BSCS-F23-016

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A Hybrid Recommendation System Considering Visual Information for Predicting Movies

In partial fulfilment of the requirements for the degree of

Bachelor of Science in Computer Science

Supervisor: Munazza Sher

Department of Computer Sciences

Bahria University, Lahore Campus

June 2024

C e r t i f i c a t e

We accept the work contained in the report titled.

"A Hybrid Recommendation System Considering Visual Information for Predicting Movies"

written by

MUHAMMAD ABDULLAH JAVED

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as a confirmation to the required standard for the partial fulfilment of the degree of Bachelor of Science in Computer Science.

Approved by:

Supervisor: Munazza Sher

____(Signature)

June 15, 2024

DECLARATION

We hereby declare that this project report is based on our original work except for citations and quotations which have been duly acknowledged. We also declare that it has not been previously and concurrently submitted for any other degree or award at Bahria University or other institutions.

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Date: June 15, 2024

Specially dedicated to

my beloved mother and father

(**MUHAMMAD ABDULLAH JAVED**)

my beloved mother and father

(**ANNAS BIN KHALIL**)

ACKNOWLEDGEMENTS

We would like to thank everyone who had contributed to the successful completion of this project. We would like to express our gratitude to our research supervisor, Miss Munazza Sher for her invaluable advice, guidance, and her enormous patience throughout the development of the research.

In addition, we would also like to express our gratitude to our loving parents and teachers who had helped and given us encouragement.

Muhammad Abdullah Javed
Annas Bin Khalil

A Hybrid Recommendation System Considering Visual Information for Predicting Movies

ABSTRACT

Choosing the best movie predict system is a necessary step for boosting user experience and interest in current streaming service platforms. But all these existing methods such as collaborative filtering have its own weakness like cold-start issues, issues of scalability and the propensity of these methods to generate popular items. Based on this, our study would try to take on this challenge by introducing a hybrid recommendation algorithm that employs the advantages of different recommendation methods. By doing so, we intend to improve recommendation accuracy, user satisfaction, and overall platform performance. In response to the limitations of existing movie recommendation systems, our study proposes a novel hybrid recommendation system named "Alternating Least Square - Convolutional Neural Network Recommendation" (ACR). ACR integrates the ALS matrix factorization technique with the power of Convolutional Neural Network (CNN), specifically utilizing VGG16, for image feature extraction. The anatomy of ACR involves incorporation of additional elements into the ALS matrix factorization model by emphasizing the effect of convolutional neural networks and specifically the VGG16 architecture for feature extraction. In developing our methodology, we have utilized the strengths of collaborative filtering as well as content analysis to improve recommendation accuracy and user satisfaction and the performance of the platform. With this, our RMSE was computed at 0. 8315 by using ACR.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER 1

INTRODUCTION

1.1 Background

Existing methods in recommending movies present difficulties that reduce customer satisfaction and system performance. One of the biggest difficulties associated with the application of collaborative filtering is cold start issue, in which users with low ratings have little history of past interactions. It also magnifies the problem of expanding capacity when the number of users and movies in the movie catalog goes up – resulting in decreased service performance and growing computational demand. The other weakness is the popularity bias: These systems tend to promote popularity; that is recommend popular items to users even though they are not in demand – thus decreasing the coverage of the options that are available to the user. In addition, the lack of attention to the exclusively explicit user-item interaction limits the applicability of recommendations since it ignores the secondary information, such as movies' genres or the theme, that may be crucial for an accurate and useful recommendation. To deliver superior movie recommendations that are contextually appropriate and varied the above mentioned challenges will require the use of improved algorithms and taps to user preferences. This is seen as the problem of using only textual data for the recommendation, wherein different words have different interpretations in different circumstances. Thus, a holistic approach to information retrieval for the recommendation system should involve a wider range of inputs to improve personalization of the experience for the user.

1.1.1 Collaborative Filtering

This works by finding similar group of people who are like the targeted people by examining their similar interest. This method works well for e-commerce type products. A visualization for CF is shown in figure 1.1.

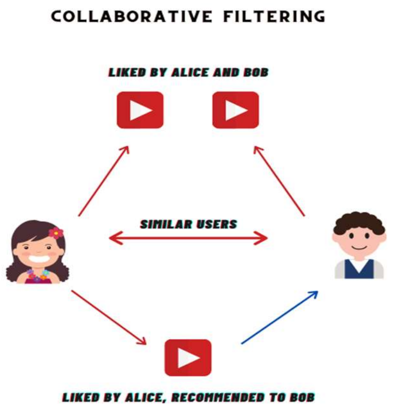

Figure 1.1: Collaborative Filtering

1.1.2 Content Based Filtering

Likeness between the items of that user is found. User's history is also taken for locating similar items. It uses item features to recommend other items like what the user likes. A visualization for collaborative filtering is shown in figure 1.2.

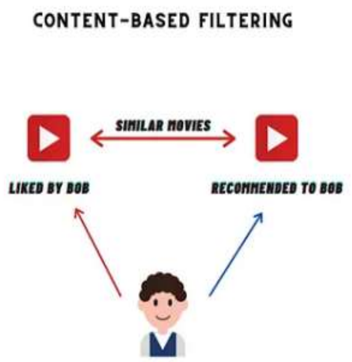

Figure 1.2: Content Based Filtering

1.1.3 Hybrid Approach

1.1.3.1 Weighted

A weighted hybrid recommendation system combines multiple recommendation approaches, assigning weight to each method based on their performance to a particular user or item. This system leverages the power of different recommendation ways to provide more perfect and valid recommendations.

1.1.3.2 Cascade

This defines a ranked structure recommendation system in which the major recommender system produces the major result, with help of a subordinate model, we resolve some issues of a primary result. for example, we extract features from posters for movies combining with our primary main recommendation system.

1.1.3.3 Switching

A switching hybrid recommendation system combines a variety of techniques to enhance the precision and relevance of recommendations. In such systems, instead of combining recommendations from various techniques using weighted averages or other aggregation methods, the system dynamically selects the best-performing technique for each user or item.

