Movie Recommendation System

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ABSTRACT

Movies are all time favorite entertainment media for everyone. Movie Recommendation systems are very popular these days, people like to get recommendations from other users, or based on the ratings of the movie. We are building a Movie Recommendation System based on the datamining algorithms. We are using different classification techniques like KNN, SVD and Clustering algorithm like K-means Clustering. Based on these algorithms we are going to evaluate the performances and accuracy of these models.

INTRODUCTION

Movies are one of the top all-time sources of entertainment. People enjoy watching, reviewing, and discussing them. For many people reviewing and rating movies is a passion. A movie can have fans and critics too. So, in a crowded entertainment market, movie streaming services and advertisers need to present viewers with the most relevant movies possible to maintain customer interest and loyalty.

Many companies now use data mining algorithms to create a recommendation system to match users with movies they would likely enjoy. A movie recommendation system can leverage data collected from users to identify patterns in an individual or group's viewing history, then use this insight to identify movies to recommend to a specific viewer. This project will use a database of user-submitted movie ratings to explore ways to generate movie recommendations and predict how users may rate future movies. Multiple algorithms will be used in order to compare their performance and practicality.

LITERATURE SURVEY

One of the better-known recommender algorithms is the Netflix Recommender System [1]. The algorithm originally began as a simple predictor of how many stars a user would rate a movie on a scale of one to five based on previous ratings but has grown into a multi-faceted system that generates many different types of recommendations according to other types of data Netflix now collects. For example, it can recommend titles that are popular among the entire user base, or movies that are similar to a single movie a viewer has watched based on a similarity algorithm.

Another system, MovieGEN, relies more on direct user input by asking viewers to respond to a list of questions and then generate recommendations based on their answers [2]. It uses both clustering and SVD to generate recommendations. Other systems use clustering to identify groups of users with similar tastes [3] or TF-IDF to find similar movies [4].

PROPOSED WORK

We will use movie rating data from the MovieLens dataset. This dataset is almost clean and can be used directly with some minimal pre-processing. We will perform basic cleaning to check for null values (movies without genres, missing ratings, invalid ratings). We will also combine the separate csv files for ratings and movies into a single table so ratings are linked to movie genres. Lastly, we will create a user genre rating table with average ratings for each genre of movie for each user.

This Project “Movie Recommendation System” generally will use two major techniques:

1. Content-based filtering uses algorithms which will identify similar items to items the user already likes i.e., items that have comparable properties independent of other users' data. A common algorithm for content-based filtering is “Term Frequency-Inverse Document Frequency" or TF-IDF. This is the most used algorithm to convert text into vectors and is widely used to extract features across various NLP applications but can also be applied to a recommender system. Another common algorithm is dot product / sum of product. For our movie recommendation system, content-based filtering will be used to identify movies that are similar to those that viewers have rated highly based on their genres.
2. Collaborative-based filtering uses data from other users to make recommendations to a given user. Methods include clustering, which groups similar users together and uses the top-rated movies from a user's cluster as recommendations, and classification algorithms like KNN and SVD.

The problem with a collaborative filtering is the cold start problem, once the model is deployed, the main concern is that the system cannot draw any inferences for movies or users about which it has not yet gathered sufficient information.

We will explore both content-based and collaborative-based filtering methods and seek to create an optimal movie recommendation system using techniques from previous recommender systems. While the Netflix recommendation system is highly developed and combines many different techniques, for our purposes and with the limited features in our dataset we will focus on simpler algorithms. We also do not have the ability to use an interactive process like MovieGEN’s question system as we do not have direct access to the millions of users in our dataset. Therefore, we will focus on collaborative-based filtering using clustering and classification, and content-based filtering using TF-IDF and dot product.

We will use K-means clustering to divide reviewers into clusters with similar taste in movies based on their average ratings of different genres. Clusters can be used to predict a user’s rating for a movie they have not seen yet based on the cluster average rating. “Top” movies for each cluster can be found by identifying the highest-rated movies for each cluster. Different k values will be used to find the optimum number of clusters.

DATA SET

The Dataset that we are using for this project is from MovieLens Dataset. There are different sizes of the dataset provided, so we will use the “Latest Full” dataset for the project which has 27 million data points. The “Latest Small” dataset can be used for testing the model which has nearly 100,000 data points. The data can be accessed in the URL: <https://grouplens.org/datasets/movielens/> with the permission of the MovieLens organization. We completed their contact form and successfully got permission to use the dataset in our project.

MAIN TECHNIQUES APPLIED

Our Project is going to recommend the movies based on the classification and clustering techniques.

In Classification, we are using two main techniques.

