can handle 200 reviews using MS SQL server. We learned it to have a concise data set, the implementation of user-based collaborative filtering results with better output and efficiency. A recommendation system is an information filtering tool that wants to predict the ratings of users and articles, mainly from big data, to suggest their likes. The movie recommendation system provides a mechanism for users to rate users with similar interests. This makes the referral system a core part of e-commerce websites and apps. This article focuses on movie recommender systems with the main objective of proposing a recommender system through data clustering and computational intelligence.

KEYWORDS: Recommendation System, Movie Recommendation, content based, collaborative filtering.

I. INTRODUCTION

A recommender system is a type of information filtering system that assumes user preferences and makes recommendations based on their preferences. Currently, a wide range of referral system applications are available. The popularity of recommendation systems is gradually increasing day by day and is implemented on almost all online platforms. Typically, these systems can retrieve and filter information based on user preferences and can use this data to make their recommendations in the coming period. Due to the advancement of the referral system, users always expect better results. They have a low advantage over services that are incapable of making sensible recommendations. If a music streaming app can't predict and play a song based on a user's preferences, the user will simply stop using it. This has resulted in technical companies being much focused on fine-tuning their recommendation structure. But, the problem is more complicated than it looks.

Every user has different preferences. In addition, even the taste of a single customer can differ depending on many aspects, such as mood, season, or type of activity the user is performing. For an instance, the type of music one would prefer to listen during exercising varies critically from the

II. RELATED WORK

MOVREC [2] is a movie recommendation system introduced by D.K. Yadav et al. based on collaborative filtering. Collaborative filtering uses user-supplied information. This information is analyzed and a movie is recommended to users who are ranked with the highest rated movie first. Luis M Capos [3] et al analyzed two traditional recommendation systems, content-based filtering and collaborative filtering. Since both have their own disadvantages, he proposed a new system which is a combination of Bayesian network and collaborative filtering. A hybrid system presented by Harpreet Kaur et al. [4] The system uses content mixing as well as a collaborative filtering algorithm. The setting of the films is also taken into account when introducing. User-to-user relationships and user-to-item relationships play a role in the recommendation.

User-specific or item-specific information grouped together to form a cluster by Utkarsh Gupta et al. [5] using chameleon. This is an efficient technique based on hierarchical clustering for recommendation system. To predict the rating of an item, a voting system is used. The proposed system has lower error and better clustering of similar elements. Urszula Kuzelewska et al. [6] group suggestions to deal with the recommender system. Two methods of calculating cluster representation have been presented and evaluated. The Centroid-based solution and the memory-based collaborative filtering method were used as the basis for comparing the performance of the two proposed methods. As a result, the accuracy of the generated suggestions has increased significantly compared to the centroid-only method. Costin Gabriel Chiru et al. [7] recommend Movie Recommender, a system that uses known user

information to provide movie recommendations. This system tries to solve the problem of unique recommendations because it ignores specific user data.

The user's psychological profile, his viewing history and data related to watching movie scores from other websites are collected. They are based on an overall similarity calculation. The system is a hybrid model that uses both content-based filtering and collaborative filtering. To predict the difficulty level of each case for each practitioner Hongli Lin et al. proposed a method known as Content Based Collaborative filtering (CBCF). The algorithm is divided into two phases, the first is content-based filtering to augment the existing trainee case review data, and the second is collaborative filtering to provide final predictions. The CBCF algorithm deals with the advantages of both CBF and CF, while overcoming their disadvantages.

III. METHODOLOGY

The proposed system

To prepare for the design of the movie recommendation system, we decided to analyze the different approaches in the literature with the aim of learning and understanding the advantages and disadvantages of each approach. After our analysis, we decided to go with a hybrid approach that combines both collaborative filtering and content-based filtering techniques. Such an approach would overcome the limitations of content-based and collaborative filtering, exploiting the advantages of both techniques.

The two-part hybrid recommendation set is quite efficient, but under certain data and domain characteristics, different hybrids can achieve different results. For our planned recommendation system, we decided to try a way to include content-based descriptors in collaborative filtering by combining content features (keywords and tags) and user ratings. More specifically, content features will be used to enhance collaborative filtering.