1.2 Problem Statements

The current recommendation approaches for feature films as disjoint approaches to CF and CBF are not good for prediction of user preferences. Collaborative filtering mechanism depends completely on user-item interactions [1] and ignores the item attributes while content-based filtering mechanism completely ignores user preferences and strictly relies on item attributes. This leads to recommendations that can be ineffective for a user since they are not personalized, diverse and accurate [2]. This gap forms the basis of our project and our goal of developing hybrid recommender system that is capable of applying both CF and CBF. We hope to make recommendation systems not only more accurate but also more effective from the users and the platform's perspective by recommending movies with greater diversity and personalization.

1.3 Aims and Objectives

i) To Develop a unique, dual based method for hybridization between the collaborative filtering approach and the content attribute filtering approach.
ii) To remove popularity biasness.
iii) To mitigate against the issue of giving recommendations for items that are most wanted by everyone, and also to consider minority preferences.
iv) To improve recommendation precision and make use of additional information besides users' actions, for example, movie genres and thematic topics.

1.4 Scope of Project

The subject of this project involves designing an MR system that integrates both collaborative and content-based filtering recommendation for predicting movies. It entails using an algorithm that combines both the collaborative filtering technique and the content-based filtering technique in an effort to enhance the preciseness of the movies recommended as well as the number of different movies suggested. This work involves acquiring and preparing large datasets regarding movie information/profiles, user likes/dislikes, and movie images/posters. Also, to achieve the goal, object recognition from images would be applied using convolutional neural networks (CNNs), and the obtained features would be further incorporated into the collaborative filtering, for example, using the Alternating Least Squares matrix factorization.

To collect data the first step is to gather sufficient and suitable dataset [3] of movie ratings and posters which may consist of user-item interactions and Movie Metadata (Posters). The gathered data will then be preprocessed to eliminate any inconsistency in the gathered data so that they generate valid results in building the recommendation system. In this regard, four basic means of evaluating the system such as RMSE, MAE, and MAPE will be used to test its functionality.

CHAPTER 2

LITERATURE REVIEW

With the rising advancement in technology and the increase in the use of the internet, movie recommendation systems have become significant in improving the interaction and pleasure of users in the entertainment industry. The movie's image posters are fetched from the IMDB's website. Those posters are then used with CNN. The CNN predict genres of the movie based on the forecasted genres the movies are recommended to end user based on their similarity [4]. CF, one of most common recommendation algorithms, relies mostly on the behaviour of users [5]. And it could reach prediction based on previous behaviour data of existing users. The authors said that the movie recommendation system gives suggestions and predictions based on just bi-rating or uni-rating parameters [6]. The sentiment to determine the movie's popularity, is unreliable and not so important. The models couldn't provide good recommendation because of large gap between the historical information of discrete ratings and continuous ratings. Some are generating high popularity and another's too low popularity of the same movie. In 2021, authors developed stock market prediction [7] by Naive Bayes, Black Friday sale prediction [8], and Amazon food review [9] with more machine learning models on Spark and got an accuracy of more than 90% with a good running time. The author has introduced "visual similarity" among items, which is the measurement of chance among items that are like in terms of a visual effect or "styles". Monitoring of real e-commercial site information reveal that users love to buy similar items or items with similar "style", which indicates that optical information can be considered a reliable feature for recommendation [10]. Secondly, a matrix supplement method is put forward to combine an item resemblance matrix with the user-item matrix for CF. At last, a new recommendation model introduced that takes advantages of visual similarity to collaborative filtering. The author suggested that the straightforward CNN performs unwell when trying to grip rotated, bent, or other irregular image positionings. As such, the planned work investigated the use of PCA and the deep learning architecture of VGG16. The PCA is used normally to extract important features from the dataset of an image. The dataset of National Institutes of Health Chest X-ray is taken; this has 112120 images for X-ray of 30805 different patients. Accuracy is used in the present work for evaluation. VGG 16's accurateness was rated as 79.1%. The accuracy has been increased up to 96% by the PCA approach [11]. To test the efficiency of a new recommendation algorithm, real-world MovieLens datasets were selected. With the input data, the unseen features of the movies and users were extracted using DL in order to train the deep-learning network algorithm model to guess movie scores. The RMSE scores attained 0.9908 and 0.9096 for the test sets of MovieLens 100 K and 1 M datasets, respectively, with a learning rate of 0.001. The scoring calculation results show improvement in accuracy after including the potential features and associations in multimodal data with deep-learning technology [12]. Author uses a mix of hybrid features of the items and the rating data of users to suggest a novel CB recommendation model that will suit the rating-based recommender scenario. Experimentally, the outcomes show that the proposed model has improved recommendation performance in the case of scarce data in comparison to conventional methods. Apart from that, offline training and online recommendation enable the model to work on large datasets with higher efficiency [13].

Table 2.1: Literature Review

Paper	**Year**	**Summary**	**Methodology**	**Algorithms**	**Main findings**
Exploiting Visual Contents in Posters and Still Frames for Movie Recommendation [14]	2018	Unique advantage lies in the fact that unfixing weights in previous few layers of the VGG16, so that features can be	The methodology involves integrating visual content into movie recommendation through the unified visual	Unified Visual Contents Matrix Factorization (UVMF), CNN integration into probabilistic MF.	Introduces UVMF model that outperforms other benchmark methods.

		learned and adapted to the task of movie recommendation, beats other standard methods in recommendation accurateness	content matrix factorization (UVMF) model.		
Web-Based Movie Recommender System [15]	2020	suggest movies to users based on their profile using diverse recommendation algorithms.	Includes a comparison of many recommendation algorithms	SVD, ALS, Boltzmann machines	ALS outperform other methods.
Matrix Factorization + for Movie Recommendation [16]	2016	Visual features are lacking in existing context-based approaches for movie recommendations.	A model for movie recommendations using visual features, incorporating low-level and high-level visual features	The specific algorithm introduced in the study is a novel model for movie recommendations	The novel model for movie recommendations incorporates visual features from movie.
FLEX: A Content Based Movie Recommender [17]	2020	A movie recommendation framework follows a content-based filtering approach.	Based on a hybrid of existing methods like Doc2Vec and tf-idf, utilizing features such as movie plots, ratings	Doc2Vec, tf-idf	Based on a hybrid approach, aiming to provide personalized recommendations aligned with customer interests to enhance engagement.