1. SVD Algorithm: Singular Value Decomposition is an unsupervised and collaborative filtering algorithm which is one of the widely used algorithms for recommendation and Dimensionality reduction systems. The Singular Value Decomposition (SVD) of a matrix is a factorization of that matrix into three matrices. The Singular Value Decomposition (SVD), a method from linear algebra that has been generally used as a dimensionality reduction technique in machine learning. SVD is a matrix factorization technique, which reduces the number of features of a dataset by reducing the space dimension from N-dimension to K-dimension (where K<N). In the context of the recommender system, the SVD is used as a collaborative filtering technique. It uses a matrix structure where each row represents a user, and each column represents an item. The elements of this matrix are the ratings that are given to items by users.

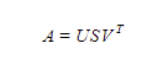
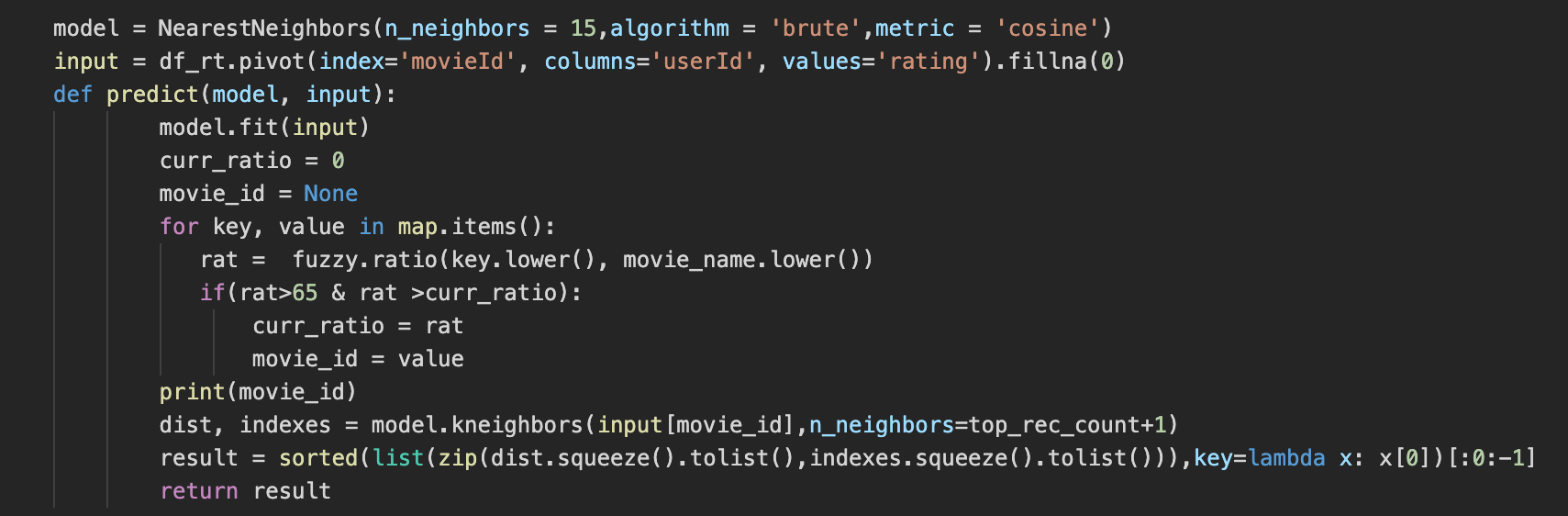


FIGURE 1

The factorization of this matrix is done by the singular value decomposition. It finds factors of matrices from the factorization of a high-level (user-item-rating) matrix. In Figure 1, The singular value decomposition is a method of decomposing a matrix into three other matrices as given below: Where A is a m x n utility matrix, U is a m x r orthogonal left singular matrix, which represents the relationship between users and latent factors, S is a r x r diagonal matrix, which describes the strength of each latent factor and V is a r x n diagonal right singular matrix, which indicates the similarity between items and latent factors. The latent factors here are the characteristics of the items, for example, the genre of the music. The SVD decreases the dimension of the utility matrix A by extracting its latent factors. It maps each user and each item into a r-dimensional latent space. This mapping facilitates a clear representation of relationships between users and items. [5]

1. In previous method of collaborative filtering-based recommendation, we used SVD to recommend movie as per user ID or user’s other choices and ratings given to the other movies. In this method we tried to design an algorithm to suggest movie recommendation based on movie Id or movie title. Similar thing happens in Netflix search, when we search for a movie like “God Father”, it will show other movies as well apart from “God Father”. We need to find the similarity among movies. KNN or nearest neighbor is a very good choice in this category. We will use the movies.csv and ratings.csv for this nearest neighbor approach. While finding distances there are different approaches (ball\_tree, kd\_tree) to find the distances. However, we will be using the brute force method where the algorithm attempts to determine the best approach from the training data. Also, the distances among points are calculated using the cosine metrics. Cosine similarity determines angle between two vectors. We had the other option of Euclidean distance to measure the similarity but in high dimensional data cosine similarity will perform better.



