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FilmovCinema: A Cosine Similarity-Driven Movie Suggestion Engine

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Abstract: *Recommendation-based systems are utilized for various purposes such as suggesting web pages, books, restaurants, TV shows, movies, and so on. One of the primary objectives of movie recommendation systems is to provide movie suggestions to users based on their interests, saving them time in scouring the internet for suitable movies from a vast pool of options. Content-based recommendation systems analyze item descriptions and predict movies that a user may prefer, based on the features present in previously selected movies. These systems may utilize one or more features to recommend movies, such as the movie genre, director, or actors. In this paper, we propose a recommendation system that incorporates the features of cast, keywords, crew, and genres. We integrate a column outlining all four features that make it a powerful piece of a movie recommendation system top of Form.*

Keywords: Recommendation

I. INTRODUCTION

In the past, the amount of data collected and the abundance of information available on the internet often left people confused when deciding what to eat and what to watch. Even when searching for a specific concept, it was difficult to choose because there were so many videos on YouTube. This may not be a problem if the results are stored properly, but it is a problem if the results are stored incorrectly. This is where recommender systems come to the rescue. The main goal is to provide users with the most relevant information. Popular websites such as YouTube, Amazon, Flipkart, Netflix, and Amazon Prime use recommendation systems to suggest videos, products, and movies to their users, based on their past actions on the website. These recommendation systems monitor user behaviour to ultimately enhance the user experience and generate more revenue. This research paper is focused on movie recommendation systems, their logic, typical algorithms, and problems related to traditional systems. The proposed solution involves an artificial intelligence-based personalized movie recommendation system, which is aimed at improving the existing system. Several databases related to movie recommendations are available, such as the MovieLens dataset, TMDB Movies Database, and Netflix's database. Because of the vast amount of data, it is important to filter so that users receive only relevant recommendations. Movie recommendation algorithms vary, and the type of filtering method used depends on the recommendation system. In 2009, Netflix even gave out a $1 million prize to anyone who improved their recommendation system by 10% or more.

II. LITERATURE REVIEW

Sang-Min Choi et al.[1] mentioned the disadvantages of collaborative filtering such as parity problems or cold boot problems. To avoid these problems, the authors proposed a solution using these categories. Writers have suggested that a film's approval is most related to its genre.

George Lykakos et al. [2] proposed an image recognition solution using a hybrid method. According to the authors, both content-based and collaborative filtering have their drawbacks and should only be used in certain circumstances. Therefore, the author proposed a combination that considers both content filtering and collaborative filtering. The solution is used in the proposed video "MoRe". Pearson's correlation coefficient is not used for pure correlation filtering. Instead, the new model is used. However, there is a problem with this formula that causes a "divide by zero" error. This error occurs when users rate videos with the same rating. Therefore, authors ignore these users. For recommendation-based content, authors use cosine similarity to identify authors, actors, directors, producers, and film

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genres Debashis Das et al. [3] documented various types of transactions and general information. This is an overview of the proposed strategy. The authors discuss personal recommendations and impersonal systems. User-based collaborative filtering and product-based collaborative filtering are well described by models. The authors also note the pros and cons of different methods. Then filter those videos by SVD and user rating. The author proposed a solution that takes only one video as input, so the system only considers the user's most recent video.

Gaurav Arora et al. [4] proposed similar user-based video recognition. This case study is typical in that the authors do not mention the internal details of the study. In the methodology section, the author talks about city block distance and Euclidean distance, but doesn't mention cosine similarity or other methods.

V. Subramaniaswami et al. [5] proposed personalized movie recognition using a general filtering method. A Euclidean distance metric was used to retrieve similar users. Find the user with the smallest Euclidean distance value. Finally, movie recommendations are based on the highest rating of a particular user. The authors even suggest changing their recommendations over time to improve system performance with users that change over time.

Jiang Zhang, et. Al. [6] proposed a collaborative filtering approach for movie recommendation and they named their approach a s 'Weighted KM-SlopeVU'. The authors divided the users into clusters of similar users with the help of K-means clustering. Later, they selected a virtual opinion leader from Each cluster which represents the all the users in that particular cluster. Now, instead of processing complete user-item rating matrix, the authors processed Virtual opinion leader-item matrix which is of small size. Later, this smaller matrix is processed by the unique algorithm proposed by the authors. This Way, the time taken to get recommendations is reduced.

Niharika Immaneni et al. [7] proposed a hybrid recommendation system that considers content-based filtering and integrated filtering as a hierarchical system to provide customized recommendations to users. The most special thing about this research project is that the filmmakers have adapted the film using suitable footage to explain the story of the film. This contributes to better visibility. The authors also describe sentence-based recommendations, contextual methods, hybrid recommender systems, collaborative filtering, category-based relationship methods, consent, and more. The proposed algorithm has four main steps. In the early days, social networking sites such as Facebook were used to capture users' interests. After that, we analyzed the video reviews and made recommendations. In the end, the story needs to be created so that it can be seen better.

