International Journal of Advances in Engineering and Management (IJAEM)
Volume 5, Issue 3 March 2023, pp: 1685-1690 www.ijaem.net ISSN: 2395-5252

Hybrid Movie Recommendation System

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Date of Submission: 20-03-2023 Date of Acceptance: 30-03-2023

ABSTRACT: In this paper, a hybrid approach thatcombines content-based filtering, collaborative filtering, using Support Vector Machine as a classifier, and genetic algorithm is presented in the proposed methodology. Comparison are made and results are shown, showing that our proposed approach shows an improvement in the accuracy, quality, and scalability of the movie recommendation system than the pure approaches in three areas: accuracy, quality, and scalability.The advantages of both approaches are combined in a hybrid manner, which also helps to minimize their individual drawbacks.

KEYWORDS: Recommendation systems,Content based,collaborative filtering, hybrid, Machine learning.

I. INTRODUCTION

An information filtering paradigm known as a recommendation system, also referred to as a recommendation engine, seeks to anticipate user preferences and make recommendations in line with these preferences. These methods have developed and are now widely employed in a variety of industries, including movies, music, novels, apparel, restaurants, food, and other services.

These platforms compile data about a user's choices and behavior, then exploit that knowledge afterwards. Make your suggestions more precise. A important part of life is watching movies. There are many different types of movies, including those made for entertainment, those made for instruction, animated films for kids, horror films, and action films. Simply put, the numerous genres of movies—such as comedy, suspense, animation, action, etc.—distinguish them from one another.

The release year, language, director, and other factors can all be used to distinguish between various movies. There are many movies to choose from when watching movies online, so browse for our most viewed favorites first. The burden of searching for our favorite movies for a long time is reduced by the use of movie recommendation systems, which help us find our favorite films among all of these different film genres. Therefore, it is essential that the movie has a solid, dependable recommendation system and should only suggest films that either completely match our likes or are most suitable with them.The movie suggestion system is a very useful and important tool. However, given the disadvantages of a wholly collaborative strategy, movie recommendations Systems also struggle with scalability and offer poor recommendations.

This project's objective is to provide trustworthy movie recommendations to the public. The project's goal is to improve the recommendation system's movie quality, accuracy, and scalability as compared to pure techniques. By using a hybrid strategy that combines collaborative filtering and content-based filtering, the overburden is removed. In social media platforms, recommendation systems are used as a way of information filtering.As a result, there is much of room for research in this field to improve the accuracy, scalability, and quality of movie-recommending systems.

The system of recommendations is very effective and important. However, because there are problems with the "Pure Collaboration" model, insufficient movie recommendation systems, and scalability problems.

The suggested movie recommendation system offers more accurate similarity measurements and higher-quality recommendations than the current mechanism for making movie recommendations, but the computation time is longer than the existing system. This problem can be resolved by employing the clustered strategy.The suggested method aims to enhance the quality and scalability of the movie recommendation system.By combining Content-Based Filtering and Collaborative Search, we take a hybrid method.

Filtering will allow the various ways to benefit from one another. We used the cosine similarity measure to quickly and accurately determine how similar the various movies in the current data set are to one another and to shorten the computation time for the movie recommendation engine.

In our research, we employ three different algorithms to develop a machine learning recommendation model. The first technique iscosine similarity, the second is matrix factorization, and the third is singular value decomposition.

After the algorithm implementation is complete, train and test the model. To obtain the outcome, we must train the model. Until the model suggests a varied set of movies to various people, we will test it repeatedly.

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Over the years, numerous recommendation systems have been developed employing collaborative, content-based, or hybrid filtering methods. These systems have been created using a variety of big data and machine learning approaches.The different kinds of recommendation systems are described in Fig. 1

