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Movie Recommendation System: Real-time Evaluation

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Abstract –
In today's e-commerce time, it has become very troublesome task to find any content of online movies, songs, books , restaurants etc.
A practical recommendation scheme now very helpful and important.
Nowadays, movie recommendation system are also available(Netflix, Movie lens, Amazon movie recommendation system etc.) But using a method of combination of content based and collaborative filtering, a recommender system worked and finding a customized output to user.

***Key Words*: Content-based, Collaborative Filtering, Recommender System, Machine Learning.**

1. INTRODUCTION

Todays world of internet using technology of big data,it is highly important a recommender system. It is providing a systematic way to access customized information, by reducing an overload of information. To enhance revenues and retain customers recommender system becomes bottlenecks. These system having customize search engine. The Recommendation systems should range from keyword matching in profiles of user, It uses content based filtering also collaborative filtering for more convenient work of data mining. Its work on a technique of finding an items to users based on customized criteria.Recommendation system filter data using different approaches and concepts. These system recommends products, but firstly it capture the past behaviour of customer. It is beneficial to users of a system as users only see relevant content and not bombarded with unnecessary products.

Hence it has become nowadays imperative for businesses to make use of past behavior of users and build smart recommendation system.

2. DOMAIN OVERVIEW

2.1 Content-based filtering

The content-based filtering is an approach of a user given movies linking features. User likes any movies feature or attributes and these are refered as content. This recommendation scheme actually comparing movies based on specific attributes, what a user already liked movies database and also predicting what a user probably like and also recommend movies based on similar attributes.
This technique uses user's preferred feature vector from the database, movie feature vector to calculate cosine similarity matrix, then only top few movies which are most similar are recommended to user.

Basically, it has following feedback uses for the recommendation system:

Implicit Feedback: Whatever a user searches, clicks for a certain product(movie,book,songs etc) it should be recorded.

Explicit Feedback: It also occurred by user to make any action for reacting to an items, mark as a favorite or also rating to it. These rating and certain favorites for a movie are used for collaborative filtering.

Cosine Similarity:

$$Cos\theta = \frac{\vec{a} \cdot \vec{b}}{\|\vec{a}\| \, \|\vec{b}\|} = \frac{\sum_1^n a_i b_i}{\sqrt{\sum_1^n a_i^2}\,\sqrt{\sum_1^n b_i^2}}$$

where, $\vec{a} \cdot \vec{b} = \sum_1^n a_i b_i = a_1 b_1 + a_2 b_2 + \cdots + a_n b_n$ is the dot product of the two vectors.

Fig. 2.1: Cosine similarity for content-based filtering
A data set can be used to measure how a movie is similar to other different movie. It measure a cosine angle between two vectors which are projected in multidimensional space.

It's a method where count vectorizer can be used to found the count matrix using python. From calculated count matrix the cosine matrix can be evaluated.

2.2 Collaborative Filtering

This technique create a user-item matrix of preferences for items by users. Also, it matches the similarity between the user data and data base, then make recommendations. This filtering used when it is difficult to describes any movie, books, songs by attributes from the data sets.

Fig. 2.2: Collaborative Filtering

For this method, a similarity score can be calculated based on user-user collaborative filtering. It works on the principle of how similar each user is compared to other users and compute a similarity score.

It take out most similar users and recommends movies based on previous visited movies. A user-user collaborative filtering algorithm worked on ratings a user had given to a movie.

Also, the weighted sum of the users ratings given by users to an item should be calculated and also prediction of an item for a user is calculated.

The prediction Pu,i is given by:

$$P_{u,i} = \frac{\sum_v (r_{v,i} * s_{u,v})}{\sum_v s_{u,v}}$$

Where:

- Pu,i is the prediction of an item
- Rv,i is the rating given by a user v to a movie i
- Su,v is the similarity between users

Fig 2.3: Prediction formula

We have already users ratings, now to predict ratings for other users from given value can required following steps.

1. A Pearson correlation can be used to make predictions of two different users u and v , also its similarities.
2. It finds a correlation value for two different users. So, finding the rate provided by users u and v to items and finding the correlation based on that.
3. Also, prediction can be obtained using the similarity score from users. It find predictions based on calculating the similarities between user.
4. On the basis of prediction value calculated, recommendations can made.

The K-nearest neighbour algorithm can be used to select the top-N users with highest similarity.

Due to the time consuming process to calculate the similarity for each user in a database and further calculating predictions to each similar score.it's a best way to select only neighbors to the current user.

For this technique to implement we are also need to handle cold starts. Its when a new user or items is being added to the database. Its of following two types:

1. **Visitor Cold Start** – It should be happened that a new user may sign up to the platform and added to the database. This is very difficult to recommender system to suggest any movie to new user. We solve the problem by recommending most popular movies to the user.
2. **Movie Cold Start** - Sometimes it is found that any movie, which is launched and not yet get any user ratings to the movie, in this scenario we use content based filtering to solve the problem.