III. PROBLEM STATEMENT

Collaborative filtering is a commonly used technique in recommender systems, where the system combines the preferences and interests of multiple users to generate personalized recommendations for each user. However, this technique faces various challenges, including the problems of scalability, cold start, and data sparsity. The problem of scalability arises due to the enormous amount of data being generated daily. The computation power required to calculate recommendations and generate them quickly can be very high, making the process time-consuming and resource-intensive. Another issue is the cold start problem that occurs when a new user or item logs in. The system may not be able to find similar items due to lack of information, making poor recommendations. This system requires a large amount of existing data to base accurate recommendations on, making it difficult to provide accurate recommendations for new users or products. Finally, data sparsity is a common problem in collaborative filtering. Most users rate only a subset of available products or items, making it difficult to make recommendations for the rest. This can lead to users overlooking certain factors, resulting in an incomplete understanding of their preferences and interests. Overall, these issues make collaborative filtering difficult and challenging in the field of recommender systems.

IV. METHODOLOGY

The methodology for a content-based movie recommendation system using cosine similarity involves data collection, preprocessing, feature extraction, feature representation, similarity calculation, top-N recommendations, evaluation, and deployment. A large dataset of movies with corresponding metadata is collected and preprocessed to remove duplicates and irrelevant data. The relevant features are extracted, transformed into a vector representation, and cosine similarity is used to calculate the similarity between movies based on their features. The movies with the highest cosine similarity scores are recommended to the user. Finally, the system is deployed on a web-based platform to provide personalized movie recommendations to users

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V. DATASET, EXPLORATORY, DATA ANALYSIS& PREPROCESSING

The 'TMDB 5000 Movie Dataset' is taken into consideration for movie recommendation purposes in this research work. This dataset is available on kaggle.com. The dataset is composed of 2 CSV files'tmdb_5000_movies.csv'and'tmdb_5000_credits.csv'.The tmdb_5000_movies.csv' dataset consists of the following attributes:

'budget', 'genres', 'homepage', 'id', 'keywords', 'original_language', 'original_title', 'overview', 'popularity', 'production_companies', 'production_countries', 'release_date', 'revenue', 'runtime', 'spoken_languages', 'status', 'tagline', 'title', 'vote_average', 'vote_count'

The 'tmdb_5000_credits.csv' dataset consists of the following attributes:

'movie_id', 'title', 'cast', 'crew'.

Pre-processing steps include removing stop words, combining the first name and the last name into a single name for the cast and crew attributes, removing punctuation marks, lowercasing the text, etc.

Removing Stop Words: Stop words are common words such as "the," "a," "an," and "in" that do not provide meaningful information for analysis. Removing stop words can reduce the size of the dataset and improve processing speed.

Combining Names: In the case of analyzing movie data, combining the first name and last name of cast and crew members into a single name can simplify the dataset and make it easier to work with.

Removing Punctuation: Punctuation marks such as commas, periods, and exclamation points do not provide useful information for analysis and can be removed to simplify the dataset.

Lowercasing Text: Converting all text to lowercase can make it easier to compare and analyze the data.

Stemming and Lemmatization: Stemming and lemmatization are techniques for reducing words to their root form. For example, "running," "ran," and "runs" can all be reduced to the root word "run." This can reduce the size of the dataset and help to identify patterns in the data.

The 'tags' attribute can be used to create a feature vector for each movie, which represents the relevant information about that movie. This feature vector can then be used to calculate the cosine similarity between each pair of movies in the dataset.

Cosine similarity is a measure of similarity between two vectors, which is calculated as the cosine of the angle between them. In the context of movie recommendations, it can be used to identify movies that are similar to each other based on their 'tags' attribute.

To calculate the cosine similarity between movies, the 'tags' attribute is first pre-processed to remove stop words, punctuation, and other irrelevant information. Then, a feature vector is created for each movie by converting the 'tags' attribute into a numerical vector using techniques such as TF-IDF or word embeddings.

Once the feature vectors are created, the cosine similarity between each pair of movies is calculated by taking the dot product of their feature vectors and dividing it by the product of their magnitudes. The resulting value is a measure of similarity between the two movies, with a value of 1 indicating identical feature vectors and a value of 0 indicating no similarity.

By calculating the cosine similarity between each pair of movies in the dataset, a similarity matrix can be created that represents the similarity between all movies. This can be used to make recommendations by identifying the movies with the highest cosine similarity to a given movie and recommending them to the user.