			recommendation generation.		
Design and Implementation of Movie Recommender System Based on Graph Database [18]	2017	The degree of recommendation of a movie is stated by the magnitude of the node and the depth of the edge.	Based on a user-based collaborative filtering algorithm, utilizing a graph database, and visualizing movie recommendations.	user-based collaborative filtering algorithm	Presents a movie recommender system constructed on CF and graph database technology and utilizes data visualization for improved user experience.
Prediction of individual preference for movie poster designs based on graphic elements using machine learning classification [19]	2021	Machine learning classification predicts specific preference for movie poster designs based on graphic elements.	facilitated the ML computation to correlated graphic elements within each poster design with individuals' subjective preference judgments selected among three categories, Like, Neutral, and Dislike	decision tree classifier, XGboost in the Scikitlearn	Prediction Accuracy achieved 71%. Hits the objects in poster.
A Lightweight Model of VGG-16 for Remote Sensing Image	2021	A lighter model built on VGG-16 can selectively extract some features of remote sensing	It involves CNN model for classification.	VGG-16 for remote sensing image categorization	VGG-16, reaching over 98% accuracy.

Classification [20]		images, remove unnecessary information, identify and categorize remote sensing images.			
Image Classification Based On improved VGG Network [21]	2021	The training parameters of the better VGG model are condensed to 10.65% of the novel model.	An improved VGG-16 model with modifications and utilizing four data augmentation methods for image classification on cifar10 dataset.	VGG-16 model, data augmentation methods	Classification accuracy achieved 94%
Image Based Recommender System using Transfer Learning [22]	2022	Traditional recommender systems use user feedback such as ratings, likes/dislikes. Images are considered in this paper.	Uses VGG-16 to extract image features. Then use cosine similarity to get similar images.	SVD, VGG-16	Without image consideration RMSE was 1.95 and after consideration it was reduced to 1.67

CHAPTER 3

DESIGN AND METHODOLOGY

The integration of a hybrid approach based on ALS collaborative filtering and VGG-16, a CNN, yields improved accuracy as well as diversification in the offered movie suggestions. Specifically, this section outlines the theoretical basis for the hybrid system integration and offer the architectural plan and components of the system.

3.1 System Architecture

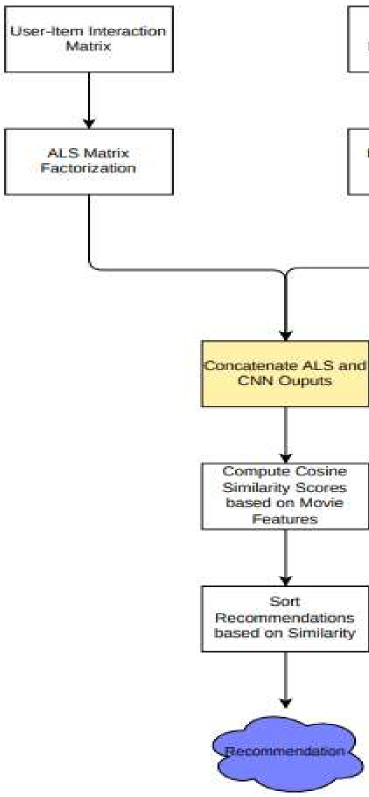

Figure 3.1: Block Diagram

The design of the hybrid recommendation system that we propose in this paper can be expressed in terms of a system architecture (see figure 3.1) as a combination of collaborative and content-based filter that uses a series of sub-processes. Fundamentally, such architecture is established in order to align synergistically the two centralized methodologies to improve the quality and variety of recommendations.

3.2 Collaborative Filtering

The algorithm we have used for collaborative filtering is Alternating Least Squares (ALS). It is a matrix factorization algorithm. It Utilizes user-item interaction data to construct a user-item matrix representing the strength of connections between users and items as shown in figure 3.2.

We are employing matrix factorization technique to decompose the user-item matrix into latent factors, taking underlying patterns in user likings and item attributes.

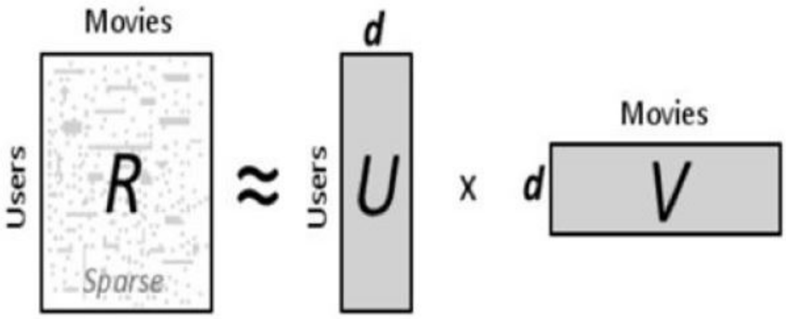

Figure 3.2: User-Movie Interaction

We are predicting ratings using ALS algorithm which is based on user similarity. The Output of ALS is shown in Table 3.1.

Table 3.1: ALS Output

userId	movieId	rating	prediction
3184	148	4.0	3.378334
1242	148	3.0	2.7581484
1605	148	2.0	2.1193135
840	148	1.0	2.9952784
1150	148	2.0	2.5563385
424	148	4.0	2.651739
3053	148	3.0	2.7773268
3151	463	5.0	3.6111734

The rating column represents **actual rating** of movie and prediction represents **predicted ratings** which is done by ALS.

3.3 Feature Extraction

VGG-16 stands as a pioneering CNN architecture famous for its depth and simplicity. Originally designed for image classification tasks, VGG-16 has found widespread application beyond its initial purpose. In our project, VGG-16 plays a pivotal role in extracting visual features from movie-related images, such as posters.

As demonstrated in the figure 3.3, VGG-16 have a total of 16 layers which comprise 13 convolutional and 3 fully connected layers Most impressive particularly with regard to the number of layers, this power house was specifically designed to capture high level of details and features embedded on the image. Because VGG-16 draws on pre-trained weights from the ImageNet dataset, it uses a strong and efficient method of feature extraction, which benefits even applications with small amounts of training data in areas such as movie recommendation.