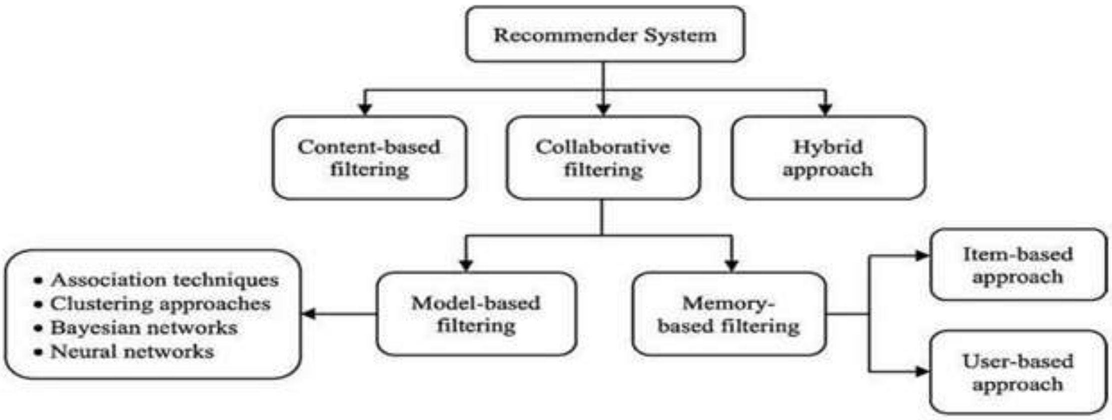

Fig. 1 Types of recommender systems

Content- based Recommendation System :

All of the data pieces are gathered into various item profiles in content-based recommendation systems[4] based on their attributes or descriptions. For instance, the features of a book would be the author, publisher, etc. The movie director, actor, etc., are examples of features in the case of a motion picture. When a user gives an item a positive rating, all of the other things in that item's profile are combined to create the user profile.

This user profile comprises all the item profiles whose products have received favourableuserratings. The user is then given recommendations for items based on this user profile, as seen in Fig. 2.

This method has the downside of requiring in-depth knowledge of the item features in order to make an appropriate recommendationavailable for all items. Additionally, this strategy has a limited ability to build on the users' current preferences or interests. However, there are lots of benefits to this strategy.

This technique has the swift ability to dynamically adjust to the changing user preferences, which tend to vary over time. This algorithm does not require the profile information of any other users because other users have no bearing on the suggestion process as one user's profile is unique to that person alone. This guarantees the safety and privacy of user information. Content-based strategies can circumvent the cold-start problem, i.e., this strategy can propose an item even when that item has not yet been rated by any user, if new items contain sufficient descriptions. Systems like personalized news recommendation systems.

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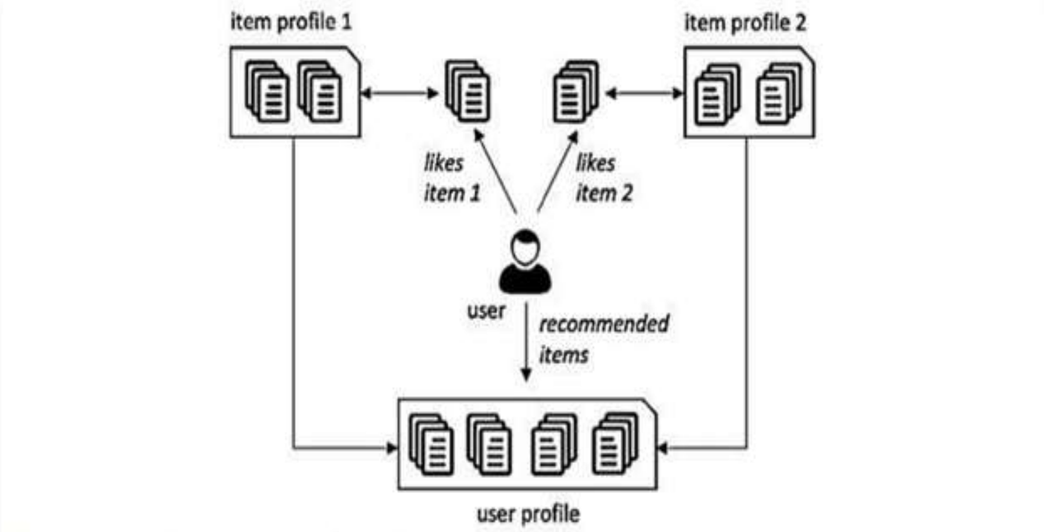


Fig. 2 Content-based recommender system

Collaborative Filtering System[3] for Movie Recommendations Collaborative filtering systems analyse user behaviour and preferences and predict what they would enjoy based on similarity to other users. User-based recommendation and item-based collaborative filtering systems recommendation are the two types.User-basedfiltering, User-based preferences are widely used for creating personalized systems. The foundation of this strategy is consumer preferences. Before the process starts, users rate a few movies (1-5) by using a scale.

Ratings can be both implicit and explicit. Users who specifically rate an item do so by giving it a score or by giving it a thumbs-up or thumbs-down icon. Because not all users are keen on offering advice, it can occasionally be challenging to get explicit reviews. These circumstances give us the chance to collect implicit ratings based on their behaviour.

