# Sri Lanka Institute of Information Technology



# **Information Retrieval and Web Analytics – IT3051**

B.Sc. (Hons) in Information Technology

Movie Recommendation System – Final Report

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#### DECLARATION

We hereby declare that the assignment submitted is original except for source material explicitly acknowledged. All the members of the group have read and checked that all parts of the piece of work, irrespective of whether they are contributed by individual members or all members as a group.

#### ABSTRACTION

Our project, "Building a Personalized Movie Recommendation Engine," addresses the contemporary challenge of information abundance. In this era, where choices abound, the need for tailored recommendations is evident. Our project aims to create an advanced recommendation engine that enhances user engagement by providing precise and captivating movie suggestions. To achieve this, we employ a multi-faceted approach, including data preprocessing, recommendation algorithms, and a user-friendly interface.

#### **ACKNOWLEDGEMENT**

The successful completion of this project would not have been possible without the invaluable support and guidance of several individuals and resources. We extend our sincere appreciation to Mr. Samadhi Chathuranga, our module lecturer, and assistant lecturers for their unwavering assistance and encouragement throughout the assignment. The lectures and course materials provided a solid foundation for conducting research and preparing the final submission.

We are also grateful to our colleagues who generously shared their insights and recommendations, contributing to the improvement of this report. The collaborative effort of our project team was fundamental to its successful execution.

## 1. Background

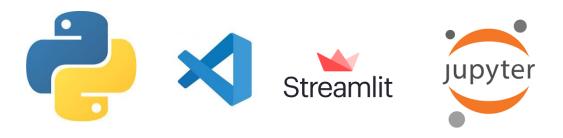
What has led to the essential status of recommender systems?

In our modern era of abundant choices, recommender systems have emerged as essential tools for enhancing user experiences. They act as personalized guides, helping users discover content or products that align with their preferences, from suggesting movies and shows to recommending social connections or online shopping items. The simple act of recommending popular items to everyone pales in comparison to the sophisticated algorithms employed by dedicated recommender systems.

From a business perspective, these systems are invaluable. The more personalized and accurate the recommendations, the more engaged users become, resulting in increased revenue for the platform. In some cases, as much as 35-40% of revenue for tech giants can be attributed to the effectiveness of their recommendation systems. This report will explore the different types of recommendation systems, shedding light on their workings and their profound influence on user engagement, satisfaction, and platform profitability. Understanding and harnessing these systems is key to delivering tailored, enjoyable experiences to users while simultaneously driving success for the platforms that employ them.

# 2. Choice of Technology

The project was developed using several key tools in Python, including Visual Studio Code, Jupyter Notebook, and Streamlit. Jupyter Notebook served as the primary platform for data preprocessing and model development, constituting the backend of the application. For the frontend, we leveraged Streamlit, a Python library that enabled us to create an interactive and user-friendly user interface. This integration of the frontend and backend was seamlessly achieved through Streamlit, enhancing the overall user experience.



Task	Technology
Model development	Python
Frontend Application Tool	Streamlit

# 3. Description of the original datasets

### Movies Dataset

Variable name	Definition	Type of the variable
budget	The budget in which the movie was made.	Int
genre	The genre of the movie, Action, Comedy, Thriller etc.	Object
homepage	A link to the homepage of the movie.	Object
id	This is the movie_id as in the first dataset.	Int
keywords	The keywords or tags related to the movie.	Object
original_language	The language in which the movie was made.	Object
original_title	The title of the movie before translation or adaptation.	Object
overview	A brief description of the movie.	Object
popularity	A numeric quantity specifying the movie popularity.	Float
production_companies	The production house of the movie.	Object
production_countries	The country in which it was produced.	Object
release_date	The date on which it was released.	Object
revenue	The worldwide revenue generated by the movie.	Int
runtime	The running time of the movie in minutes.	Float
status	"Released" or "Rumored".	Object
tagline	Movie's tagline.	Object
title	Title of the movie.	Object
vote_average	average ratings the movie recieved.	Float
vote_count	the count of votes recieved.	Int