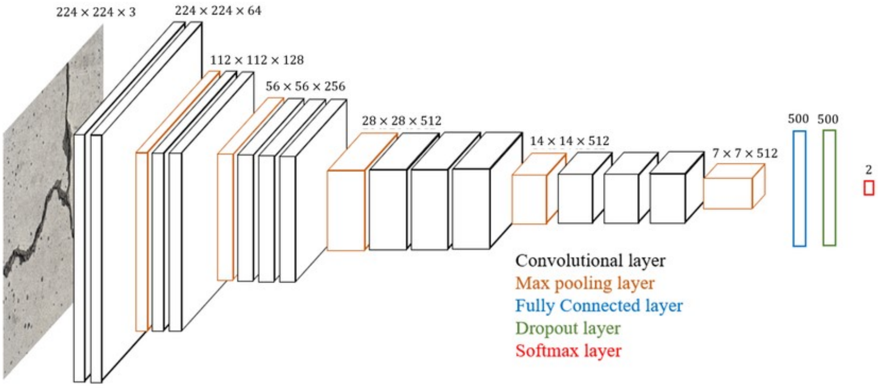

Figure 3.3: VGG-16 Architecture

When embedded in the context of our hybrid recommendation system, VGG-16 provides valuable added features concerning the allocation of high-level visual features from movie posters. Subsequently these extracted features are fed into the recommendation model thus improving the recommendation model's ability to pick other characteristics relating to the movies. In order to extract features from the image, VGG-16 applies filters on the image as illustrated in the figure 3.4.

Figure 3.4: Filters applied on Movie Poster

3.4 Hybridization

The following are our proposed steps in hybridization that ensure we obtain a fine synergy from combining the advantages of CF (ALS) and CBF (VGG-16 + PCA) to arrive at the improved recommendations for movies. Here's an overview of the strategy:

3.4.1 ALS Results Generation

The first set of movie recommendations is initially produced using the ALS model of collaborative filtering relying on the user-item interactions. From the results of interaction matrix, ALS gives recommendations by making an assumption that other users or items are similar to one another.

3.4.2 Movie Poster Content Identification

To extract features from the movie posters, a feed-forward convolutional neural network known as VGG-16 is used to get the features of images. These features represent the general form of the elements in the posters such as shape, layout and colour.

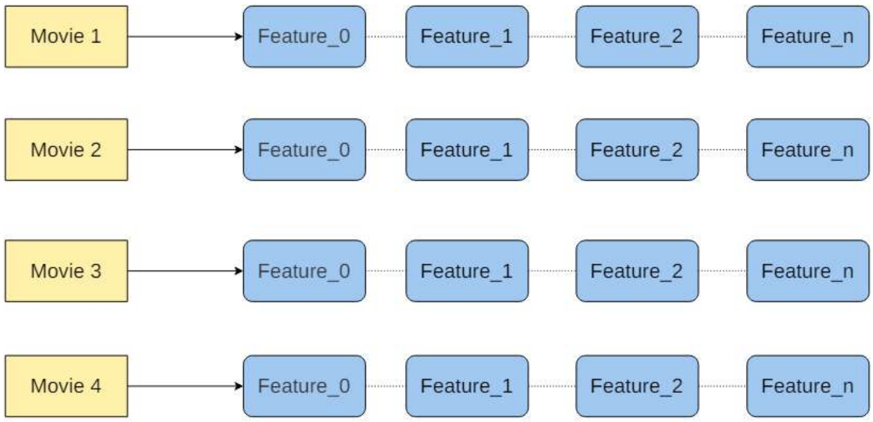

Figure 3.5: Extracted Movie Posters

Movie posters extracted from the model are stored in a Hash Table like structure as indicated in Figure 3.5 with MovieID as keys and list of feature values as the value and these were extracted using VGG-16.

3.4.3 Dimensional Reduction with PCA

As a result of the feature maps from VGG-16 layers, the poster features are in high dimensions, and PCA is used to dimensionality reduce the features to a fewer dimension. This particular step helps decrease the computational intensity and level of noise inherent in poster features but retains their key characteristics in the process.

3.4.4 Interlinking the ALS results with poster features

The ALS recommendations and the reduced poster features are then merged depending on the movie ID. This link connects the two recommendation matrices and links the collaborative filtering recommendations to the content-based movie poster features.

Table 3.2: Combined Poster features with ALS

userId	**movieId**	**rating**	**prediction**	**feature_0**	**feature_1**	**feature_2**	**feature_3**	**feature_4**	**...**
673	148	5.0	2.943212	0.209787	1.000000	0.195656	0.137711	0.443711	...
4387	148	1.0	2.531729	0.209787	1.000000	0.195656	0.137711	0.443711	...
2383	148	2.0	2.703885	0.209787	1.000000	0.195656	0.137711	0.443711	...
1242	148	3.0	2.788594	0.209787	1.000000	0.195656	0.137711	0.443711	...
840	148	1.0	3.246411	0.209787	1.000000	0.195656	0.137711	0.443711	...
...	...	...	...	...	...	...	...	...	...
2280	3910	3.0	4.124915	0.851341	0.696987	0.437636	0.609575	0.600440	...
1753	3910	4.0	3.976731	0.851341	0.696987	0.437636	0.609575	0.600440	...
1449	3910	3.0	3.354278	0.851341	0.696987	0.437636	0.609575	0.600440	...
3371	3910	1.0	3.737503	0.851341	0.696987	0.437636	0.609575	0.600440	...
1584	3910	4.0	3.208488	0.851341	0.696987	0.437636	0.609575	0.600440	...

3.4.5 Sorting ALS Results Based on Poster Features

The integration of the recommendations is carried out by arranging them according to the similarity measures calculated with the help of cosine similarity strategy. This step makes it easier for similar picture movies to be ranked highly in the list allowing increased chances of better recommendation relevancy and variety. Equation to describe it is illustrated below:

$$\cos(\theta) = \frac{\mathbf{A} \cdot \mathbf{B}}{\|\mathbf{A}\|\|\mathbf{B}\|} = \frac{\sum\limits_{i=1}^{n} A_i B_i}{\sqrt{\sum\limits_{i=1}^{n} A_i^2} \sqrt{\sum\limits_{i=1}^{n} B_i^2}}$$

3.4.6 Final Recommendations

These sorted refined results are the final recommendations of the movie that would be recommended. These recommendations incorporate both collaborative filtering insights and content-based poster features, providing users with more accurate, diverse, and personalized movie suggestions.