First, we are creating a sparse matrix where row will be the movieId, column will be userId and the value will be ratings. We will fit this matrix as input to the Nearest Neighbor model. Also, we will prepare a mapping for mapping movie Id to title. At the time of prediction, we will first find a movie title which is matching keywords to certain levels using a python library and this will be our test point. If we are searching for a movie which has exactly same title then it will be the starting point otherwise other movies which has similar name. Like if we search for “God Father 2” and that movie is not available then “God Father” will be found as a starting point. In the next step we will predict nearest movies which is similar to this starting point using the previously prepared Nearest Neighbor model. Once we find the nearest movies and their ids, we will use the previously prepared map to find the corresponding movie title to show the final result.

1. In Clustering, we are using K-means algorithm.

EVALUATION METHODS

1. For clustering, the fit of the clusters will be evaluated by the sum of the squared error (SSE). The lower the SSE, then the more similar are the Users/Movies. A high SSE suggests that the Movies/Users in the same similar segment have a reasonable degree of differences between them and may not be a true (or usable) segment. We will also look at the silhouette coefficient to judge how well-separated our clusters are. The silhouette coefficient ranges from 1 to –1. Positive values mean clusters are more separate, while negative values mean there may be confusion or incorrect assignments to clusters.
2. The optimum number of clusters will be chosen based on the elbow method and silhouette coefficient.
3. Evaluation of the SVD Algorithm

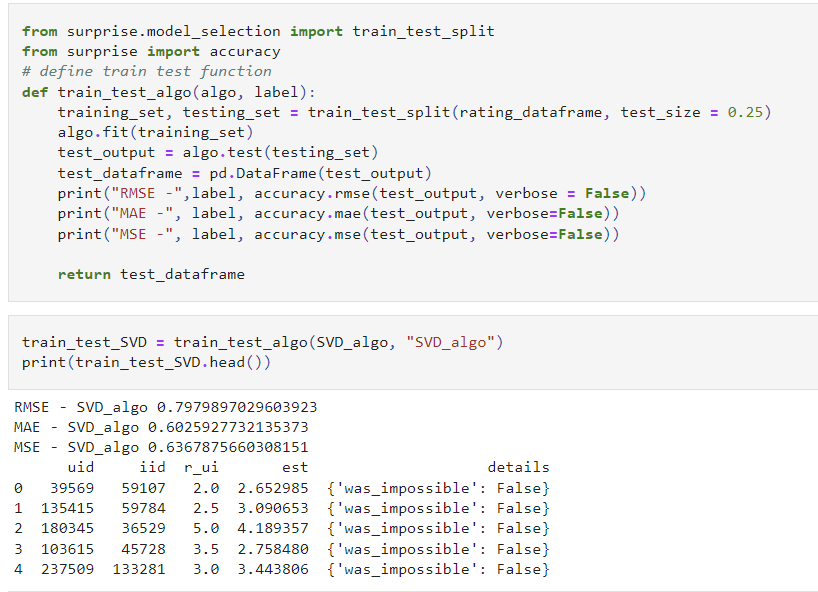


FIGURE 2

For evaluating the SVD algorithm, we use train-test split evaluation, in which we split dataset into 75% for training and 25% for testing. The above figure 2 shows the Root mean square error, mean absolute error, and Mean squared error for the SVD algorithm.

TOOLS

The following tools are going to be used to develop the project.

1. Python

Python programming language is the core tool to build our project. The data extraction, data cleaning, pre-processing and all the models and algorithms will be built using python programming language.

1. Pandas

We will use the Pandas Python module to work with the dataset. The major role of Pandas in our project is extraction of the data, creating data frames, and working with the data frames.

1. Scikit

Scikit is a Python library that contains various classification, regression, and clustering algorithms. We will use the clustering, KNN, SVD, and TF-IDF modules in particular.

1. Matplotlib

Matplotlib is a plotting library for the [Python](https://en.wikipedia.org/wiki/Python_(programming_language)) programming language and its numerical mathematics extension [NumPy](https://en.wikipedia.org/wiki/NumPy). In our project, we use matplotlib to plot the graphs or visualize the results.

