Overview

Objective: The goal of this project is to design and implement a movie recommender system that provides personalized recommendations to users based on their preferences and viewing history. The system employs various collaborative and content-based filtering techniques to enhance the accuracy and relevance of movie suggestions.

Key Components:

1. **Data Collection:**
    - Utilized a movie dataset containing information about movies, genres, user ratings, and tags.
    - Explored and cleaned the dataset to prepare it for modeling.
2. **Exploratory Data Analysis (EDA):**
    - Analyzed the dataset for sstructure understanding, features, and distributions.
    - Visualized key patterns, such as user preferences and movie popularity, to gain insights.
3. **Content Based Filtering:**
    - Implemented a content-based recommender system using movie genres.
    - Explored the use of TF-IDF vectors to represent movie content and calculate similarities.
4. **Neighborhood Based Collaborative Filtering (KNN):**
    - Implemented a neighborhood-based collaborative filtering model using SciKit Learn's KNN.
    - Explored both user-based and item-based collaborative filtering approaches.
    - Evaluated the model's performance using metrics such as RMSE and MAE.
5. **Model Based Collaborative Filtering (SVD):**
    - Implemented a model-based collaborative filtering approach using the Surprise library and Singular Value Decomposition (SVD).
    - Evaluated the model's performance and explored hyperparameter tuning.

6. **Hybrid Approach:**
    - Recommended a hybrid model that combines the strengths of content-based and collaborative filtering approaches.
    - Highlighted the potential benefits of leveraging both user-item interactions and content features.

Business Understanding:

Objective:

The primary objective of the recommender system project is to enhance user satisfaction and engagement on the MovieLens platform by delivering personalized and relevant movie recommendations. The recommender system aims to provide users with tailored suggestions based on their historical movie ratings and tagging activities, ultimately improving their overall experience.

Scope:

The project will focus on implementing a collaborative filtering-based recommender system, leveraging the ml-latest-small dataset from MovieLens. The recommendations will be centered around user preferences, ensuring that users discover movies aligned with their tastes and interests. The scope includes both explicit ratings and user-generated tags as valuable indicators of user preferences.

Success Criteria:

The success of the recommender system will be evaluated based on several key performance indicators (KPIs):

User Engagement:

Increase in the number of user interactions with the platform, including ratings, tags, and time spent on the website.

Recommendation Accuracy:

Improvement in the precision and relevance of movie recommendations, reducing instances of irrelevant or disliked suggestions.

User Satisfaction:

Positive feedback from users, measured through surveys, reviews, and user ratings.

Platform Adoption:

Growth in the number of registered users and active users leveraging the recommendation features.

Data Understanding:

Data Source:

The dataset (ml-latest-small) consists of 100,836 ratings and 3,683 tag applications across 9,742 movies. The data were generated by 610 users between March 29, 1996, and September 24, 2018.

The data used in this project will be pulled from 4 different separate file:

1. Movies Data (movies.csv):

Contains movie information, including titles and genres.

Columns:

- movieId: Unique identifier for each movie.
- title: The title of the movie, which also includes the year of release in parentheses.
- genres: A pipe-separated list of genres to categorize the movie (e.g., Action|Adventure|Comedy).

2. Links Data (links.csv):

Provides identifiers for linking to external movie-related sources (IMDb, TMDb).

Columns:

- movieId: Unique identifier for each movie, consistent with other data files.
- imdbId: Identifier for movies used by IMDb (Internet Movie Database).
- tmdbId: Identifier for movies used by TMDb (The Movie Database).

3. Ratings Data (ratings.csv):

Each entry represents a user's rating for a specific movie.

Contains user ratings on a 5-star scale for movies.

Columns:

- userId: ID representing the unique identifier for each user.
- movieId: Unique identifier for each movie.
- rating: User's rating for the movie on a 5-star scale with half-star increments (0.5 to 5.0).
- timestamp: The timestamp when the rating was recorded, represented in seconds since midnight Coordinated Universal Time (UTC) of January 1, 1970.

4. Tags Data (tags.csv):

Contains user-generated metadata (tags) about movies.