### Credits Dataset

Variable name	Definition	Type of the variable
movie_id	A unique identifier for each movie.	Int
title		Object
cast	The name of lead and supporting actors.	Object
crew	The name of Director, Editor, Composer, Writer etc.	Object

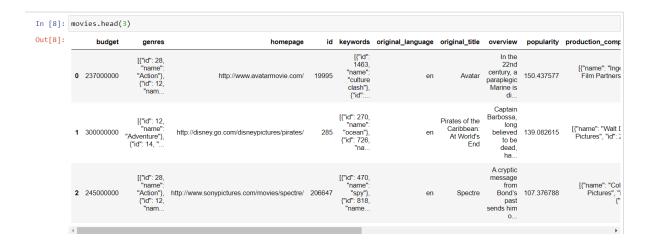
 $Dataset\ Link:\ \underline{https://www.kaggle.com/datasets/tmdb/tmdb-movie-metadata/data}$ 

## 4. Data Identification

• Data collection and identification of the features of data

movies.info(), credits.info() provides essential information about the dataset containing movie details and credit details . This function is useful for a quick overview of the dataset's structure and size.

```
In [4]: movies.info()
           <class 'pandas.core.frame.DataFrame'>
           RangeIndex: 4803 entries, 0 to 4802
           Data columns (total 20 columns):
                                         Non-Null Count Dtype
            # Column
            0
                                         4803 non-null
                                                           int64
                budget
                                         4803 non-null
                                                           object
                 genres
                                                           object
int64
                 homepage
                                         1712 non-null
                                          4803 non-null
                keywords
                                         4803 non-null
4803 non-null
                                                           object
object
                 original_language
                 original_title
                                         4803 non-null
                                                           object
                                         4800 non-null
                 overview
                                                           object
                popularity 4803 non-null production_companies 4803 non-null
                                                           float64
                                                           object
                production_countries
                                         4803 non-null
            11
                release date
                                         4802 non-null
                                                           object
                                         4803 non-null
                                                           float64
            13
                runtime
                                         4801 non-null
                spoken_languages
                                          4803 non-null
                                                           object
            15
                status
                                         4803 non-null
                                                           object
                tagline
                                         3959 non-null
                                                           object
            17 title
                                         4803 non-null
                                                           object
            18 vote_average
                                         4803 non-null
                                                           float64
           19 vote_count 4803 non-null dtypes: float64(3), int64(4), object(13)
                                                           int64
           memory usage: 750.6+ KB
In [5]: credits.info()
         <class 'pandas.core.frame.DataFrame'>
         RangeIndex: 4803 entries, 0 to 4802
         Data columns (total 4 columns):
# Column Non-Null Count Dtype
          0 movie id 4803 non-null
                                            int64
          1 title
2 cast
                          4803 non-null
                          4803 non-null
                                            object
                          4803 non-null
                                            object
         dtypes: int64(1), object(3) memory usage: 150.2+ KB
```



```
credits.shape
Python
(4803, 4)
```

# 5. Data Preprocessing

```
movies = movies.merge(credits,on='title')
Python
```

Movies, Credits, the two datasets will be merged based on the 'title' column to streamline and simplify the data for more convenient analysis and insights.

- In here it has run to gain an idea on the influence of different languages to the data.
- Since the majority are in English, this column is considered irrelevant for our recommendation system.

```
# Keeping important columns for recommendation
movies = movies[['movie_id','title','overview','genres','keywords','cast','crew']]
Python
```

After a careful observation on the columns of the merged dataset it was clear that, 'movie\_id,' 'title,' 'overview,' 'genres,' 'keywords,' 'cast,' and 'crew', are only only the essential columns for the recommendation system.



• A quick overview on the selected columns to further examine the preprocessing steps.



To obtain a view of the dataset's dimensions, which includes the number of rows and columns. This is a useful step to assess the size of the merged dataset.