RESULTS

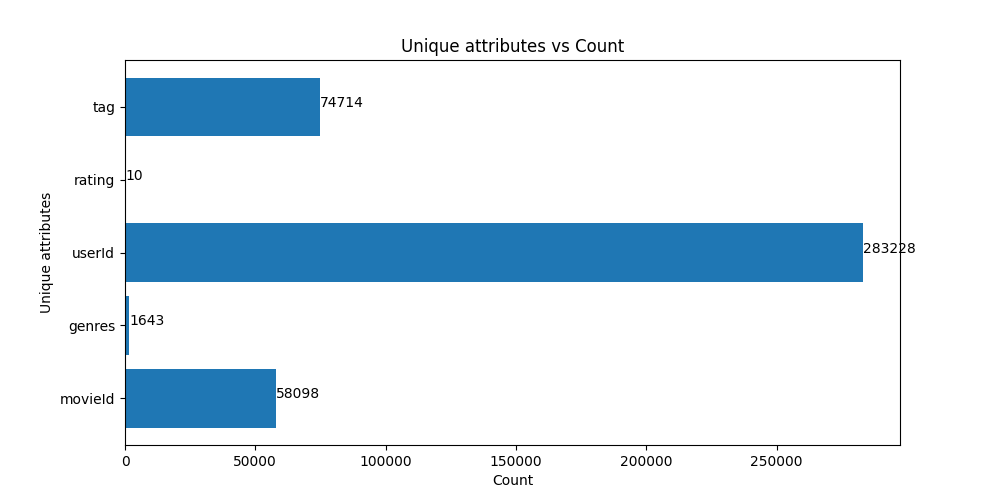


FIGURE 3

Figure 3 shows the Distinct count of each unique attribute like, number of tags, rating, userID, genres, movies. The Dataset used Latest Full 27 Million data points.

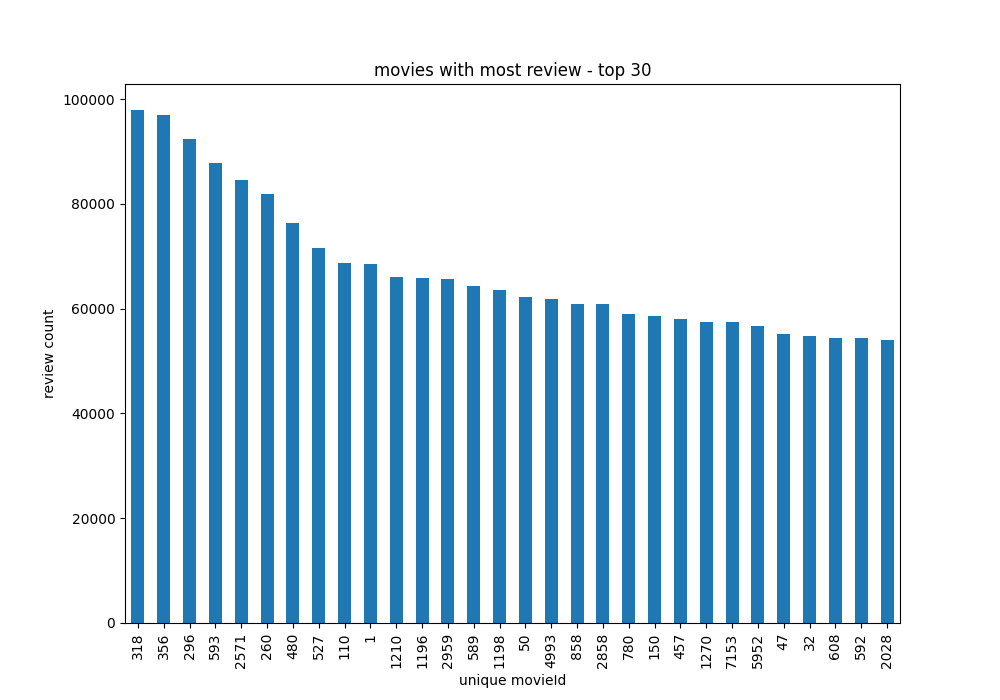


FIGURE 4

Figure 4 is a histogram of the top 30 most-reviewed movies from the full dataset.

