

Content Based Movie Recommendation System

¹Dr Shaifali M. Arora, ² Dr Anshul Pareek, ³Dr Poonam

¹Associate Professor, ECE Department, Maharaja Surajmal Institute of Technology

^{2,3}Assistant Professor, ECE Department, Maharaja Surajmal Institute of Technology

ABSTRACT

In today's digital world, there is a boundless increase in the digital content related to videos, books, movies, food etc. and it has become a tiresome task for users to find the content of their choice from this content. Therefore, there arises a need of recommendation system, that can help user to shortlist the item of their taste and liking by spending minimum time. Recommender System is basically a filtering system that help users to shortlist the content by overcoming information overload. It predicts data for users based upon the previous information/interests about the user and makes recommendation according to the interest model of users. There is also an incipient growth among the digital content providers whose motive is to engross as many operators on their service as possible and that too for maximum time. As this increases their weightage in any recommender system. A movie recommendation system plays a significant role in our social life as this system suggests a set of movies to users based upon their interests. The system is basically a filter that gathers the information from the past history and interests of users, and accordingly give outcome. With the advancement in technology and agile growth in machine learning techniques, the accuracy in the outputs of these recommendation systems is also increased. In this paper, content-based movie recommendation system has been proposed. that uses traits like director, actor, description, genre etc. for making suggestions to users. The perception behind the designed algorithm is that if a user liked a specific type of movie or show, a similar movie or a show will be liked by him/her.

Introduction:

In today's digital world, it has become an irksome task to find the content of one's liking in an endless variety of content that are being consumed like books, videos, articles, movies, etc. On the other hand, there has been an emerging growth among the digital content providers who want to engage as many users on their service as possible for the maximum time. This gave birth to the recommender system wherein the content providers recommend users' the content according to the users' taste and liking. A recommender system is basically an information filtering system that takes the information like rating, preference, past experience to predict the recommendation for the user. Various websites like Amazon, Netflix, Youtube, Tinder use prediction/recommendation engines to suggest the interest items to users based upon his/her previous history. World cinema has released more than 500000 movies, which is a number beyond one person's search control. The search engines are therefore designed to help the users to decide the movie from such a big heap.

Machine learning and AI are the approaches that help in filtering out the choices and predicting appropriate recommendations to the user based upon their past choices. The accuracy of prediction increases if sufficient data is available. But in these approaches, the challenging task is when there is no previous history of user is available. To make prediction in such case two ways has been suggested in literature, first- such users can be recommended with the highest rated/ most popular items. Such recommendations may not be accurate because

these are not specific to a particular user but same for all new users. Second solution is to ask for the interests of new users and based upon that recommendation is provided to them.

A Simple Recommender system offers generalized suggestions to all the users depending upon the popularity and (sometimes) genre of the movie. In this general model the most popular movies will get high probability of being recommended to the users. So this model doesn't give personalized suggestions to the users. This system can be improved by adding various recommender features. Steps to design a recommendation system are shown in Fig 1 .

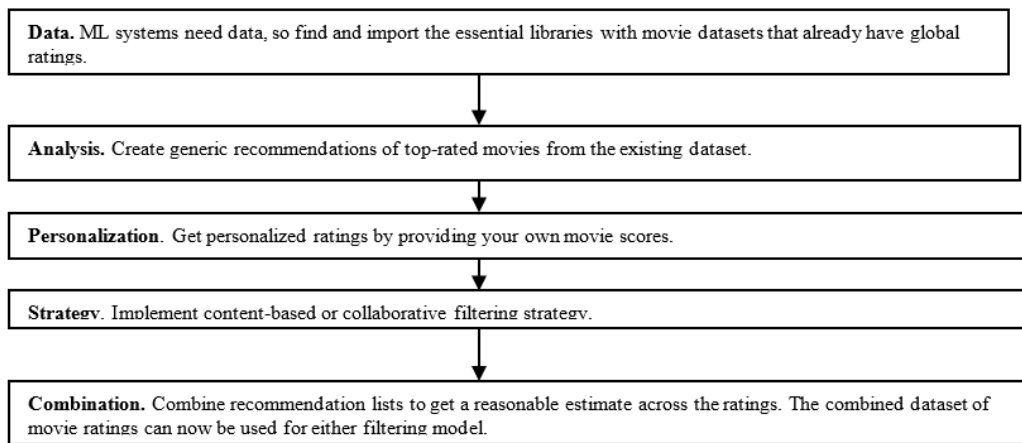


Fig 1: Steps to design a Movie Recommendation System (MRS)