### Checking null values

```
#handle list of dictionaries inside columns
movies.isnull().sum()

... movie_id 0
title 0
overview 3
genres 0
keywords 0
cast 0
crew 0
dtype: int64
```

In data preprocessing, checking for missing values is a crucial step. Addressing missing data is crucial to ensure the quality and completeness of our dataset for robust recommendation system development. By identifying and handling missing values, we aim to enhance the accuracy and reliability of our recommendations, providing users with a more seamless experience.

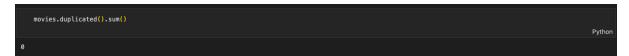
• The output of "movies.isnull().sum()" reveals that the 'overview' column has three missing values.

```
movies.dropna(inplace = True)
Python
```

• Ensuring dataset's quality, the code "movies.dropna(inplace=True)" is used to remove rows with missing values from the "movies" dataset.



Now it has no missing values in the dataset.



This is used to count the number of duplicate rows within the "movies" dataset.

#### Genre column

```
movies.iloc[0]['genres']
#type(movies.iloc[0]['genres']) #In genre column there has the id too, should keep only the 'genre'.

Python
'[{"id": 28, "name": "Action"}, {"id": 12, "name": "Adventure"}, {"id": 14, "name": "Fantasy"}, {"id": 878, "name": "Science Fiction"}]'
```

In the 'genres' column of our dataset, it has come to our attention that it contains both genre names and their corresponding IDs. To ensure data consistency and relevance for our recommendation system, we have opted to retain only the 'genre' names, which are integral to our analysis.

- This function effectively converts the 'genres' column, originally in string format, into a list.
- By doing so, it allows us to remove genre IDs while keeping the 'genre' names.

This conversion is important to ensure the accuracy and relevance of the genre-based recommendations in the recommendation system.

```
movies['genres'] = movies['genres'].apply(convert_genre_column)
Python
```

Applies the function.



- Now that the 'genre' column has been appropriately formatted, it is ready for use in our recommendation system.
- We will apply similar steps to format the 'keyword' column, ensuring consistency and relevancy in our dataset.

```
movies.iloc[0]['keywords'] #Same as genre column, should remove the unnessary id

Python

'[{"id": 1463, "name": "culture clash"}, {"id": 2964, "name": "future"}, {"id": 3386, "name": "space war"}, {"id": 3388, "name": "space colony"}, {"id": 3679, '
```

```
movies['keywords'] = movies['keywords'].apply(convert_keyword_column)
Python
```

mo	vies['keywords']	Python
0	[culture clash, future, space war, space colon	
	[ocean, drug abuse, exotic island, east india	
	[spy, based on novel, secret agent, sequel, mi	
	[dc comics, crime fighter, terrorist, secret i	
	[based on novel, mars, medallion, space travel	
4804	[united states-mexico barrier, legs, arms, pap	
4805		
4806	[date, love at first sight, narration, investi	
4807		
4808	[obsession, camcorder, crush, dream girl]	
Name:	keywords, Length: 4806, dtype: object	

	movies.hea	d(2)					
							Python
	movie_id	title	overview	genres	keywords	cast	crew
0	19995	Avatar	In the 22nd century, a paraplegic Marine is di	[culture clash, future, space war, space colon	[culture clash, future, space war, space colon	[{"cast_id": 242, "character": "Jake Sully", "	[{"credit_id": "52fe48009251416c750aca23", "de
1	285	Pirates of the Caribbean: At World's End	Captain Barbossa, long believed to be dead, ha	[ocean, drug abuse, exotic island, east india 	[ocean, drug abuse, exotic island, east india	[{"cast_id": 4, "character": "Captain Jack Spa	[{"credit_id": "52fe4232c3a36847f800b579", "de

```
movies['cast'] = movies['cast'].apply(convert_cast_column)
Puthon
```