Columns:

- userId: ID representing the unique identifier for each user.
- movieId: Unique identifier for each movie.
- tag: User-generated metadata describing a movie, typically a single word or short phrase.
- timestamp: The timestamp when the tag was applied, represented in seconds since midnight Coordinated Universal Time (UTC) of January 1, 1970.

```
## Import Necessary Libraries

import pandas as pd
import numpy as np

# Datasets
movies = "data/ml-latest-small/movies.csv"
links = "data/ml-latest-small/links.csv"
```

```
ratings = "data/ml-latest-small/ratings.csv"
tags = "data/ml-latest-small/tags.csv"

data = {"movies":None, "links": None, "ratings": None, "tags": None}

for key in data.keys():
    data[key] = pd.read_csv(f"data/ml-latest-small/{key}.csv")
```

Exploring Dataframes

Datasets Lengths

```
print("Length of each dataset:")
for k, v in data.items():
    print(k, ":",len(v))
```

```
Length of each dataset:
movies : 9742
links : 9742
ratings : 100836
tags : 3683
```

Displaying top 5 componennts of each dataset

```
data["movies"].head()
```

	movieId	title	genres
0	1	Toy Story (1995)	Adventure|Animation|Children|Comedy|Fantasy
1	2	Jumanji (1995)	Adventure|Children|Fantasy
2	3	Grumpier Old Men (1995)	Comedy|Romance
3	4	Waiting to Exhale (1995)	Comedy|Drama|Romance
4	5	Father of the Bride Part II (1995)	Comedy

```
data["links"].head()
```

	movieId	imdbId	tmdbId
0	1	114709	862.0
1	2	113497	8844.0
2	3	113228	15602.0
3	4	114885	31357.0
4	5	113041	11862.0

```
data["tags"].head()
```

	userId	movieId	tag	timestamp
0	2	60756	funny	1445714994
1	2	60756	Highly quotable	1445714996
2	2	60756	will ferrell	1445714992
3	2	89774	Boxing story	1445715207
4	2	89774	MMA	1445715200

```
print("Summary of each dataset:\n")
for k, v in data.items():
    print(k, "\n")
    print(v.info())
    print("="*100, "\n")
```

```
Data columns (total 3 columns):
 #   Column   Non-Null Count  Dtype 
---  ------   --------------  ----- 
 0   movieId  9742 non-null   int64 
 1   title    9742 non-null   object
 2   genres   9742 non-null   object
dtypes: int64(1), object(2)
memory usage: 228.5+ KB
None
====================================================================================================

links

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 9742 entries, 0 to 9741
```

```
dtypes: float64(1), int64(2)
memory usage: 228.5 KB
None
================================================================================

ratings

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 100836 entries, 0 to 100835
Data columns (total 4 columns):
 #   Column     Non-Null Count   Dtype  
---  ------     --------------   -----  
 0   userId     100836 non-null  int64  
 1   movieId    100836 non-null  int64  
 2   rating     100836 non-null  float64
 3   timestamp  100836 non-null  int64  
dtypes: float64(1), int64(3)
memory usage: 3.1 MB
None
================================================================================

tags

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3683 entries, 0 to 3682
Data columns (total 4 columns):
 #   Column     Non-Null Count  Dtype 
---  ------     --------------  ----- 
 0   userId     3683 non-null   int64 
 1   movieId    3683 non-null   int64 
 2   tag        3683 non-null   object
 3   timestamp  3683 non-null   int64 
dtypes: int64(3), object(1)
memory usage: 115.2+ KB
None
================================================================================
```

```
print("Colums of each dataset:\n")
all_columns = []
for k, v in data.items():
```

```
    print(k, "\n")
    all_columns += list(v.columns)
    print(list(v.columns))
    print("="*100, "\n")

print("all unique columns", set(all_columns))
```

```
Colums of each dataset:

movies

['movieId', 'title', 'genres']
====================================================================================================

links

['movieId', 'imdbId', 'tmdbId']
====================================================================================================

ratings

['userId', 'movieId', 'rating', 'timestamp']
====================================================================================================

tags

['userId', 'movieId', 'tag', 'timestamp']
====================================================================================================

all unique columns {'movieId', 'title', 'rating', 'genres', 'tag', 'tmdbId', 'imdbId', 'userId', 'timestamp'}
```