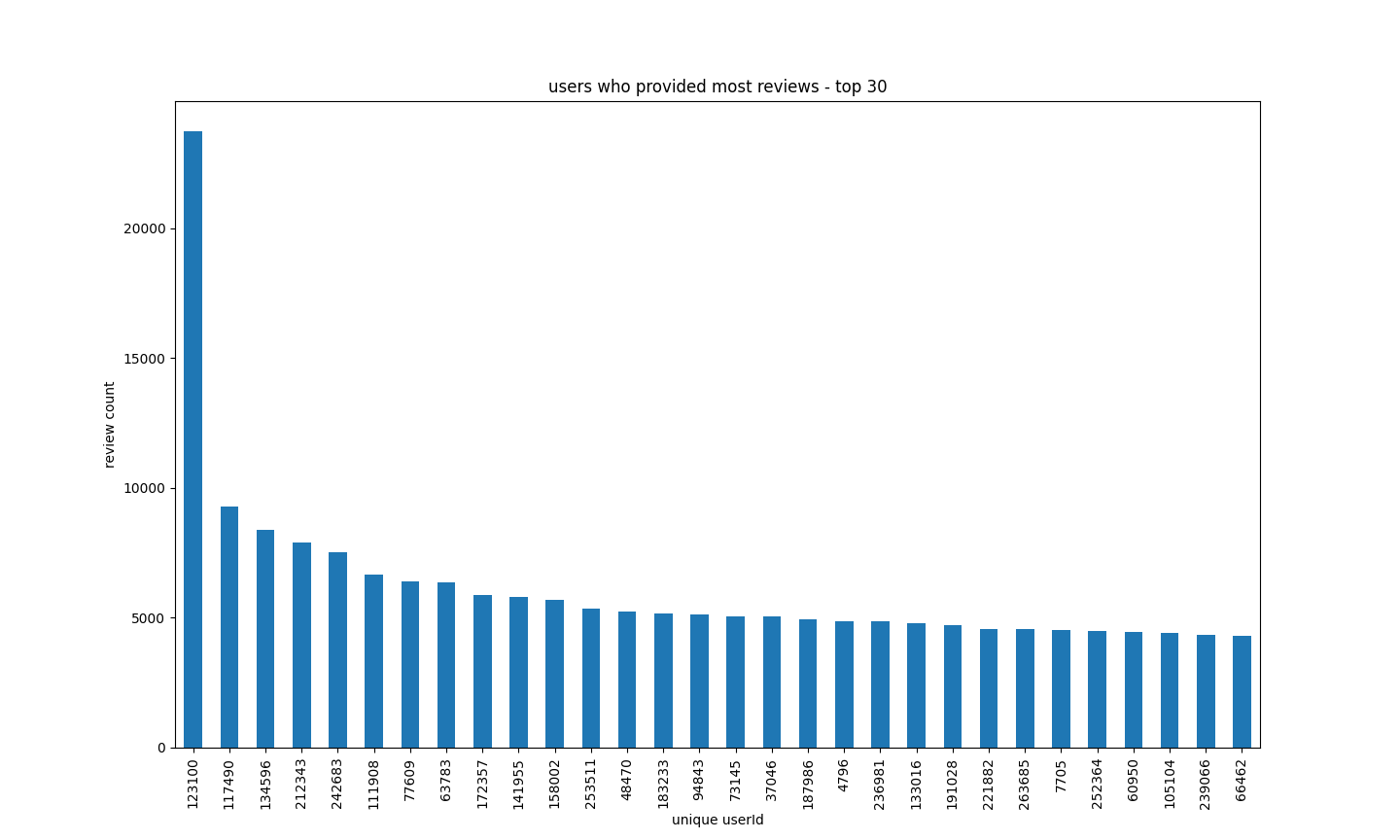


FIGURE 5

Figure 5 is a histogram of the top 30 users with the most reviews

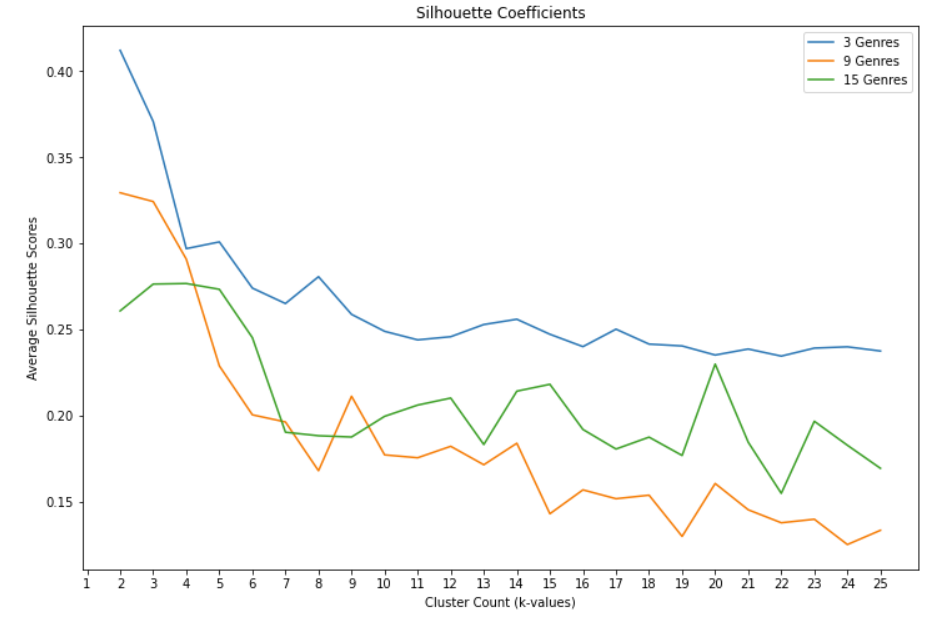


FIGURE 6

Figure 6 shows a plot of the silhouette coefficients of k-means clustering using 3, 9, and 15 genres based on the reduced dataset.