- In the original dataset, the 'cast' column contained unsuitable information. To facilitate further processing and align with the requirements of our system, we made the decision to represent only the first three cast members.
- Above function is written to convert the column's string representation into a list, allowing us to extract and retain the names of up to three cast members.

```
movies['cast']

Python

[Sam Worthington, Zoe Saldana, Sigourney Weave...

[Johnny Depp, Orlando Bloom, Keira Knightley, ...

[Daniel Craig, Christoph Waltz, Léa Seydoux, R...

[Christian Bale, Michael Caine, Gary Oldman, A...

[Taylor Kitsch, Lynn Collins, Samantha Morton,...

...

[Carlos Gallardo, Jaime de Hoyos, Peter Marqua...

[Edward Burns, Kerry Bishé, Marsha Dietlein, C...

[Edward Burns, Kerry Bishé, Marsha Dietlein, C...

[Baniel Henney, Eliza Coupe, Bill Paxton, Alan...

[Borew Barrymore, Brian Herzlinger, Corey Feldm...

Name: cast, Length: 4806, dtype: object
```



```
# handle crew

movies.iloc[0]['crew']

Python

[{"credit_id": "52fe48009251416c750aca23", "department": "Editing", "gender": 0, "id": 1721, "job": "Editor", "name": "Stephen E. Rivkin"}, {"credit_id": "539
```

As for the output for crew column, it is vivid that cast column is contained with some unneccasary data.

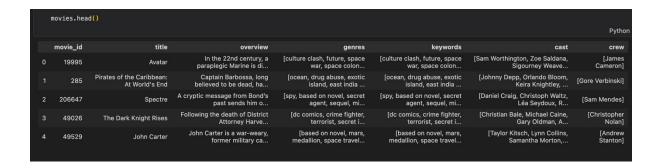
- 'crew' column originally contained various crew members and their roles.
- To refine the data for our recommendation system, we have implemented the 'fetch director' function and it extracts the name of the director, a critical figure in a movie's production which will be important to the recommendation system.

```
movies['crew'] = movies['crew'].apply(fetch_director)
Python
```

```
movies['crew']

0     [James Cameron]
1     [Gore Verbinski]
2         [Sam Mendes]
3     [Christopher Nolan]
4     [Andrew Stanton]
...

4804     [Robert Rodriguez]
4805     [Edward Burns]
4806     [Scott Smith]
4807     [Daniel Hsia]
4808     [Brian Herzlinger]
Name: crew, Length: 4806, dtype: object
```



```
# handle overview (converting to list)

movies.iloc[0]['overview']

Python

'In the 22nd century, a paraplegic Marine is dispatched to the moon Pandora on a unique mission, but becomes torn between following orders and protecting an ali
```

• a lambda function to the 'overview' column of the dataset. The lambda function uses the split() method to break each overview text into individual words.



• The objective of the above step is to tokenize the paragraph in the 'overview' column into words. In this case, the code splits the overview text into a list of words.

```
'Anna Kendrick'

"AnnaKendrick'

#Space between the words should be removed - in a situation of the same word being in few places

def remove_space(L):

L1 = []

for i in L:

L1.append(i.replace(" ",""))

return L1

Python
```

Above step is a crucial step that removes spaces between words in situations where the same word appears in different places within the dataset, ensuring uniformity and enhancing data accuracy.





```
# Concatenate all

movies['tags'] = movies['overview'] + movies['genres'] + movies['keywords'] + movies['cast'] + movies['crew']

Python
```

• Concatenates data from multiple columns in the "movies" dataset into a new 'tags' column, forming a comprehensive set of descriptors for use in our recommendation system.



```
movies.iloc[0]['tags']

Python

['In',
'the',
'22nd',
'century,',
'a',
'paraplegic',
'Marine',
'is',
'dispatched',
'to',
'the',
'monon',
'Pandora',
'non',
'a',
'a',
'a',
'b',
'but',
'becomes',
'forn',
'between',
'following',
'rorders',
'and',
'protecting',
''AliciaVela-Balley',
'Rikidavela-Balley',
'Rikidavela-Balley',
'Rikidavela-Balley',
'JuleneRence',
```

Remove unnecessary columns.