Merging Dataframes

```
# merging movies df and link df using an inner join
movies_df = data["movies"]
links_df = data["links"]
```

```
# Using join with movies_df as the left DataFrame
merged_movies_links = movies_df.join(links_df.set_index("movieId"), on="movieId", how="inner")

# Display the shape of the resulting DataFrame
print(merged_movies_links.shape)
```

```
(9742, 5)
```

```
merged_movies_links.head()
```

	movieId	title	genres	imdbId	tmdbId
0	1	Toy Story (1995)	Adventure|Animation|Children|Comedy|Fantasy	114709	862.0
1	2	Jumanji (1995)	Adventure|Children|Fantasy	113497	8844.0
2	3	Grumpier Old Men (1995)	Comedy|Romance	113228	15602.0
3	4	Waiting to Exhale (1995)	Comedy|Drama|Romance	114885	31357.0
4	5	Father of the Bride Part II (1995)	Comedy	113041	11862.0

```
# Left outer join with ratings_df and specify suffixes
merged_data_ratings = merged_movies_links.join(data["ratings"].set_index("movieId"), on="movieId", how="left", lsuffix='

# Left outer join with tags_df and specify suffixes
df = merged_data_ratings

# Display the first few rows of the resulting DataFrame
print(f"Final Merged Data has {df.shape[0]} rows and {df.shape[1]} columns:")
df.head()
```

```
Final Merged Data has 100854 rows and 8 columns:
```

	movieId	title	genres	imdbId	tmdbId	userId	rating	timestamp
0	1	Toy Story (1995)	Adventure|Animation|Children|Comedy|Fantasy	114709	862.0	1.0	4.0	9.649827e+08
0	1	Toy Story (1995)	Adventure|Animation|Children|Comedy|Fantasy	114709	862.0	5.0	4.0	8.474350e+08
0	1	Toy Story (1995)	Adventure|Animation|Children|Comedy|Fantasy	114709	862.0	7.0	4.5	1.106636e+09
0	1	Toy Story (1995)	Adventure|Animation|Children|Comedy|Fantasy	114709	862.0	15.0	2.5	1.510578e+09
0	1	Toy Story (1995)	Adventure|Animation|Children|Comedy|Fantasy	114709	862.0	17.0	4.5	1.305696e+09

```
df[['userId', "movieId"]]
```

	userId	movieId
0	1.0	1
0	5.0	1
0	7.0	1
0	15.0	1
0	17.0	1
...	...	...
9737	184.0	193581
9738	184.0	193583
9739	184.0	193585
9740	184.0	193587
9741	331.0	193609

100854 rows × 2 columns

```
print(f"The Final dataframe has {df.shape[0]} rows and {df.shape[1]} columns")
```

```
The Final dataframe has 100854 rows and 8 columns
```

Data Cleaning

Sorting Out Missing Values

The code below:

This code checks for missing (NaN) values in each column of a Pandas DataFrame (df) and prints out only the columns that have missing values.

- Checking for Missing Values
- Looping Through Each Column
- Printing Only Columns with Missing Values
-

```
# Checking for missing values in each column
missing_values = df.isna().sum()

for column, count in missing_values.items():
    if count > 0:
        print(f"The {column} column has {count} missing values")
```

```
The tmdbId column has 13 missing values
The userId column has 18 missing values
The rating column has 18 missing values
The timestamp column has 18 missing values
```

The code below:

This code calculates the percentage of missing (NaN) values in each column of a Pandas DataFrame (df) and creates a table showing only the columns that have missing values.