Algorithms and flow chart

Algorithms we have used for recommendation system are

➤ Content based algorithm

The content-based system recommends items like this user has liked or suggested in the past. If articles are liked, similar articles will be featured. It relies on the properties of each element to measure similarity. Content view is based on the fact that we need to know the content of both users and items. Recommendations are based on the content of items rather than other user's opinion. [8]

behavior and not on the present context. It is not dependent on any additional information. It is used by 'Amazon'. [8]

➤ Item-Item collaboration

It uses the user's item rating matrix and establishes correlations between the items. It finds items that are closely correlated and recommends the items with the highest correlation. The advantages of this method no knowledge about item features is needed. It has better stability because correlation between limited number of items instead of very large number of users. It reduces sparsely problem. [1]

➤ K-means clustering algorithm

K-means is one of the simple unsupervised learning algorithms that solves the well-known clustering problems. The procedure follows a simple and easy way to classify a given data set through a certain number of clusters (assume k clusters) fixed a priori. The main idea is to define k centers, one for each cluster. These centers must be placed skillfully because a different location will lead to a different outcome. So the best option is to place them as far away as possible. The next step is to take each point belonging to a given dataset and associate it with the nearest center. When there are no points pending, the first stage is completed and the group's early age is completed. At this point, we need to recalculate the new k centroids that are the centers of the resulting clusters from the previous step.

Steps:

We have provided the following steps for recommending the movies:

- Get the data of movies containing attributes title, movieid and genre.



TABLE 1. GET DATA OF RATING

	User_id	Item_id	rating
0	0	50	5
1	0	172	5
2	0	133	1
3	196	242	3
4	186	302	3

- Get the data from of rating containing attributes userid, movieid and rating stamp.

TABLE 2. MERGE TWO DATASETS

	Item_id	Title
0	1	Toy story (1995)
1	2	Golden eye (1995)
2	3	Four rooms (1995)
3	4	Get shorty (1995)
4	5	Copycay (1995)

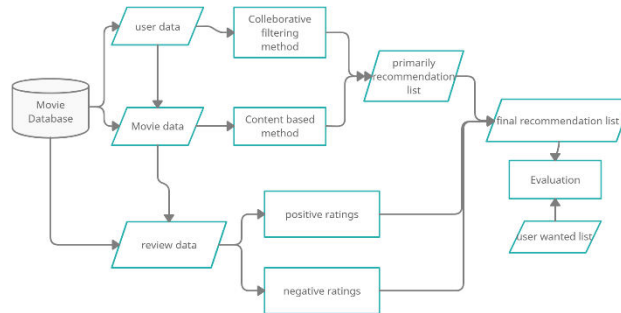
- Merge these 2 datasets together
- Create a rating data frame with average rating and number of ratings.
- Set the number of rating column with rating.

TABLE 3. CREATING A RATING DATA FRAME

title	ratings	No. of ratings
Til there was you (1997)	2.333333	9
1-900(1994)	2.600000	5
101 Dalmatians	2.906257	109
12 angry man(1997)	4.344000	125
187(1997)	2.024390	41

Flow Chart:

FIG 1 FLOW CHART



IV. FUTURE SCOPE

Although this web application is well established to provide a platform for designers to comprehensively evaluate recommendation systems using different evaluation metrics, still There is much more work to be done in the ‘coming’ future.

- Expand to support more algorithms. The application now only supports three collaborative filtering algorithms, user-based, item-based and biased matrix-factorization.
- As the application is readily extensible for recommendation algorithms, it is expected to include more other algorithms, such as hybrid algorithms, content-based algorithms, demographic-based algorithms, etc.
- Include more evaluation criteria. In literature, there are many proposed metrics to measure the performance of recommender systems.
- In addition, there are also many different variations of a certain metric, such as multiple approaches to measuring coverage. Although a number of important metrics are available in the current system, different regions often have different requirements for evaluating performance criteria recommendation systems. Hence, it is necessary to include more evaluation metrics in the system. For example, extra metrics include serendipity, learning rate, confidence, etc.

V. RESULT ANALYSIS

Based on the proposed experimental scenarios, the following gives the results and analysis of them.

Fig 2 and Fig 3 shows the results of the proposed beyond accuracy metrics for the two algorithms, Fig 5 and Fig 5 shows the similarity of two movies which is performed on the TMDB dataset-5000 movies respectively.

1. Content Based Test Case:

In this prediction accuracy of different type movie is checked.

FIG 2 CONTENT-BASED TEST CASE

action1	3.909247
action2	3.810282
action3	3.807445
romantic2	-2.154389
romantic1	-3.306206
romantic3	-4.376174
dtype: float64	



2. Collaborative Filtering-Based Test Case:

In this prediction accuracy of different movie is checked based on their ratings and correlation between users and items by entering movie name.