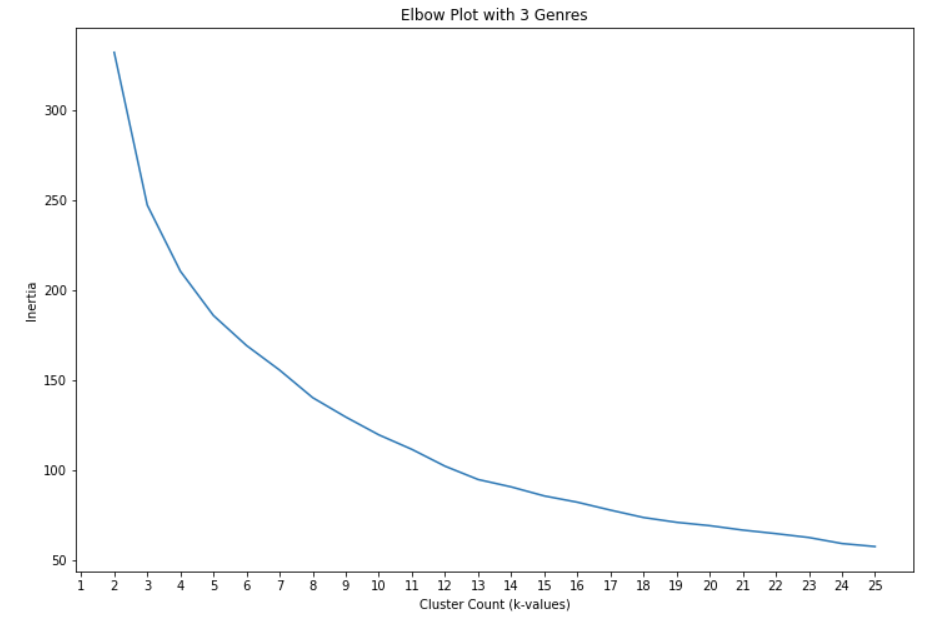


FIGURE 7

Figure 7 shows the elbow plot for a k-means clustering model using 3 genres (action, comedy, drama) and reduced dataset

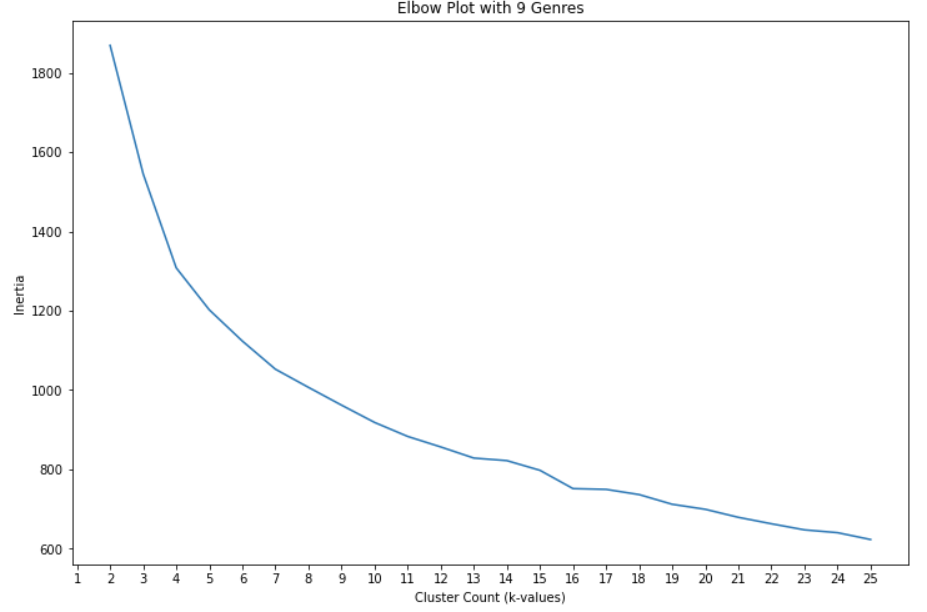


FIGURE 8

Figure 8 shows the elbow plot for a k-means clustering model using 9 genres ('Action', 'Adventure', 'Comedy', 'Crime', 'Drama', 'Mystery', 'Romance', 'Sci-Fi', 'Thriller') and reduced dataset