After concatenating, the overview, cast, crew, and genre columns will be removed since we concatenated those to the tags column.

```
new_df['tags']=new_df['tags'].apply(lambda x: " ".join(x))

Python

C:\Users\04775\AppData\Loca\\Temp\inykernel_41816\684433885.py:1: SettingWithCopyWarning:

A value is trying to be set on a copy of a slice from a DataFrame.

Try using .loc[row_indexer,col_indexer] = value instead

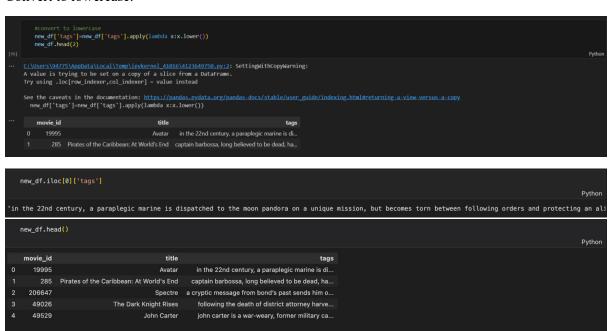
See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy

new_df['tags']=new_df['tags'].apply(lambda x: " ".join(x))
```

The code transforms the lists within the 'tags' column of the new data frame ,'new\_df' into strings by using the join method.



#### Convert to lowercase.



Summarization on what's next: we'll discuss the essential steps taken to prepare our movie dataset for content-based recommendations. Additionally, we'll explore how cosine similarity is utilized to measure the likeness between movies, a key component in content-based recommendation systems.

### Stemming

Integration of NLTK and Porter Stemmer for Text Processing

```
### aperform stemming
#### mow can apply count vectorizer since all the columns were preprocessed
import nltk.stem import Porterstemmer

[58]

ps=Porterstemmer()

Python

Python
```

Utilizing NLTK and Porter Stemmer:

- NLTK Library: NLTK serves as the cornerstone of our text processing and analysis
  endeavors. It equips us with a comprehensive set of tools and resources for working with
  textual data, enabling us to delve deeper into text-based analysis.
- Porter Stemmer: We've specifically incorporated the Porter Stemmer, a well-established algorithm for stemming words. Stemming, the process of reducing words to their root form, is instrumental in simplifying text data for more precise analysis.

Create a function to perform stemming.

For providing users with precise and relevant movie recommendations, stem function plays a pivotal role in our text processing and analysis efforts, and it is expertly tailored to convert paragraphs or text into a list of words.

Functionality and Significance:

- Converting Text to Words: The 'stems' function expertly breaks down text into individual words, which is a foundational step in text-based analysis.
- Porter Stemmer Integration: By applying the Porter Stemmer, we standardize and simplify the text data, transforming words into their root forms, which is essential for precision in text analysis.

```
new_df['tags']-new_df['tags'].apply(stems)

Python

C:\Users\94775\AppBata\Loca\\Temp\inykernel_41816\1522715913.py:1: SettingHithCopyMarning:
A value is trying to be set on a copy of a slice from a DataFrame.

Try using .loc[row_indexer_col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
new_df['tags']-new_df['tags'].apply(stems)
```

• Applies the custom 'stems' function to the 'tags' column in the 'new\_df' dataframe. This operation converts the text within the 'tags' column to its stemmed form, reducing words to their root forms,

Tags column after applying the stem function.



• Perform Count Vectorizer

**Utilizing Count Vectorization:** 

• Count Vectorizer Implementation: We have instantiated the Count Vectorizer as 'cv' with a maximum of 5000 features and the inclusion of English stop words. This vectorizer is a pivotal component in transforming our text data into numerical format for further analysis.

Objective and Benefits:

• The implementation of Count Vectorization is aimed at converting our text-based 'tags' data into a numerical representation. This transformation is critical for mathematical analysis, such as calculating cosine similarity, and is a significant step in the process of making content-based movie recommendations. The inclusion of English stop words further streamlines this text-to-numeric conversion.



The code "vector = cv.fit\_transform(new\_df['tags']).toarray()" represents the Count Vectorizer, previously configured as 'cv,' to transform the textual data in the 'tags' column of the 'new\_df' dataframe into a numerical format, represented as a NumPy array.



 Provides information about the shape of the 'vector' NumPy array, which represents the transformed and numerical data derived from the Count Vectorization. It reveals the dimensions, indicating the number of rows and columns in the array.