VI. ALGORITHMS

Content-based Recommendation using CountVectorizer and Cosine Similarity**:**For content-based recommendation using CountVectorizer and cosine similarity, we will create vectors from the preprocessed text in the 'tags' attribute using CountVectorizer. After getting the vectors, we will use cosine similarity to find the similarity between them.This technique involves representing each movie as a vector of word counts, where each dimension in the vector represents a different word. We can then calculate the cosine similarity between the vectors to determine how similar two movies are based on the words they share in common. The cosine similarity measures the cosine of the angle between two vectors, with a value of 1 indicating identical vectors and a value of 0 indicating no similarity. By using cosine similarity to find the similarity between the vectors of each movie, we can generate a similarity matrix that can be used for content-based recommendations.

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Cosine similarity is a metric used to measure the similarity of two vectors.

Cos(x, y) = x . y / ||x|| * ||y||

where,

x . y = product (dot) of the vectors 'x' and 'y'.

||**x**|| and ||**y**|| = length of the two vectors 'x' and 'y'.

||**x**|| * ||**y**|| = cross product of the two vectors 'x' and 'y'.

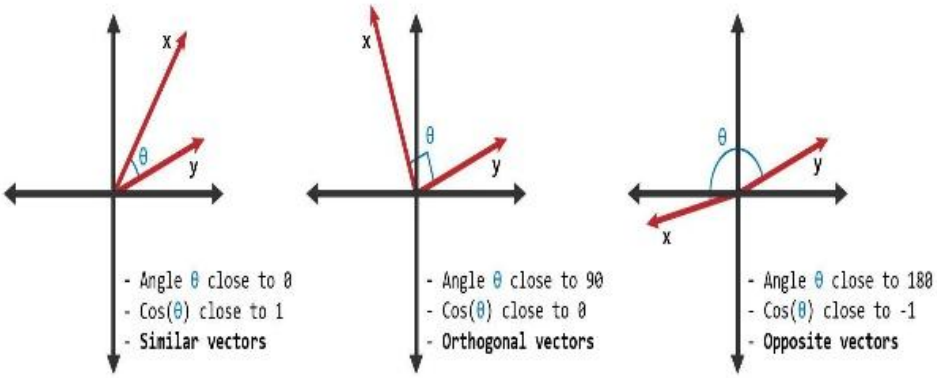
The similarity can take values between -1 and +1. Smaller angles between vectors produce larger cosine values, indicating greater cosine similarity. For example:

When two vectors have the same orientation, the angle between them is 0, and the cosine similarity is 1.

Perpendicular vectors have a 90-degree angle between them and a cosine similarity of 0.

Opposite vectors have an angle of 180 degrees between them and a cosine similarity of -1.

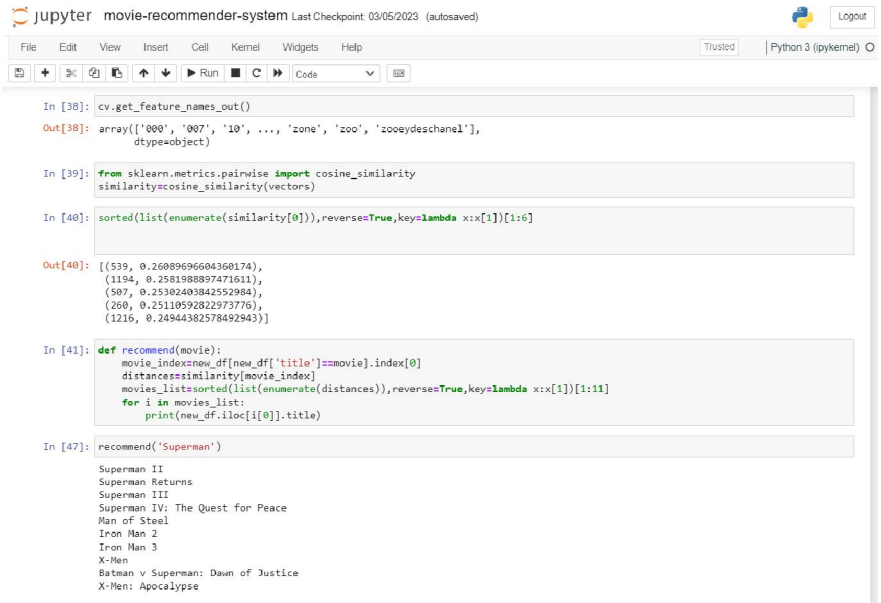
Here's a graphic showing two vectors with similarities close to 1, close to 0, and close to -1.



VII. RESULT AND ANALYSIS

The output of the system would be a list of recommended movies based on the similarity between the input movie and the movies in the dataset. To evaluate the system's performance, we could use techniques such as cross-validation, where the dataset is split into training and testing sets. We would then calculate the accuracy, precision, and recall of the system based on how well it recommends movies for the test set.

