Movie Recommendation System Using KNN, Cosine Similarity and Collaborative Filtering

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Abstract. The movie recommendation system is becoming increasingly popular in the digital era. With the continuous emergence of a vast amount of movie resources, users are facing more and more choices. Therefore, an intelligent movie recommendation system can assist users in quickly finding movies that match their personal preferences, thereby enhancing user satisfaction and movie-watching experience . Our movie recommendation system recommends high-rated and well-reviewed films and TV shows to the general audience based on Netflix viewers' ratings for them. These are the movies and shows that are considered worth watching. We utilize the Netflix open dataset, which consists of a large number of user ratings and movie information [1]. By merging the movie and rating datasets and performing data cleansing and preprocessing, we obtain a dataset suitable for models. Subsequently, we represent the movie rating data using sparse matrices and train a k-nearest neighbours (k-NN) algorithm to achieve personalized movie recommendations [2].Our approach considers both user rating preferences and movie similarities, enabling accurate and personalized recommendations for users. Through evaluation experiments and user surveys, we validate the effectiveness of our recommendation system in terms of accuracy and user satisfaction [3]. This research is significant for improving the effectiveness of movie recommendation systems and enhancing user experiences.

Keywords: Movie recommendation system; KNN; Cosine Similarity; Collaborative Filtering.

1. Introduction

With the rise of online streaming platforms like Netflix, Amazon Prime Video, and Hulu, there is an increasing demand for personalized movie recommendations. These platforms offer a vast library of movies, but users often face difficulties in choosing what to watch. Therefore, building an effective movie recommendation system has become crucial.

Collaborative filtering is a popular recommendation algorithm that utilizes similarities between users or items to make recommendations. In the context of movie recommendations, collaborative filtering has achieved significant success. Research has shown that by leveraging user rating data and analyze patterns from other users' behavior, collaborative filtering can accurately predict user preferences and recommend relevant movies [4]. However, in practical applications, collaborative filtering algorithms also face challenges. Firstly, user rating data is often sparse, meaning users only rate a subset of movies, leading to incomplete data for similarity calculations. Secondly, there is a cold-start problem, where new users or newly released movies lack sufficient historical data for personalized recommendations. Hence, further optimization and improvements are necessary to enhance the accuracy and personalization of collaborative filtering algorithms [5].

This paper aims to design and implement a movie recommendation system based on collaborative filtering algorithms. We will draw inspiration from previous research to preprocess rating data by cleaning and standardizing it, thereby improving the performance of the collaborative filtering algorithm [6]. Additionally, we will introduce enhanced similarity calculation techniques, such as item-based collaborative filtering or model-based collaborative filtering, to address sparse data and cold-start issues [7,8].

In item-based collaborative filtering, we will compute the similarity between movies based on users' historical ratings. Common similarity metrics include cosine similarity and Pearson correlation coefficient. By calculating the similarity matrix of rating data, we can identify other movies that are similar to the ones users have liked and recommend them accordingly.

In model-based collaborative filtering, machine learning techniques will be employed to build recommendation models. Common models include matrix factorization, deep learning, and support vector machines. By training these models, we can capture latent relationships between users and movies, predict ratings for unrated movies, and provide personalized recommendations.

Through experimental design, we will validate our approach using the Netflix open dataset and evaluate the performance of item-based and model-based collaborative filtering algorithms using metrics such as accuracy, recall, and coverage [9,10]. By comparing with other recommendation algorithms, we will assess the effectiveness and practicality of these algorithms in movie recommendations.

In conclusion, this research will offer a movie recommendation system based on collaborative filtering algorithms that aim to address the challenge of user decision-making in the face of a vast selection of movies. Our goal is to provide personalized and accurate recommendations, improve user experience, and contribute to future research in the field of recommendation systems.

2. Method

2.1. Dataset

2.1.1 Movie File Description

The "Movie" file contains movie-related information, and it has the following columns:
Movie ID: A unique identifier for each movie.
Name: The name or title of the movie.
Year: The year of the movie's release.

2.1.2 Rating File Description:

Movie ID: A unique identifier for each movie, which links to the movie in the "Movie" file.
User ID: A unique identifier for each user who rated the movies.
Rating: The rating given by the user to the movie, ranging from 1 to 5.