• Calculates the number of unique feature names extracted by the Count Vectorizer. These feature names represent the words or terms from the text data that have been transformed into numerical features.

#### Cosine Similarity

To make content-based movie recommendations, it's essential to measure the similarity between movies based on their textual descriptors. In this context, we've applied the cosine similarity metric, which is a critical component of our recommendation system.

Cosine Similarity Calculation:

- Utilizing scikit-learn: We've employed the cosine\_similarity function from scikit-learn to calculate similarity scores. This function operates on the numerical representation of movie descriptors derived from the Count Vectorization process.
- How Cosine Similarity Works: Cosine similarity quantifies the cosine of the angle between
  two vectors, which, in our case, represent the descriptor vectors of movies. Higher similarity
  scores indicate that two movies share more common descriptors, indicating a closer match in
  content.



Check the similarity between each word.

```
| Similarity | Sim
```

#### Get the Recommendations

The function takes a user's selected movie as input and calculates the cosine similarity between that movie and all other movies in our dataset. The key steps include:

- User's Movie Input: The function begins by taking the user's choice of a movie as input. This is the reference point for generating recommendations.
- Index Identification: It identifies the index of the chosen movie in our dataset, allowing us to pinpoint its position for subsequent calculations.
- Similarity Calculation: Using the cosine similarity scores previously calculated, the function sorts of movies in the dataset by their similarity to the user's chosen movie.
- Recommendations Display: The top five movies with the highest similarity scores are
  presented as recommendations to the user. These recommendations are generated based on the
  content and style of the user's chosen movie.

Import trained model as a pickle file for create the web application.

```
#use this to create the system
import pickle
pickle.dump(new_df,open('artifacts/movie_list.pkl','wb'))
pickle.dump(similarity,open('artifacts/similarity.pkl','wb'))

Python
Python
```

## **User Rating Implementation**

```
# Function to append user ratings to an existing CSV file

def add_user_ratings_to_csv(user_id, movie_id, rating, csv_file):

new_data = {'userId': [user_id], 'movieId': [movie_id], 'rating': [rating]}

new_ratings = pd.DataFrame(new_data)
```

```
# Append the new ratings to the existing CSV file
existing_ratings = pd.read_csv(csv_file)
updated_ratings = pd.concat([existing_ratings, new_ratings], ignore_index=True)

# Save the updated ratings to the CSV file
updated_ratings.to_csv(csv_file, index=False)

# Input user ratings for 5 movies and append to the existing CSV file
for i in range(5):

user_id = int(input(f"Enter User ID for Movie {i+1}: "))

movie_id = int(input(f"Enter Movie ID for Movie {i+1}: "))

rating = float(input(f"Enter Rating for Movie {i+1}: "))

# Append the user rating to the existing CSV file 'ratings_small.csv'
add_user_ratings_to_csv(user_id, movie_id, rating, 'ratings_small.csv')
```

### Get Top Rated Movies Based on the User Feedbacks

Import necessary packages to implement the user feedback part

```
1 import pickle
2 from surprise import Reader, Dataset, SVD
3 from surprise, model selection import cross_validate, train_test_split
4 import pandas as pd
5
```

• Load the dataset, which is having the rating information of the user, to train the model to identify the top rated movies based on the user feedbacks

```
reader = Reader()
ratings = pd.read_csv('ratings_small.csv')
ratings.head()

data = Dataset.load_from_df(ratings[['userId', 'movieId', 'rating']], reader)
```

 Split the dataset into train and test data to train the model, so that can use the model to recommend movies based on user feedbacks.

```
trainset, testset = train_test_split(data, test_size=0.2) # 80% training, 20% testing
```

• Singular value Decomposition (SVD) complex matrix has been used to train the ratings part

```
13
14     svd = SVD()
15
16     cross_validate(svd, data, measures=['RMSE', 'MAE'], cv=5, verbose=True)
17
18     trainset = data.build_full_trainset()
19
20     svd.fit(trainset)
```