MRS use different filtering techniques and filtering algorithms to find out the best possible result. There are two popular Machine Learning algorithms 1) content-based recommendation system 2) collaborative filtering-based recommendation system for designing MRS. In this paper, the content-based filtering approach is used.

Content-based recommender system:

Content-based recommender system shown in Fig 2, is one of the filtering techniques in which similarity among different items is evaluated depending on the data collected for the items that are selected by users, and then according to that suggest the recommendation. In this users' and products' profiles are built and these profiles are continuously updated when the user watch/ buy a new item. So, these recommendation systems will compare the profile of user and items and then items that are most similar are recommended.

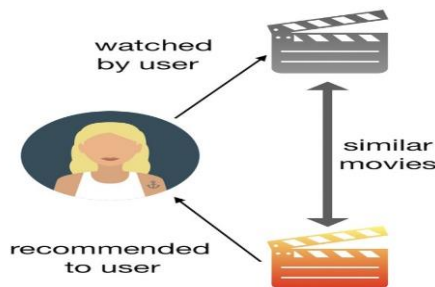


Fig 2: Content based Recommendation System

This can be explained with an example, if a movie like ‘Mission Impossible’ with ‘Tom Cruise’ as actor, is liked by the user, then some other action movies of same actor can be recommended to him/her so here the two features are worked upon in the recommendation system are actor and the other is ‘Action’.

In the above example while filtering, two types of data could be used. First, the interests of the user, their personal information such as their gender, age or, sometimes the history of user can also be used. This collected data is stored in a vector named user. Second vector is formed by collecting the information related to similar items i.e. item vector. U

Cosine similarity is evaluated to suggest the recommendations is given by

$$\cos(\theta) = \frac{\sum_i U_i I_i}{\sqrt{\sum_i U_i^2} \sqrt{\sum_i I_i^2}}$$