For instance, it indicates a favourable preference if a person buys more of a product than once. In terms of movie systems, if a user watches the complete movie, we can assume that they have some abilities similar to the movie. You should be aware that there are no exact rules for creating implicit ratings. Next, we begin by counting each user's predetermined number of nearest neighbors. To ascertain the relationship between user evaluations, we employ Pearson correlation.

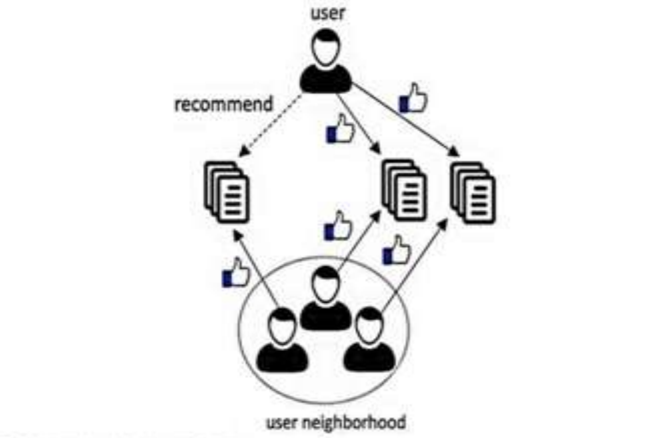


Fig. 3 User-based collaborative filtering

Item-based filtering:item-based filtering, as opposed to user-based filtering, focuses on how similar users of an object are as opposed to the users themselves. The most analogous objects are determined in advance.

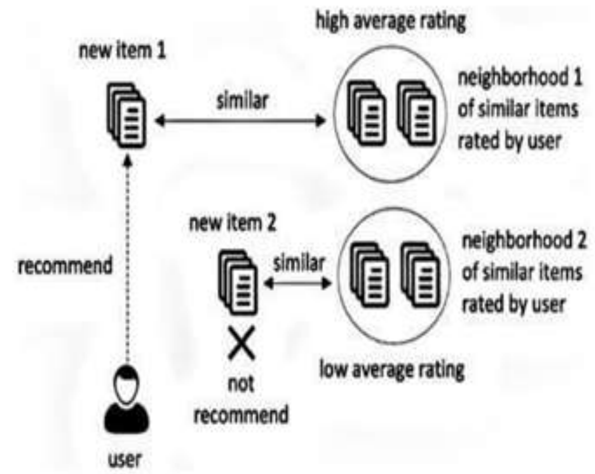
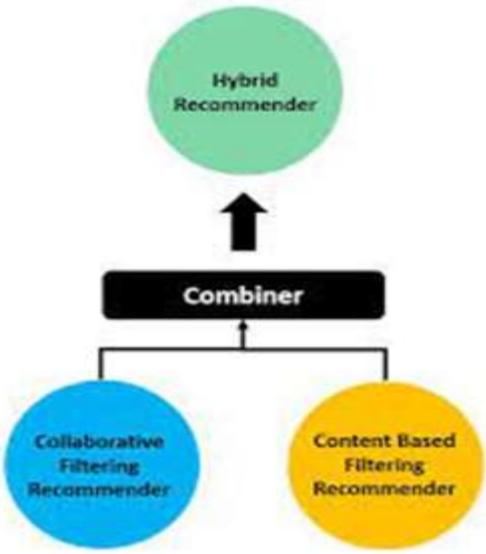


Fig. 4 Item-based collaborative filtering

Hybrid filtering:

A hybrid technique combines two or more techniques and uses them all at once to overcome the shortcomings of each separate recommendation technique. Different methods can be used to include diverse techniques. The findings from several techniques may be combined in a hybrid algorithm, which may also combine content-based filtering with collaborative methods or collaborative filtering with content-based methods. In many recommendation applications, this hybrid integration of many approaches often improves performance and accuracy.The popularity of hybrid recommendation systems is growing right now. Collaborative filtering and content-based filtering can be combined to increase effectiveness.There are numerous approaches to construct hybrid recommendation systems, including adding CF capabilities to CB methods, or simply combining the results of CF and CB recommendations. There are various types of hybridization methods namely weighted hybridization, switching, mixed, features combination, features augmentation, cascade, meta-level.



The Proposed Solution:

The objectives of this thesis project are to investigate various forms of recommendation systems, determine which has the lowest error rate, and compute the root mean square error of each type. There are many different types of recommendation systems, but not all of them are appropriate for a given issue or circumstance. Our objective is to determine the optimal method for enhancing movie classification, which is necessary for enhancing content-based recommendation systems, collaborative filtering, and hybrid recommendation systems.