3.4.7 Pseudocode Representation

1. Initialize ALS recommendation system

2. Generate ALS recommendations based on user-item interaction data

3. Initialize VGG-16 CNN for poster feature extraction

4. For each movie:

4.1. Extract visual features from movie poster using VGG-16

4.2. Reduce dimensionality of poster features using PCA to 32 columns

4.3. Normalize the reduced poster features to ensure consistent scaling

5. Combine ALS recommendations with normalized reduced poster features based on movie ID

6. For each combined recommendation:

6.1. Calculate cosine similarity between poster features of current movie and all other movies

6.2. Sort ALS recommendations based on cosine similarity scores in descending order

7. Use the refined recommendations for movie recommendations

CHAPTER 4

DATA AND EXPERIMENTS

4.1 Data Collection and Preprocessing

For collaborative filtering experiments, the Movielens dataset [3] was utilized. This dataset comprises user ratings for various movies and serves as a benchmark dataset for recommendation systems research. Before analysis, the Movielens dataset experienced preprocessing steps to remove duplicate entries, handle missing values, and filter out outliers. The dataset was then arbitrarily separated into training, validation, and testing sets using [80/20 ratio] to facilitate model training and evaluation The description of Movielens dataset is shown in table 4.1.

For content-based filtering experiments, movie posters were collected, providing visual representations of movie artwork. Each poster was renamed with its corresponding movie ID to facilitate data management and association. Preprocessing of the movie posters involved standardizing dimensions and formats to ensure consistency across the dataset.

Table 4.1: Movielens Dataset Statistics

summary	userId	movieId	rating
count	200423	200423	200423
mean	3028.708845791152	1869.5188027322213	3.583540811184345
stddev	1729.5097969567137	1095.2322223320934	1.1171578019509012
min	1	1	1.0
max	6040	3952	5.0

Table 4.2: Movie Posters Dataset

	MLP-1M	MLP-20M
Posters	3816	26,940

Movie posters are crucial for the recommendation system. We have used 2 datasets for movie posters. Table 4.2 shows the quantity of posters in both datasets.

4.2 Collaborative Filtering Experiment

The collaborative filtering experiment utilized the Movielens dataset to train and evaluate recommendation models. The Alternating Least Squares (ALS) algorithm was developed using the pyspark collection in Python. Optimizations including but not limited to, hyperparameters tuning like the regularization was done in a bid to enhance the recommendation. The rating distribution in the movielens dataset is displayed in the below figure 4.1.

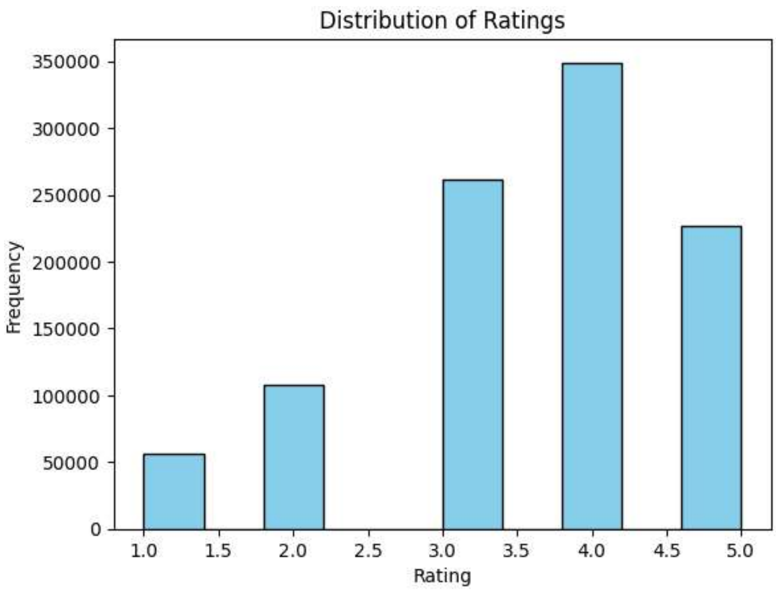

Figure 4.1: Ratings Distribution

4.3 Content-Based Filtering Experiment

The movie posters were preprocessed to extract the features using VGG-16, which is a deep learning model that works for image classification. In an attempt to let each poster be uniquely associated with the movie ID in the Movielens dataset, each of the above named posters was renamed to correspond to their movie ID. After that, for the purpose of bringing down the computational overhead, the feature vector was at down to 32 channels utilizing Principal Component Analysis (PCA).

Using the cosine similarity this dictionary could be used to generate recommendations. The recommendation of movie ‘Waiting to Exhale” is in figure 4.2.

Figure 4.2: Content based Similar Recommendations

4.4 Hybridization Experiment

Two routes were examined and proposed for using recommendations from collaborative filtering and content-based techniques. This involved selecting movies using simple selection by recompiling movie poster features by using the movie id and then sorting the overall combined recommendations by the cosine similarity scores. More specifically, this method was designed to incorporate the visual information of the movie posters into the recommendation selection process so as to increase the relevancy and variety of suggestions.

In the second approach, linear regression was applied to the fused dataset pointing to CF recommendations and CBF features. This method was designed in a way that seeks to learn a mapping from the collaborative filtering scores and the content-based features in a bid to improve on the recommendations.

Thus, based on the results of the hybridization defined above, the results that can be achieved with this approach are generally the best with manual sorting based on the Cosine similarity criterion. However, the linear regression approach when tested for its performance was not as efficient compared to the time-tested method of manual sorting.

Collectively, we can conclude that combining collaborative and content-based recommendation techniques with manual selection/sorting classified by the cosine similarity method was the most effective approach in our research. They both build upon the strengths of each other while at the same time remaining both understandable and explainable in terms of how the recommendation system adapts movies similar to a particular input.

CHAPTER 5

RESULTS AND DISCUSSIONS

Various types of metrics such as Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and Mean Squared Error (MSE) was used in evaluation on the efficiency of the hybrid recommendation system. These metrics indicate the improvement and general performance of the recommendation system with respect to the various evaluation criterions.