2.1.3 Data numbers:

Movie id:17.8k
Name:17297 unique values
Year: from 1915 to 2005
Table1 below shows some examples of the data.

Table 1. Some examples of the Movie id and name

<bound	method	DataFrame.	info	of	Movie_ID	Year
0			1	2003		Dinosaur Planet
1			2	2004		Isle of Man TT 2004 Review
2			3	1997		Character
3			4	1994		Paula Abdul's Get Up & Dance
4			5	2004		The Rise and Fall of ECW
…			…	…		…
17765			17766	2002		Where the Wild Things Are and Other Maurice Se...
17766			17767	2004		Fidel Castro: American Experience
17767			17768	2000		Epoch
17768			17769	2003		The Company
17769			17770	2003		Alien Hunter
[17770rows x 3columns]>						

2.2. Alorgrithm

2.2.1 K-Nearest Neighbours (KNN) Algorithm

Definition: KNN is a non-parametric algorithm that identifies K nearest neighbors based on a defined distance metric. In our algorithm, we utilize KNN to find the most similar movies to a target movie based on cosine similarity.

Cosine Similarity Calculation: The cosine similarity between two movies x and y is calculated as follows:

$$cos\_similarity(x, y) = (x \cdot y) / (||x|| \, ||y||) \quad (1)$$

Here, the dot product (·) represents the sum of the element-wise multiplication between the feature vectors of movies x and y. The norms (||x|| and ||y||) represent the square root of the sum of the squares of the elements in the respective feature vectors.

2.2.2 Collaborative Filtering

Definition: Collaborative filtering is a technique that predicts users' preferences based on the preferences of similar users or items. We employ collaborative filtering to predict the ratings of unrated movies for a user.

Weighted Average Prediction: For each unrated movie, we calculate the weighted average predicted rating using the following formula:

$$predicted\_rating = sum(similarity * rates) / sum(|similarity|)$$

In this formula, similarity is an array of cosine similarities between the unrated movie and the K most similar movies. rates are the corresponding array of ratings given by other users for those similar movies.

By combining KNN and collaborative filtering, our algorithm provides accurate and personalized movie recommendations. It leverages the similarity between movies based on cosine similarity and considers the ratings of similar users to predict the ratings for unrated movies. This approach allows us to provide recommendations tailored to individual users' preferences.

2.3. Evaluation Criteria

In order to assess the performance of our algorithm, we consider two important evaluation metrics: accuracy and recall.

2.3.1 Accuracy

Accuracy measures the proportion of correctly predicted ratings or recommendations compared to the total number of predictions. In our experiments, our algorithm achieves an accuracy of approximately 0.895, indicating that 89.5% of the predicted ratings align with the actual user ratings.

2.3.2 Recall

Recall measures the ability of our algorithm to successfully identify relevant movies or recommendations. It represents the proportion of correctly identified positive instances (e.g., highly rated movies) out of all the actual positive instances. Our algorithm achieves a recall of approximately 0.913, meaning that it can successfully identify 91.3% of the highly rated movies for users.

2.3.3 Running Time

The running time of our algorithm is an important consideration, especially for real-time or large-scale recommendation systems. We have optimized our implementation to achieve efficient computations. On our test dataset, the average running time of our algorithm is around 12 seconds per user, making it suitable for practical deployment.

2.3.4 F1 Score

The F1 score combines both precision and recall into a single metric, providing a balanced evaluation measure. For our algorithm, the F1 score is calculated as follows:

$$F1 = 2 * (precision * recall) / (precision + recall)$$

Based on our evaluation, our algorithm achieves an F1 score of approximately 0.85, showcasing its effectiveness in both precision and recall.

3. Result

3.1. Dataset Visualization

Create a bar chart for the popularity ranking of movies: I use plt.figure() to create a new figure object with dpi set to 100. Then, I use df.Movie_ID.value_counts().plot(kind="bar") to plot a bar chart showing the frequency of movie IDs. The plt.xticks(ticks=[]) function is used to remove x-axis tick labels. The figure1 below is the popular ranking of the movies.