Defined a function to get recommended movies for a user according to their ratings

```
# Define a function to get recommended movies for a user with a rating threshold

def get_top_rated_movies(user_id, threshold=3.5, num_recommendations=5):

# filter movies that the user has not rated

movies_not_rated_by_user = [i for i in range(1, 193609) if not trainset.ur[trainset.to_inner_uid(user_id)]

predict ratings for all unrated movies for the user

predicted_ratings = [(movie_id, swd.predict(user_id, movie_id).est) for movie_id in movies_not_rated_by_user]

# Sort the predictions in descending order of estimated ratings

predicted_ratings.sort(key=lambda x: x[1], reverse=True)

# Get the top-rated_movies above the threshold

top_rated_movies = [movie for movie in predicted_ratings if movie[1] > threshold]

return top_rated_movies[:num_recommendations]
```

Check whether the trained model is working properly or not

```
# Example usage:

45  # Example usage:

46  user_id = 3

47  recommended_movies = get_top_rated_movies(user_id, threshold=3.5, num_recommendations=5)

48  print(f"Top 5 movies recommended for User {user_id} with ratings > 3.5:")

50  for movie in recommended_movies:

51  | print(f"Movie ID: {movie[0]}, Predicted Rating: {movie[1]}")
```

• Save the trained model, so that can be used the saved model later without rerun the notebook again and again.

```
# Save the SVD model

with open('artifacts/svd_model.pkl', 'wb') as file:

pickle.dump(svd, file)

# Save the get_top_rated_movies function

with open('artifacts/recommendation_function.pkl', 'wb') as file:

pickle.dump(get_top_rated_movies, file)
```

## 5. Web Application

Imported necessary packages to enable the execution of the web application using Streamlit.

```
pappy > ...
import pandas as pd
import pickle
import streamlit as st
import requests
```

 Defined a function to display posters for each movies which are going to display by the recommendation system.

```
6
    def fetch_poster(movie_id):
        url='https://api.themoviedb.org/3/movie/{}?api_key=8265bd1679663a7ea12ac168da84d2e8&language=en-US'.format(movie_id)
        data=requests.get(url)
        data=data.json()
    poster_path=data['poster_path']
    full_path='https://image.tmdb.org/t/p/w500/" + poster_path
        return full_path
```

Defined a function to recommend top movies related to the selection of the user.

```
def recommend(movie):
index=movies[movies['title']==movie].index[0]

distances=sorted(list(enumerate(similarity[index])), reverse=True, key=lambda x: x[1])
recommended_movies_name=[]
recommended_movies_poster=[]
for i in distances[1:6]:
movie_id=movies_iloc[i[0]]['movie_id']
recommended_movies_poster.append(fetch_poster(movie_id))
recommended_movies_name.append(movies.iloc[i[0]]['title'])
return recommended_movies_name, recommended_movies_poster
```

• Set up the page configurations and added a sidebar with small description of how to use the application, so that users will be able to use the application easily along with the descriptions.

 Main content area which displays the main content of the web application including all the movies that were recommended by the system, according to the selection.

```
# Main content area

st.header('Movie Recommender System Using ML')

movie_list = movies['title'].values

selected_movie = st.selectbox(

"choose a movie",

movie_list

if st.button('Get Recommendations',key="recommend_button"):

st.spinner("Finding recommendations...")

recommended_movies_name,recommendd_movies_poster-recommend(selected_movie)

st.success("Here are some of the recommendations for your search:")

# Display recommendations in a carousel

coll,col2,col3,col4,col5=st.columns(5)

cols = [coll, col2, col3, col4, col5]

for i in range(5):

with cols[i]:

st.image(recommended_movies_poster[i], width=200)

st.write(recommended_movies_name[i])
```

• Users are given a chance to rate the system based on their experiences throughout the application, and based on their ratings, application will recommend the content.

```
#add ratings
from streamlit_star_rating import st_star_rating
st_star_rating(label = "How would you rate us?", maxValue = 5, defaultValue = 3, key = "rating")
# def function to run on click(value):
# st.write(f"**(value)** stars!")

# st.write(stars)
```