5.1 Performance Metrics

- **Root Mean Squared Error**

RMSE computes the average magnitude of the errors among the predicted and the real ratings. The lesser the RMSE value, the better the predictive accuracy.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$$

- **Mean Absolute Error**

The MAE deals the average magnitude of absolute errors. It stands for the average of the difference between the rating estimated and actual rating.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i|$$

- **Mean Absolute Percentage Error**

MAPE computes the percentage difference between forecasted and actual ratings. It offers a comparative measure of accuracy, accounting for scale differences in ratings.

$$MAPE = \frac{100}{n}\sum_{i=1}^{n}\left|\frac{y_i-\hat{y}_i}{y_i}\right|$$

- **Mean Squared Error**

MSE quantifies the average squared difference between forecasted and actual ratings. It penalizes greater errors more heavily than minor ones.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$$

5.2 Comparison with Baseline Methods

The performance of the hybrid recommendation system was related with standard methods. Across all evaluation metrics RMSE, MAE, MAPE, and MSE, hybrid system consistently outperformed the baseline methods.

Table 5.1: Comparison with Baseline Method

	ALS	**SVD**	**Hybrid Approach**
RMSE	0.8821	0.8773	0.8315
MAE	0.708	0.6888	0.6648
MSE	0.7779	0.7697	0.6914
MAPE	25.7437	26.5834	14.7669

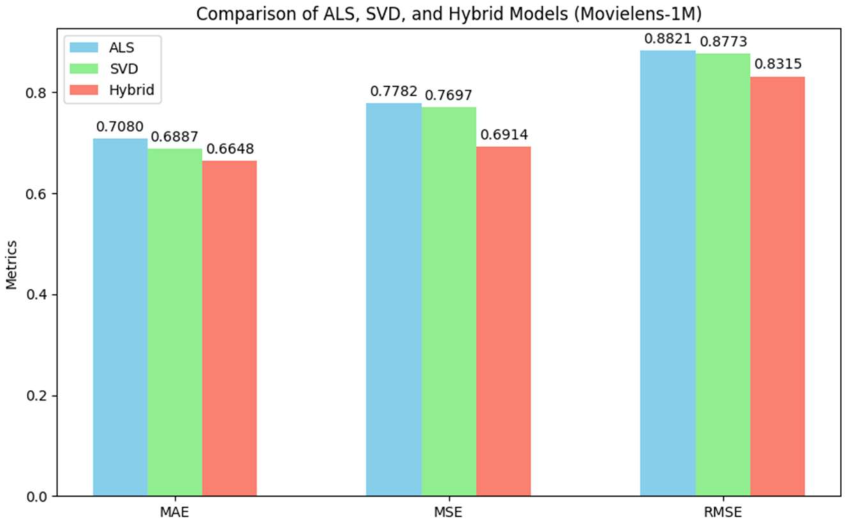

Figure 5.1: Comparison of Results

We can clearly visualize the improvements before and after the hybridization technique in figure 5.1 and figure 5.2.

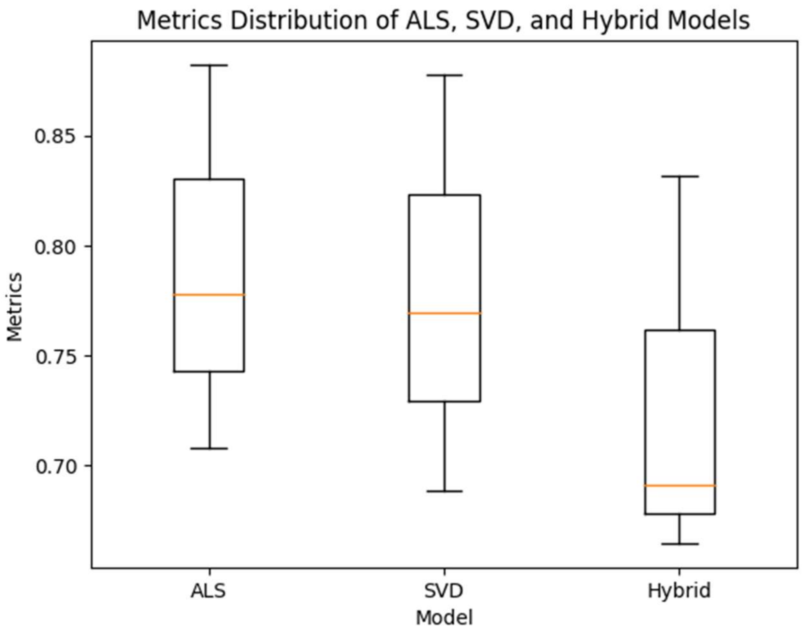

Figure 5.2: Box Plot

While comparing the two poster feature files derived from the Movielens 1m and MLP-20m datasets, it becomes evident that there exists a notable trade-off between computational time and recommendation quality. The dataset containing features for approximately 26,000 movies from the MLP-20m dataset naturally demands more computational time for processing and analysis compared to its smaller counterpart, which encompasses features for only around 3,800 movies from the Movielens 1m dataset. This increased dataset size necessitates longer processing times, particularly evident in tasks such as feature extraction and model training. However, despite the associated computational overhead, the larger dataset often leads to improved recommendation quality.

CHAPTER 6

USER MANUAL

6.1 Landing Page

Landing Pages are web specifically designed and optimized pages. They are the entry points for users who come to website. User will enter some movie name and will get some recommendations in its response based on movie poster as shown below.

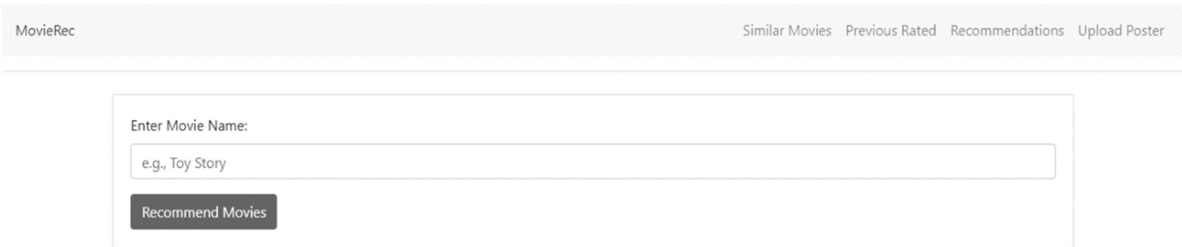

Figure 6.1: Landing Page

6.2 Recommendations

When the user will enter some movie name then he will get some recommendations in its results. It is shown in the figure 6.2.