- Calculates Missing Value Percentage
- Filters Out Columns with No Missing Values
- Creates a DataFrame for Display
- Prints the Result

```
# Calculating percentage of missing values in each column
missing_percentage = df.isna().mean() * 100

missing_percentage = missing_percentage[missing_percentage > 0]

# A DataFrame with columns and percentage of missing values
missing_table = pd.DataFrame({
    'Columns': missing_percentage.index,
    '% of Missing Values': missing_percentage.values
})
print("Percentage of Missing Values")
missing_table
```

```
Percentage of Missing Values
```

	Columns	% of Missing Values
0	tmdbId	0.012890
1	userId	0.017848
2	rating	0.017848
3	timestamp	0.017848

```
# dropped all the missing values in tmdbId,userId_x,timestamp_x,userId_y,tag,timestamp_y columns
#   movieId title   genres  imdbId  tmdbId  userId  rating  timestamp   userId_tags tag timestamp_tags

df.dropna(subset = ['tmdbId', 'userId','timestamp','rating'], inplace=True)


missing_values1 = df.isna().sum()

for column, count in missing_values1.items():
        print(f"The {column} column has {count} missing values")
```

```
The movieId column has 0 missing values
The title column has 0 missing values
The genres column has 0 missing values
The imdbId column has 0 missing values
The tmdbId column has 0 missing values
The userId column has 0 missing values
The rating column has 0 missing values
The timestamp column has 0 missing values
```

Handling Duplicate Values

```
duplicated_rows = df.duplicated().sum()
print(f'The DataFrame has {duplicated_rows} duplicated rows.')
```

```
The DataFrame has 0 duplicated rows.
```

Confirming Datatypes

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 100823 entries, 0 to 9741
```

```
Data columns (total 8 columns):
 #   Column     Non-Null Count   Dtype  
---  ------     --------------   -----  
 0   movieId    100823 non-null  int64  
 1   title      100823 non-null  object 
 2   genres     100823 non-null  object 
 3   imdbId     100823 non-null  int64  
 4   tmdbId     100823 non-null  float64
 5   userId     100823 non-null  float64
 6   rating     100823 non-null  float64
 7   timestamp  100823 non-null  float64
dtypes: float64(4), int64(2), object(2)
memory usage: 6.9+ MB
```

```
# Converting user IDs and tmdbId to object data type
df[['userId', 'tmdbId']] = df[['userId', 'tmdbId']].astype('object')
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 100823 entries, 0 to 9741
Data columns (total 8 columns):
 #   Column     Non-Null Count   Dtype  
---  ------     --------------   -----  
 0   movieId    100823 non-null  int64  
 1   title      100823 non-null  object 
 2   genres     100823 non-null  object 
 3   imdbId     100823 non-null  int64  
 4   tmdbId     100823 non-null  object 
 5   userId     100823 non-null  object 
 6   rating     100823 non-null  float64
 7   timestamp  100823 non-null  float64
dtypes: float64(2), int64(2), object(4)
memory usage: 6.9+ MB
```

Handling Outliers

The code below:

- Counts the occurrences of each unique value in the rating column.
- df.value_counts(['rating'])
- df['rating'] extracts the 'rating' column.
- .value_counts() counts how many times each unique rating appears.
- The output is a sorted Series (highest count first).

```
# Outliers in Rating Column
df.value_counts(['rating'])
```

```
rating
4.0       26816
3.0       20044
5.0       13209
3.5       13134
4.5        8551
2.0        7550
2.5        5550
1.0        2811
1.5        1791
0.5        1367
dtype: int64
```

The code below:

- This code creates an interactive box plot using Plotly Express to visualize outliers in the 'rating' column. It also finds and prints the maximum and minimum ratings in the dataset.
  - Imports Plotly Express
  - Creates a Box Plot for the 'rating' Column
  - Updates the Plot Layout

- Displays the Interactive Plot
- Finds & Prints Max/Min Ratings