FIG 3 COLLEBORATIVE FILTERING BASED TEST CASE

Amazing Spider-Man, The (2012)	3.233134
Mission: Impossible III (2006)	2.874798
2 Fast 2 Furious (Fast and the Furious 2, The) (2003)	2.701477
Over the Hedge (2006)	2.229721
Crank (2006)	2.176259
Mission: Impossible - Ghost Protocol (2011)	2.159666
Hancock (2008)	2.156098
The Amazing Spider-Man 2 (2014)	2.153677
Hellboy (2004)	2.137518
Snakes on a Plane (2006)	2.137396
Jumper (2008)	2.129716
Chronicles of Riddick, The (2004)	2.121689
Tron: Legacy (2010)	2.111843
Fantastic Four (2005)	2.083022
X-Men: The Last Stand (2006)	2.077530
Wreck-It Ralph (2012)	2.067907
Kung Fu Hustle (Gong fu) (2004)	2.067457
Godzilla (2014)	2.061653
Incredible Hulk, The (2008)	2.050104
Quantum of Solace (2008)	2.016189
dtype: float64	

3. Cosine similarity:

Fig 4 and fig 5 show the similarity metrics of two movies named avatar and spectre respectively.

FIG 4 SIMILARITY METRICS OF MOVIE AVATAR

```
sorted(list(enumerate(similarity[0])),reverse=True,key=lambda x:x[1])[0:10]
[(0, 1.0),
 (942, 0.24507154069793596),
 (47, 0.23675529137353302),
 (2409, 0.23190036174568118),
 (3162, 0.22314622713173435),
 (1216, 0.22122121613198936),
 (1444, 0.21516574145596765),
 (1920, 0.21483446221182984),
 (260, 0.21081851067789195),
 (507, 0.2099527225817517)]
```

FIG 5 SIMILARITY METRICS OF MOVIE SPECTRE

```
sorted(list(enumerate(similarity[2])),reverse=True,key=lambda x:x[1])[0:10]
[(2, 0.9999999999999996),
 (11, 0.3921144651166975),
 (29, 0.3237996688322591),
 (1346, 0.30586777135731963),
 (277, 0.2546858159868053),
 (4077, 0.2546858159868053),
 (3166, 0.25009650646952775),
 (1134, 0.21369687880543226),
 (1723, 0.21029989116983447),
 (4343, 0.2092457497388747)]
```

VI. CONCLUSION

Movie recommendation system that exists has poor performance because the recommended movie considers aspects e.g. user rated and rated movies. They have almost similar viewing tastes, by data mining and emphasis on movies based

on the intersection of the three methods mentioned above, namely user-based collaborative filtering, algorithmic on content and data mining, through which users will not only get recommended movies, but this program also provides users with advanced and complex additional mentions, because movies have high scores. Poor in 'one of the movie features produced on the basis of data mining will be fine-tuned in the three-dimensional projected hybrid film recommender system large distribution platform.

A hybrid approach is applied between context-based filtering and collaborative filtering to implement the system. This approach overcomes the limitations of each individual algorithm and improves system performance. Techniques such as clustering, similarity, and classification are used to obtain better recommendations, thereby reducing MAE and increasing accuracy and precision. In the future, we may work on a combined recommendation system that uses clustering and similarity for better performance. Our approach can be extended to other domains to recommend sites for songs, videos, places, news, books, travel and e-commerce sites, etc.

REFERENCES

- [1]. G. Linden, "IEEE Xplore," [Online]. Available: <https://ieeexplore.ieee.org/document/1167344>.
- [2]. D. A. S. V. K. G. Manoj Kumar, "A Movie Recommender System," August 2015. [Online].
- [3]. J. M. F.-L. *. J. F. H. M. A. R.-M. Luis M. de Campos, "Combining content-based and collaborative recommendations: A hybrid approach based on," revised 2010. [Online].
- [4]. E. M. S. Harpreet Kaur Virk, "Analysis and Design of Hybrid Online Movie," April 2015. [Online].
- [5]. U. G. a. D. N. Patil², "Recommender System Based on Hierarchical," 2015. [Online].
- [6]. U. Kuzelewska, "Clustering Algorithms in Hybrid Recommender System on," 2014. [Online].
- [7]. V.-N. D. ,. C. P. M. M. Costin-Gabriel Chiru, "Movie," 2015. [Online].
- [8]. D. Pandey, "aihubprojects," 11 October 2019. [Online]. Available: <https://aihubprojects.com/movie-recommendation-system-ai-projects/>.



INNO SPACE
SJIF Scientific Journal Impact Factor
Impact Factor: 8.423



ISSN INTERNATIONAL
STANDARD
SERIAL
NUMBER
INDIA



INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN SCIENCE | ENGINEERING | TECHNOLOGY

9940 572 462 6381 907 438 ijirset@gmail.com



www.ijirset.com

Scan to save the contact details