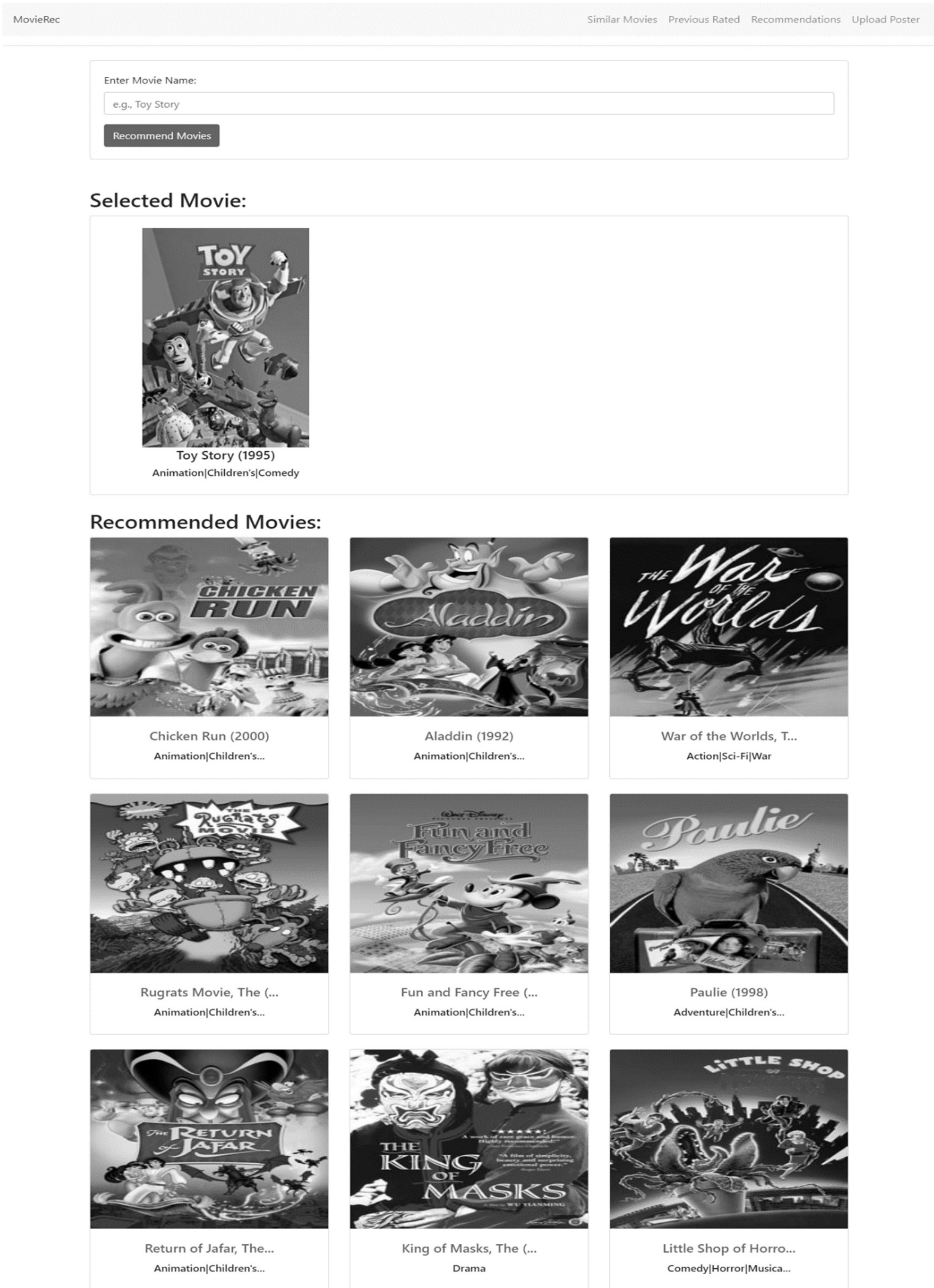

Figure 6.2: Recommendations (Similar Movie)

6.3 Upload Poster

The user can also upload poster whatever he/she wants, and the recommender will generate recommendations in its response. It should be kept in mind that the uploaded poster matches the standard of movie poster design to get good recommendations as shown below.