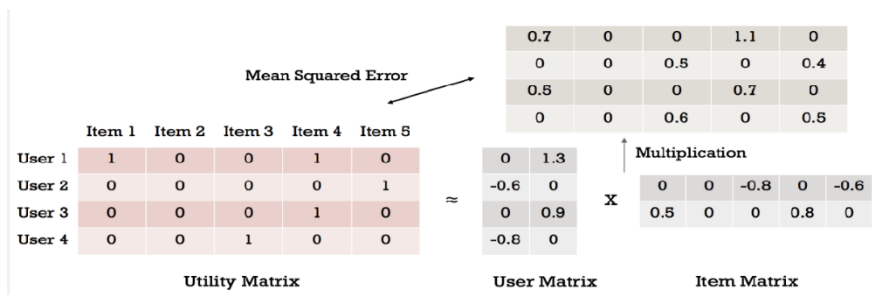


Fig 3: Similarity Calculation Matrix

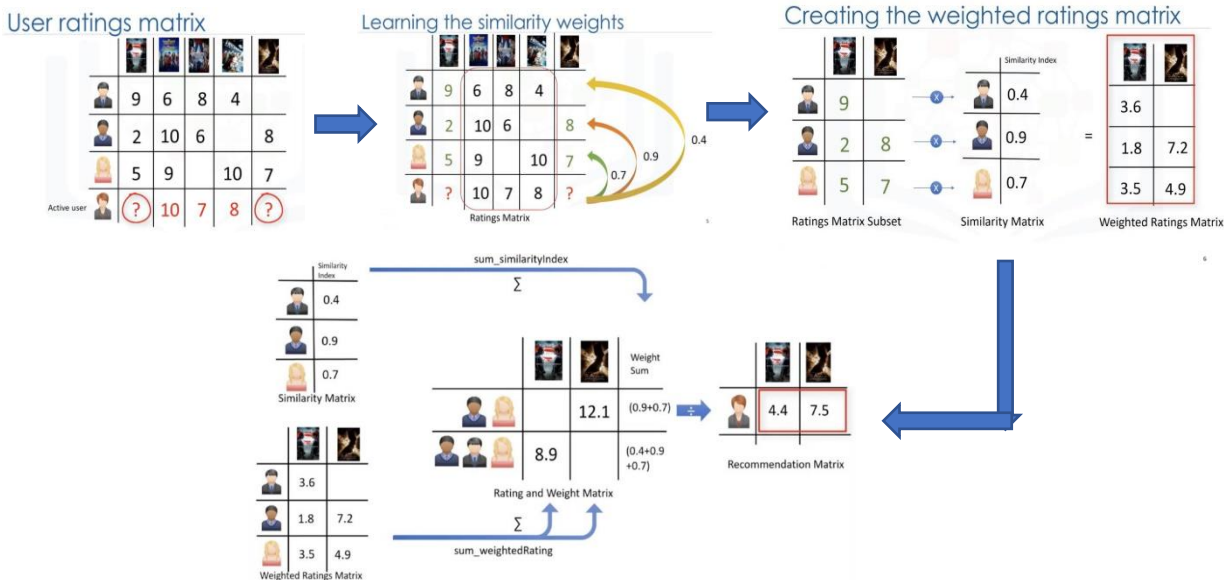


Fig 4: Steps followed in Content Recommendation System

Where user vector is given by U and item vector is given by I. Values are calculated using cosine similarity and then the matrix is sorted in the descending order. The items that are on the top are recommended to the user. The main advantage of this system is that the users get suggestions and they can select by sending small time. The user is satisfied by the type of recommendation. The only disadvantage of this technique is to new business providers because the users don't try a different type of new products. And also, if the user information matrix is changed then the cosine similarity matrix is required to be calculated again.

2. Methodology:

To design content based recommendation system with ML approach, it is required to have a big data set so as to master the algorithm. The right movie datasets that is most valuable for ML must contain information on cast, screen time, script, reviews, plot etc. In this work, TMDB dataset is taken. Following steps are followed while designing the algorithm:

1. First the data is preprocessed so as to filter out the desired information. Next from filtered data, further filtering is done based upon the votes/ ratings given to a movie. 95th percentile cutoff is chosen and the movies below that are rejected from the recommendation system. Also data is filtered on the basis that a movie has to have at least 434 votes on TMDB or the other condition is that the average movie rating is 5.244 out of 10. After these filterations only 2274 movies are qualified. This is depicted in the outcome shown in fig 5.

```
m = vote_counts.quantile(0.95)
m
434.0

# Pre-processing step for getting year from date by splliting it using '-'
md['year'] = pd.to_datetime(md['release_date'], errors='coerce').apply(
    lambda x: str(x).split('-')[0] if x != np.nan else np.nan)

qualified = md[(md['vote_count'] >= m) &
              (md['vote_count'].notnull()) &
              (md['vote_average'].notnull())][['title',
                                              'year',
                                              'vote_count',
                                              'vote_average',
                                              'popularity',
                                              'genres']]

qualified['vote_count'] = qualified['vote_count'].astype('int')
qualified['vote_average'] = qualified['vote_average'].astype('int')
qualified.shape

(2274, 6)
```