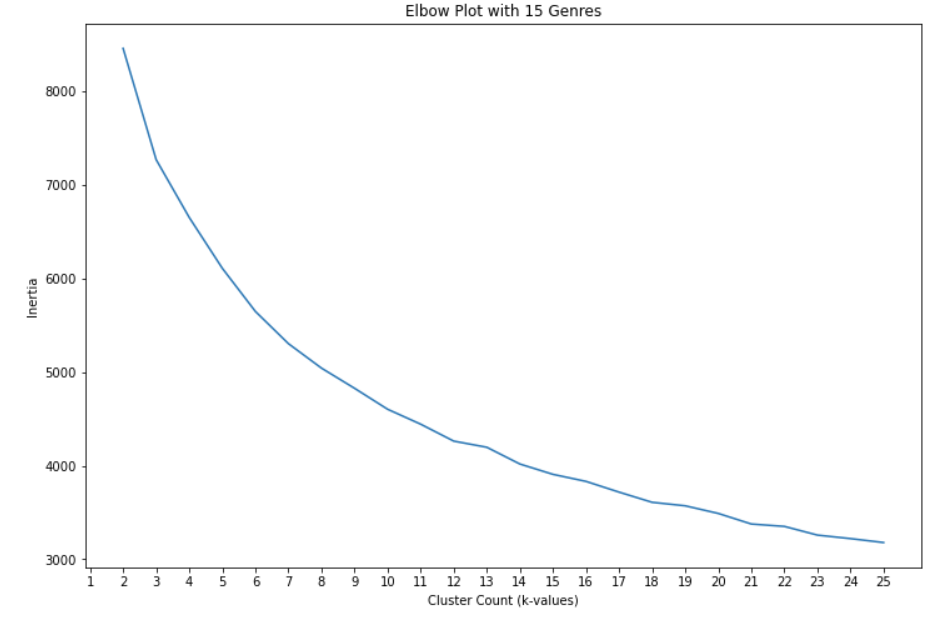


FIGURE 9

Figure 7 shows the elbow plot for a k-means clustering model using 15 genres ('Action', 'Adventure', 'Animation', 'Comedy', 'Crime', 'Drama', 'Fantasy', 'Horror', 'Musical', 'Mystery', 'Romance', 'Sci-Fi', 'Thriller', 'War', 'Western')

Conclusions: The elbow method (figures 7-9) is not a particularly accurate way to choose our k-value for k-means clustering as there is no definitive elbow or turning point in any of the graphs. The inertia does begin to level out as cluster number increases, so we focused on k-values around 10-12 which is within the range where the inertia still has a significant decrease between values and then considered the silhouette coefficient (figure 6). Surprisingly, the clusters using 9 genres are the least separate as k-values increase, while 3 genres give the most separation and 15 genres in the middle. We will focus our algorithm we apply to the full dataset on larger numbers of genres and around 12 clusters.

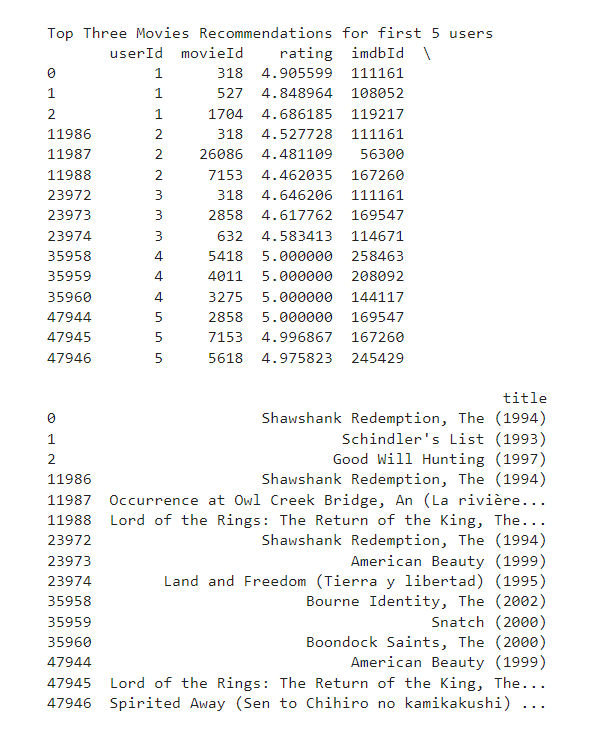


FIGURE 10

Figure 10 shows the top three movies recommended for first 5 users using the Singular Value Decomposition algorithm. Here we used the rating.csv file to train the SVD algorithm. We split dataset into 75% for training and 25% for testing. After the model is built, we created a rating prediction data frame in which it predicts the ratings for each user for all the movies. Using the SVD algorithm, the rating of the combination of userId and movieId is predicted on the scale of 0 to 5. Then the prediction results are linked to movie data frame(movie.csv – title) and link data frame (link.csv - imdbID) based on the movieId attribute to merge the data frames. The top recommendations are sorted by the top ratings by the Users. In this way, SVD algorithm gives the top recommendations by all the users.