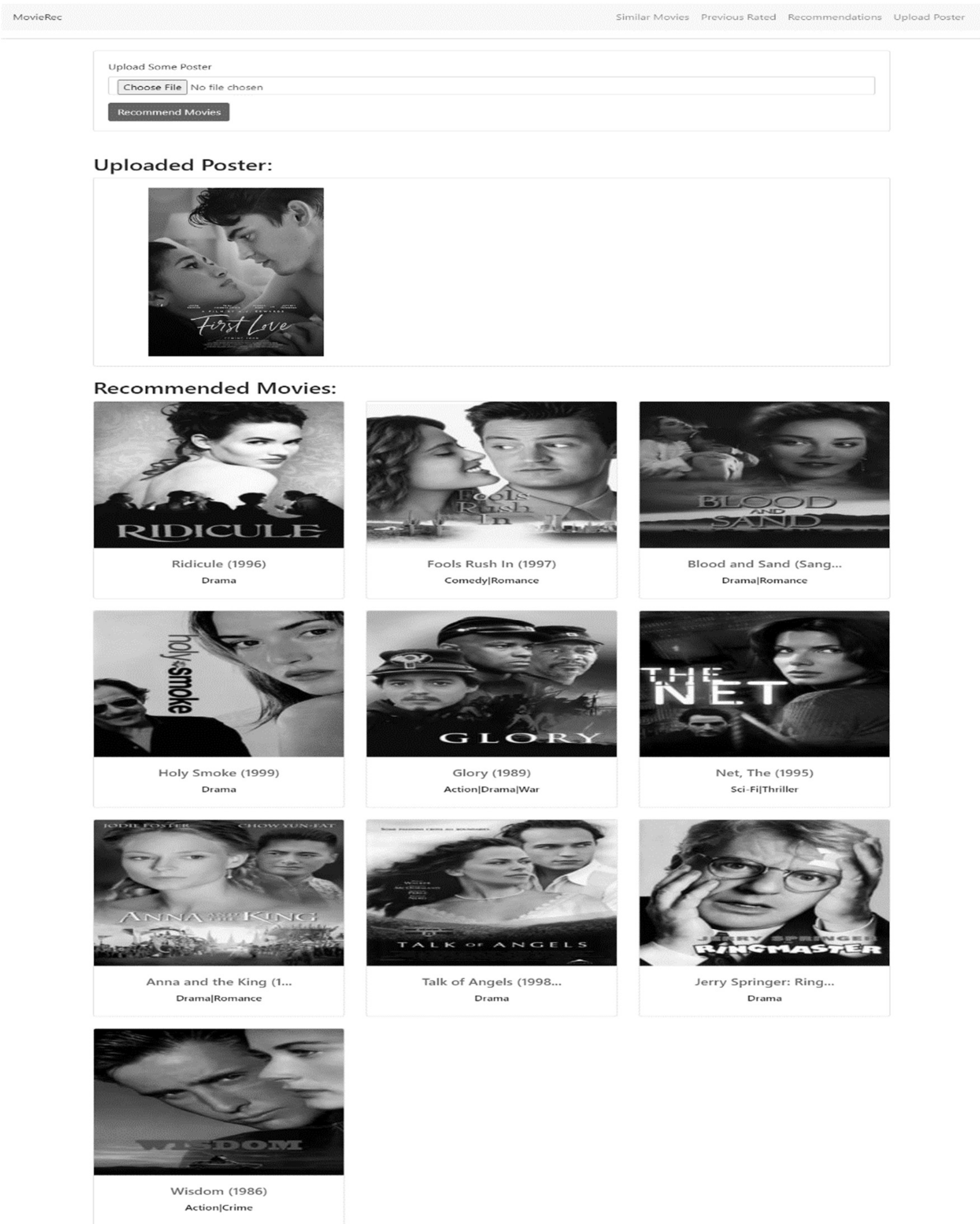

Figure 6.3: User Uploaded Poster

6.4 Predicted Ratings

The movielens dataset contains ratings of users. We have refined the recommendations by using Hybrid Model. Those recommendations can be viewed in Recommendations page by entering userid as shown below:

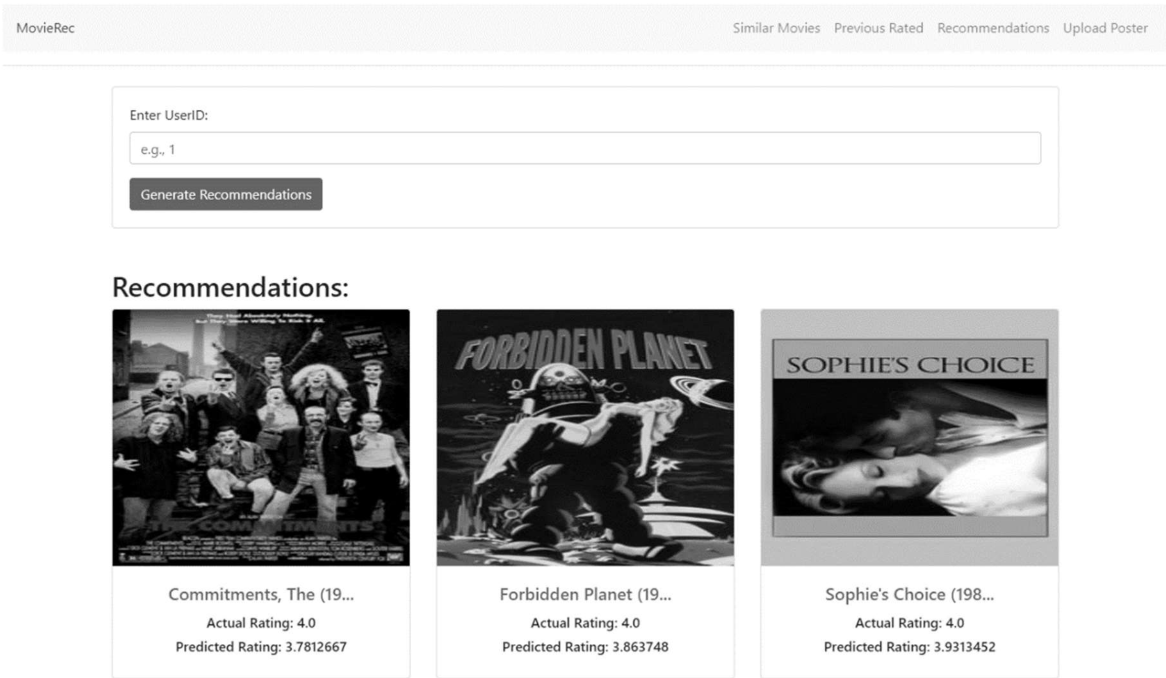

Figure 6.4: Hybrid Recommendations

CHAPTER 7

CONCLUSION AND RECOMMENDATIONS

This study has demonstrated the effectiveness of a hybrid recommendation system for predicting movie preferences by combining CF with CBF methods. Through integration of ALS with VGG-16 feature extraction from movie posters, the hybrid system achieved superior recommendation accuracy, diversity, and personalization compared to baseline methods. The evaluation results, encompassing metrics such as RMSE, MAE, MAPE, and MSE, consistently showcased the hybrid system's superiority across various evaluation criteria.

Moving forward, several recommendations can be made to further enhance the hybrid recommendation system and address potential areas for improvement. Firstly, expanding the dataset size and quality, particularly by incorporating more comprehensive movie metadata and user interaction data, could enrich the recommendation process and lead to more accurate and personalized recommendations. Additionally, exploring cutting-edge ML methods, such as deep learning and NLP, may offer opportunities to extract more informative features and improve recommendation performance further.

Moreover, optimizing computational efficiency through parallel processing, distributed computing, and feature selection techniques can help mitigate the computational overhead associated with larger datasets, enabling more scalable and resource-efficient recommendation systems.

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