As each user may have different preferences, our system determines the similarities between users and then suggests movies to users based on the ratings provided by users with similar preferences. This will provide the user a specific recommendation.

II. SYSTEM DESIGN

Load the data sets required to build a model first. The project requires the following data sets: movies.csv, ratings.csv, and users.csv. On Kaggle.com, all of these data sets are available. In essence, the project's content creates two models. Based and cooperative filtering both offer lists of movies for a given user, and by combining both, a single final list of movies that are suggested for viewing based on the person's identity is produced.

Cosine Similarity:

Cosine similarity is the measure of the similarity between a two non-zero vectors ofaninnerproduct space which measures thetrigonometric angle cosineoftheanglebetweenthe two non zero vectors.As with cosine angles, cosine similarity is employed in the recommendation system, where lower cosine similarity is deemed the least recommended material and higher cosine similarity results in better placement of the generated suggestions.

Matrix factorization:

By multiplying two different types of entities, matrix factorization can produce latent characteristics. Matrix factorization is used in collaborative filtering to determine the connection between the entities of items and users. We would like to forecast user ratings of store items using the input of user ratings so that users can receive recommendations based on the prediction.The Utility matrix is divided (or factorized) into two tall and skinny matrices, which are then used to populate the matrix

III. METHODOLOGY

The recommendation engine is the most crucial component of a movie recommendation system. Various tech businesses, like Facebook, Amazon, Netflix, and others, are implementing recommendations. Facebook mostly uses it in the "people you may know" feature to propose friends to users. Both personalized and non-personalized recommendation algorithms have been created by Amazon.

To calculate and analyse data, we require specialized Python packages used for analytics. such as SK-learn, Numpy, and pandas libraries.For example, Matplotlib is required. SK-learn includes a variety of techniques for classification, regression, and clustering, including support vector machines, random forests, gradient boosting, k-means, and DBSCAN. It is also designed to operate with Python libraries for science and mathematics called SciPy and NumPy.

NumPy is a general-purpose library for handling arrays. It is used to deal with arrays and matrices. Panther Python Pandas is one of the most well-liked Python data libraries. It provides quick, simple frameworks and data analysis. Pandas provides the in-memory 2D table object known as Data frame, which contrasts with the multi-dimensional objects offered by the NumPy module.

IV. CONCLUSION

The accuracy, quality, and scalability of the movie recommendation system are improved in this study using a hybrid strategy that combines content-based filtering and collaborative filtering, using Singular Value Decomposition (SVD) as a classifier and other techniques like matrix factorization.

The results of using the suggested hybrid approach to three separate movie datasets. If the root mean square error for each of the three methods is given as X, Y, or Z, we can compare those three numbers and choose the model with the lowest error rate.

Future Scope:

The suggested approach has considered movie genres, but in the future, as movie preferences vary with age, we can also include the user's age. For example, when we were younger, cartoon movies were more appealing to us than live-action ones. other movies The memory requirements of the proposed system should be reduced. approach with forward motion. From this point forward, the recommended approach has been followed.merely different film databases. It can also be utilized with the Film Affinity and Netflix datasets and performance may one day be computed.The attributes of various upcoming recommendation systems are listed below, along with some of the applications that will use them.

Sensing the emotional state of a user:

Affective computing will enable Recommendation systems to identify a user's emotional state and provide service recommendations in line with it.For instance, the recommendation system will suggest suitable movies based on the user's mood.

Introduce even more precise, proper features of the movie:

Common collaborative filtering suggestions substitute the rating for object features. In the future, we should extract attributes from movies like colour and subtitles that can give a more accurate description of the film.

Introduce user dislike movie list:

Recommendation systems can always benefit from user data. We will continue to gather user information and add a list of movies that users dislike. In order to generate scores that will be added to the previous result, we will also input a list of movies that we despise into the recommendation system. By doing this, we can enhance the performance of the recommendation system.

No cold start problem:

By gathering pertinent and implicit data from different online sources, future recommendation systems will be able to eliminate the "cold start problem." The major enablers for this will be social networks and other forms of pervasive connectivity.

More personalized recommendation:

By examining individual habits and actions, recommendations may be made in a more individualized and personal way. They will be able to make more specialized entertainment recommendations. For instance, modern smart TVs keep track of our watching habits, including when, how frequently, and what we watch.

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