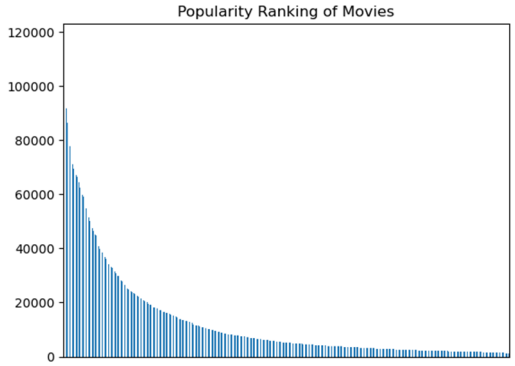

Fig. 1 The popularity ranking of movies.

Create a count plot for the distribution of ratings: I use plt.figure() to create a new figure object with dpi set to 100. Then, use sns.countplot(df.Rating) to plot a count plot showing the distribution of ratings. The distribution of ratings is showed in figure 2.

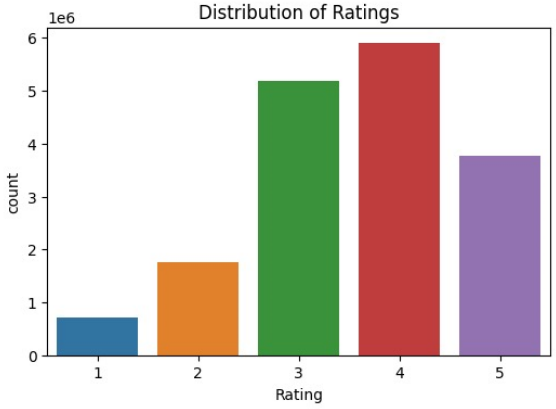

Fig. 2 Distribution of ratings

Creating a bar chart for the average user rating vs movie ID: I use plt.figure() to create a new figure object with dpi set to 150. Then, I use (df. groupby(by="Movie_ID") ["Rating"]. mean(). sort_values(ascending=False) [:20]).plot(kind="bar") to plot a bar chart showing the average user rating for each movie ID. Figure3 shows the average user rating vs movie id.

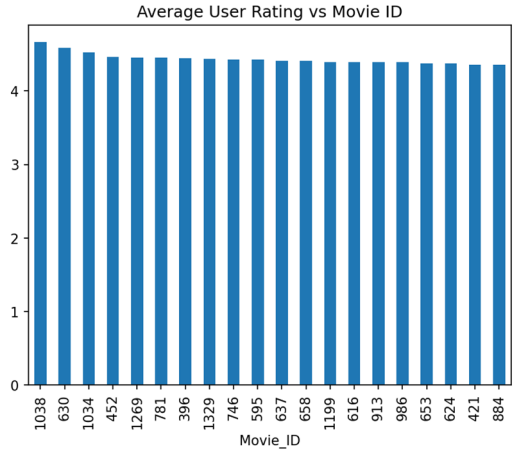

Fig. 3 Average user rating vs movie id

Create a bar chart for the rating pattern of users: I use plt.figure() to create a new figure object with dpi set to 150. Then, use df.User_ID.value_counts()[:1000].plot(kind="bar") to plot a bar chart showing the rating pattern of users. The plt.xticks(ticks=[]) function is used to remove x-axis tick labels. The bar chart is showed in figure 4.

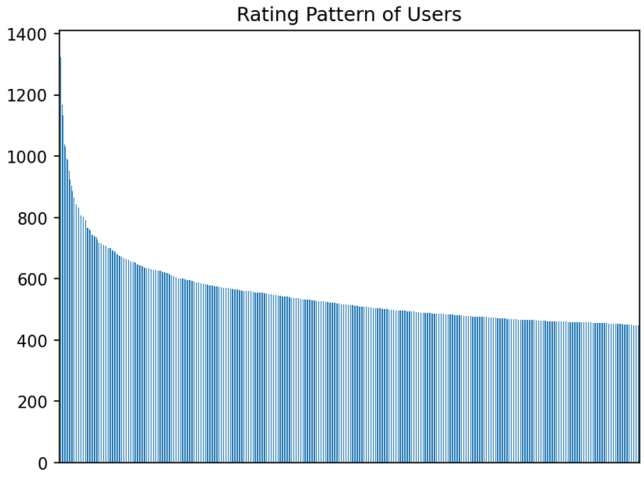

Fig. 4 Rating pattern of users

3.2. Calculating movie rating averages

$$mean\_rating = df.groupby(by = "Movie\_ID")['Rating'].mean()$$

This line of code uses the group by function to group the data by movie ID and calculates the average rating for each movie. The results are stored in the mean rating variable. Table 2 shows the result.