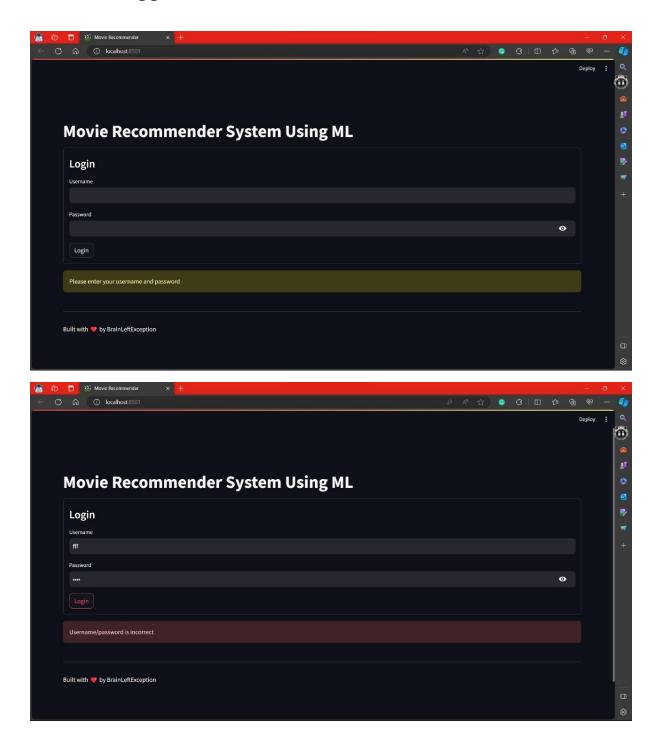
Footer of the web application

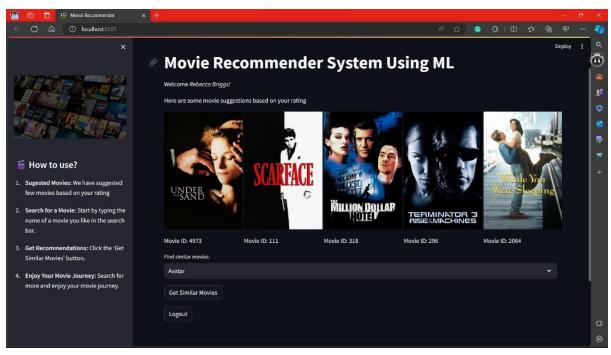
```
# Add a custom footer

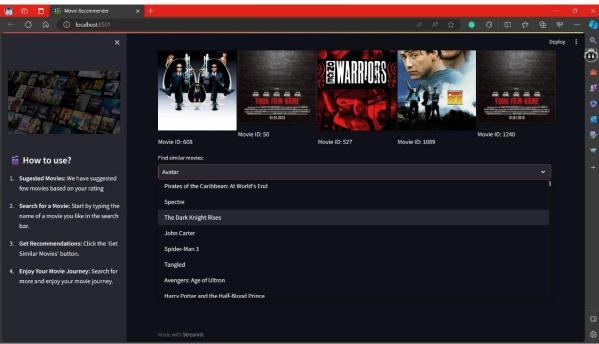
85 st.markdown("---")

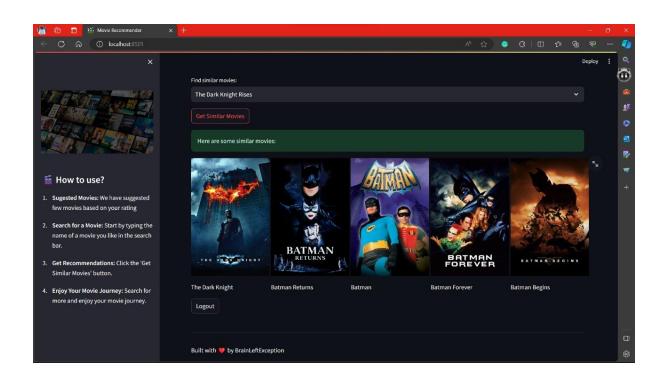
86 st.write("Built with V by BrainLeftException")
```

# 6. Web Application User Interface









# 7. Project Folder Structure