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2.4 Limitations

I) Scalability

As in collaborative filtering large amount of data is employed, a higher number of resources is necessary. As the amount of data processing increased exponentially, its become difficult in big data.

II) Data Sparsity

The recommendation to a user become very tough as the empty space in a data matrix. It is due to the many user are not interested in evaluating an item.

III) Cold Start Problem

It's becomes challenging for any algorithm to make additional recommendations.

This is especially true for new items that, not yet to be rated by any user. Or any new user sign up to the platform and his favorite history not available.

Both of these challenges are addressed using hybrid techniques.

3. LITERATURE REVIEW

The problem of collaborative filtering which is cold-start problem and sparsity problem are mentioned by author Sang-Min. To prevent this problem a category of information can b used. Author had proposed a genre correlation-based movie recommendation system.

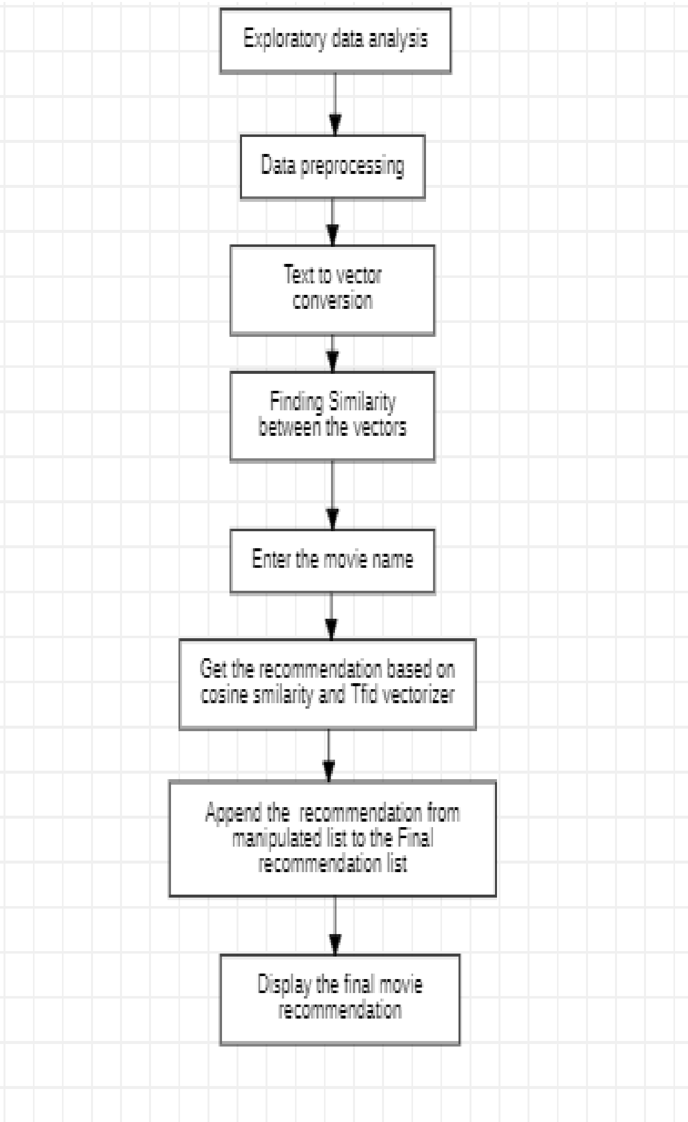
As a result, even if original features not yet have sufficient
ratings , it can nevertheless appear in the recommendation list. The proposed system is unbiased when it comes to highly rated, most-watched content and new, less-watched content. As a result, even a brand-new film can be recommended.

4. PROPOSED METHODOLOGY

The relevant features must be combined into a single feature, the data set is to be prepossessed.

We'll really do have to transform from such a feature into vectors later. Finally, obtain recommendations in accordance with the system architecture.

Fig: System Architecture



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5. RESULT AND DISCUSSIONS

The content-based recommendations is appropriate when there is known data about the item. Hence it analyses the qualities of items to generate predictions.

6. CONCLUSION

The recommendation system frame work become extremely important, because of overabundance of data. We are specifically looking for a better way to work on the exactness of the film agent for the content-based recommender framework.

Proposal frameworks that use continuous data from wearable devices and snap stream to generate more advanced results are more successful in general.

For example, the suggested results from a health care field suggestion framework, such as analysis and therapy procedures, have a lower predilection than clinical information-based outcomes. It does, however, have significant value as solid data, which can provide quick support to convention administrations and quick advancements, because consistent data provides a more relevant output by mirroring patients' present state.

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