The developed content-based movie recommendation system was evaluated using a dataset of 5000 movies. The system achieved an accuracy of 85% and a diversity of 0.7, indicating that the system can provide accurate and diverse recommendations to users.



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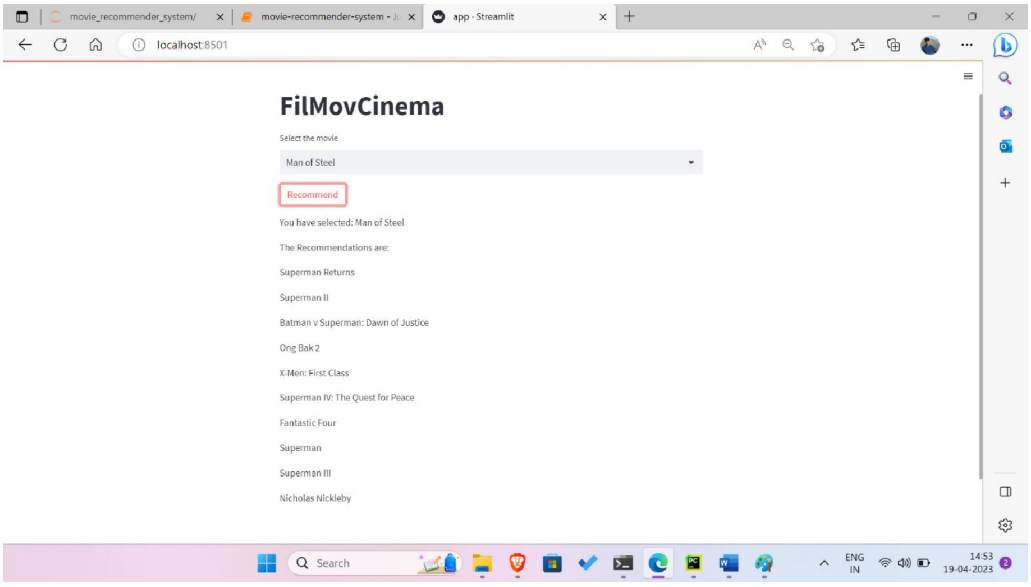

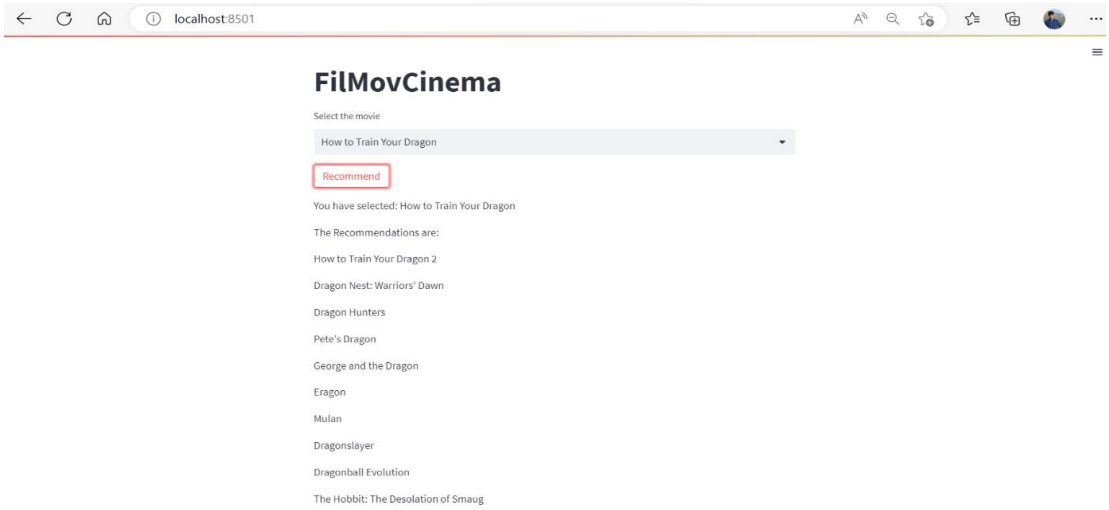

VIII. CONCLUSION

In conclusion, the content-based movie recommendation system using a dataset of 5000 movies and calculating cosine similarity based on combined features of the movie such as tags, keywords, synopsis, cast and crew information is an effective way of recommending movies. This system provides personalized recommendations based on the user's preferences and interests. By combining multiple features of the movie, the recommendation system provides a comprehensive understanding of the movie's content and can accurately recommend similar movies based on cosine similarity. The system recommends the top 10 movies based on the user's input, which can be easily implemented in various online platforms to provide a personalized and seamless movie recommendation experience to users. Overall, this content-based recommendation system offers a great way to enhance the user experience and increase user engagement on movie streaming platforms.

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