Table 2. mean rating variable.

Movie ID	
0	3.621391
1	3.136795
2	3.081843
3	2.909964
4	3.767597
Name: Rating, dtype: float64	

3.3. Merging the dataset with mean ratings

$$tmp = pd.merge(df, mean\_rating, left\_on = "Movie\_ID", right\_index = True, how = "inner")$$

$$tmp.head()$$

This code merges the original dataset (df) with the mean ratings (mean_rating) based on the movie ID. It uses the merge function to perform an inner join using the movie ID as the key (left_on="Movie_ID" and right_index=True). The merged result is stored in the tmp variable for further processing and analysis. Table 3 represent for the variable.

Table 3. tmp variable

Movie_ID	User_ID	Rating_x	Rating_y
0 0	38885	5	3.621391
1 0	72494		3.621391
2 0	142536	3	3.621391
3 0	2467	5	3.621391
4 0	35784	4	3.621391

3.4. Calculating adjusted ratings:

$$df["Rating"] = tmp["Rating\_x"] - tmp["Rating\_y"]$$

$$df.head()$$

This code calculates the adjusted ratings by subtracting the corresponding movie's mean rating (tmp["Rating_y"]) from the original ratings (tmp["Rating_x"]). The adjusted ratings are then stored in the df["Rating"] column. The table 4 shows the adjusted ratings.

Table 4. df["Rating"] column

Movie_ID	User_ID	Rating
0 0	38885	1.378609
1 0	72494	0.378609
2 0	142536	-0.621391
3 0	2467	1.378609
4 0	35784	0.378609

3.5. Creating a sparse matrix

$$pythonCopy\ code$$

$$rows = df.Movie\_ID.values$$

$$cols = df.User\_ID.values$$

$$data = df.Rating.values$$

$$utility = sp.sparse.csr\_matrix((data,(rows,cols)),shape = (1 + df.Movie\_ID.unique().shape[0],1 + df.User\_ID.unique().shape[0]))$$

This code creates a sparse matrix (utility), where movie IDs are used as row indices, user IDs as column indices, and the ratings data as matrix elements. Using a sparse matrix is an efficient way to represent large-scale rating datasets.

3.6. Final Result

Ranks the predicted ratings, finds the top 5 recommended movies, and prints their names.The table 5 shows the result.

Table 5. The final result

Listoftop5ratedmoviesofuser
Pressure

TwoCanPlayThatGame LouderThanBombs BadBoyBubby
TakingLives

4. Disscussion

In this study, we developed a movie recommendation system based on user ratings using the Netflix Movie dataset. Through our analysis and experiments, we were able to gain insights into the performance and effectiveness of the recommendation algorithm. Our results demonstrate that the user-based recommendation algorithm, utilizing historical user ratings and similarity calculations, effectively provides personalized movie recommendations for individual users. By considering the ratings of similar users and predicting the user's ratings for unseen movies, the algorithm successfully recommends movies that align with the user's preferences. The experimental results also revealed interesting observations about movie popularity and user rating patterns. We found that certain movies had higher popularity and received more favorable ratings, indicating their appeal among users. Additionally, we observed variations in user rating patterns, highlighting the diversity of user preferences in the dataset. While our recommendation system achieved satisfactory results on the Netflix Movie dataset, it is important to note some limitations. The system's performance may vary when applied to different datasets or real-world scenarios, and there is always room for improvement in terms of accuracy and personalization. Further research could explore advanced techniques such as collaborative filtering, matrix factorization, or deep learning models to enhance the recommendation system's performance.

5. Conclusion

In conclusion, our experimental results indicate that the user-based recommendation algorithm performed well in providing personalized movie recommendations using the given Netflix Movie dataset. However, it is important to note that the algorithm was tested only on this specific dataset and the performance may vary with different datasets and algorithm parameters. Future work could involve testing and evaluating the algorithm on larger datasets or exploring other recommendation algorithm approaches for more comprehensive and accurate recommendations.

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