Fig 5: 95th percentile Outcome from chart

2. First fifteen movies has been selected. Further, this filtered data recommendation is made based on description and tagline.
3. In the above output, improvement is done in this by taking into consideration the cast, crew, keywords and genre. Current dataset is merged with the crew and the keyword datasets. Different weights for the features like directors, actors, genres has been used by limiting the number of keywords and gives the output shown in fig:

```

get_recommendations('The Ugly Truth').head(10)
5127    Win a Date with Tad Hamilton!
3532    Legally Blonde
7611    Killers
6201    Monster-in-Law
6986    21
7522    When in Rome
9112    Plan B
5030    I'm No Angel
7711    Life As We Know It
1951    You've Got Mail
Name: title, dtype: object

] get_recommendations('Mean Girls').head(10)
3319    Head Over Heels
4763    Freaky Friday
1329    The House of Yes
6277    Just Like Heaven
7905    Mr. Popper's Penguins
7332    Ghosts of Girlfriends Past
6959    The Spiderwick Chronicles
8883    The DUFF
6698    It's a Boy/Girl Thing
7377    I Love You, Beth Cooper
Name: title, dtype: object

```

Fig 6: Recommendation Result with description and tagline

4. Another step towards the improvement is done by taking into consideration the rating/popularity. Therefore, these features have been further added to improve the recommendation.
5. Also, a mechanism has been added to remove bad/low rated movies of users favorite actor/director etc. Now the system will return movies which are popular and have had a good critical response.

RESULTS AND DISCUSSION

1. Content based Recommender model using Similarity Score

```

get_recommendations('The Dark Knight').head(10)
7931    The Dark Knight Rises
132     Batman Forever
1113    Batman Returns
8227    Batman: The Dark Knight Returns, Part 2
7565    Batman: Under the Red Hood
524     Batman
7901    Batman: Year One
2579    Batman: Mask of the Phantasm
2696    JFK
8165    Batman: The Dark Knight Returns, Part 1
Name: title, dtype: object

```

Fig 7: Outcome of Content based Recommender model using Similarity Score

- It has been observed that when the system is identifying Batman movies, 'The Dark Knight Rises' movie has been recommended as only genre features were added. But this movie has very bad reviews and it should not be recommended.
- This recommendation system does not take into considerations some of the important features like crew,

director of the movie, cast etc. which also are the factors while rating a movie.

- User who liked The Dark Knight movie may have high chances of liking movie like NOLAN hate other Batman movies.
2. Content-based Recommender system is based on the matching of keywords like directors and genre.

```
get_recommendations('Fingers').head(10)
2819      Black and White
7323              Tyson
1429      Two Girls and a Guy
5100      The Pick-up Artist
4021      The Long Good Friday
3768              Dinner Rush
217        The Glass Shield
2272              In Too Deep
3664              Next of Kin
4868              Time and Tide
Name: title, dtype: object
```

Fig 8: Outcome of Content based Recommender model using Similarity Score based on keyword, director and cast

- The second system took genre, keywords, cast and crew into consideration and have recognized other James To back movies because of high score given to director ,therefore these movies got highest recommendations.
3. Content based Recommender model using Similarity Score and filtering of data using minimum number of votes.
- This system recommends movies without considering the ratings of the movies. Although there are lot of common characteristics in Batman and Robin in comparison to The Dark Knight movie but this movie shouldn't be recommended as it has lot of terrible content.
 - Therefore, while designing this system a mechanism has been developed to remove bad movies and only recommend movies that are popular and high rating.

```
Improved_recommendations('The Dark Knight')
```

	title	vote_count	vote_average	year	wp
7648	Inception	14075	8	2010	7.917588
8613	Interstellar	11187	8	2014	7.897107
6623	The Prestige	4510	8	2006	7.758148
3381	Memento	4168	8	2000	7.740175
8031	The Dark Knight Rises	9263	7	2012	6.921448
6218	Batman Begins	7511	7	2005	6.904127
1134	Batman Returns	1706	6	1992	5.846862
132	Batman Forever	1529	5	1995	5.054144
9024	Batman v Superman: Dawn of Justice	7189	5	2016	5.013943
1260	Batman & Robin	1447	4	1997	4.287233

Fig 9: Outcome of Content based Recommender model using Similarity Score and filtering of data using minimum number of votes.

Conclusion:

Content based filtering give the recommendation based on the features of the given item and compare it with other items features. In this paper, a content-based recommendation system is suggested different weight to different feature. Also the movies which are low rated are removed from the recommendation system so that

these low rated movies with similar features as high rated movies are not recommended to the user.

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