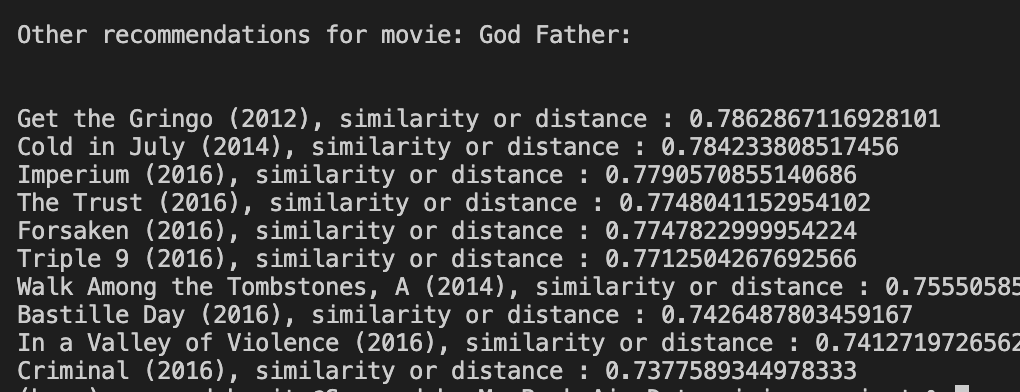


FIGURE 11

Figure 11 shows the top 10 movies recommended by a collaborative filter based recommend model when user searched for a movie name “God Father”. Distance values shows a similarity between the recommended movies and the input movie name “God Father”. We can see that the recommended movies are also crime mafia related, similar to God Father.

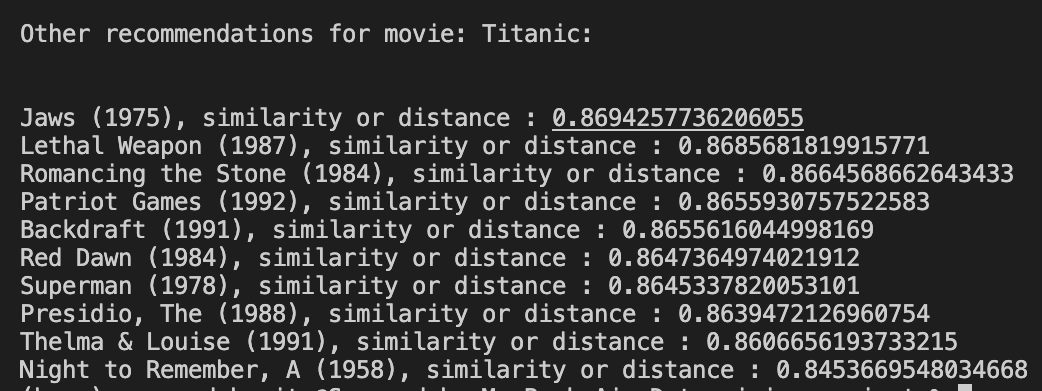


Figure 12

Figure 12 also shows similar recommendation for movie titanic. This time the model is showing sea related like Jaws or romantic movies.

REFERENCES

*1] Carlos A. Gomez-Uribe and Neil Hunt. 2015. The Netflix recommender system: Algorithms, business value, and innovation. ACM Trans. Manage. Inf. Syst. 6, 4, Article 13 (December 2015), 19 pages. DOI: http://dx.doi.org/10.1145/2843948*

*[2] Eyrun A. Eyjolfsdottir, Gaurangi Tilak, Nan Li (2008), “MovieGEN: A Movie Recommendation System”, 2008 Conference Proceedings.*

*[3] Roman, Victor (2019), “Unsupervised Classification Project: Building a Movie Recommender with Clustering Analysis and K-Means”, Towards Data Science, https://towardsdatascience.com/unsupervised-classification-project-building-a-movie-recommender-with-clustering-analysis-and-4bab0738efe6*

*[4] Nixon, Alex Escola (2020), "Building a movie content based recommender using tf-idf", Towards Data Science,* [*https://towardsdatascience.com/content-based-recommender-systems-28a1dbd858f5*](https://towardsdatascience.com/content-based-recommender-systems-28a1dbd858f5)

*[5] https://analyticsindiamag.com/singular-value-decomposition-svd-application-recommender-system/#:~:text=In%20the%20context%20of%20the%20recommender%20system%2C%20the,ratings%20that%20are%20given%20to%20items%20by%20users.*