```
import plotly.express as px

# a box plot to visualize outliers in rating column
fig = px.box(df, y='rating', title='Box Plot of Rating Outliers')

fig.update_layout(
    title=dict(text='Box Plot of Rating with Outliers', x=0.5, y=0.95),
)

fig.show()

max_rating = df['rating'].max()
min_rating = df['rating'].min()
print(f"The maximum rating is {max_rating}")
print(f"The minimum rating is {min_rating}")
```

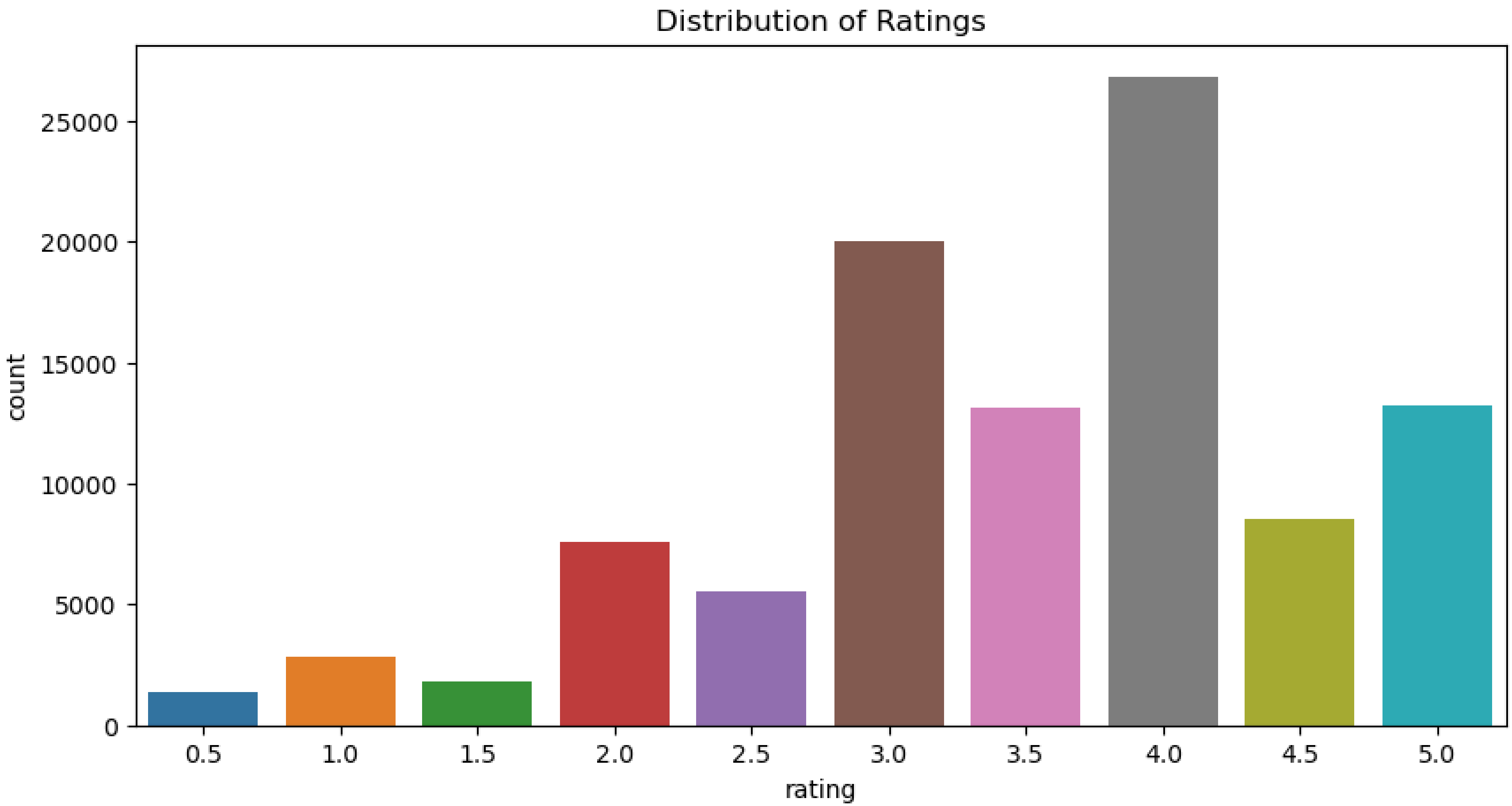
```
The maximum rating is 5.0
The minimum rating is 0.5
```

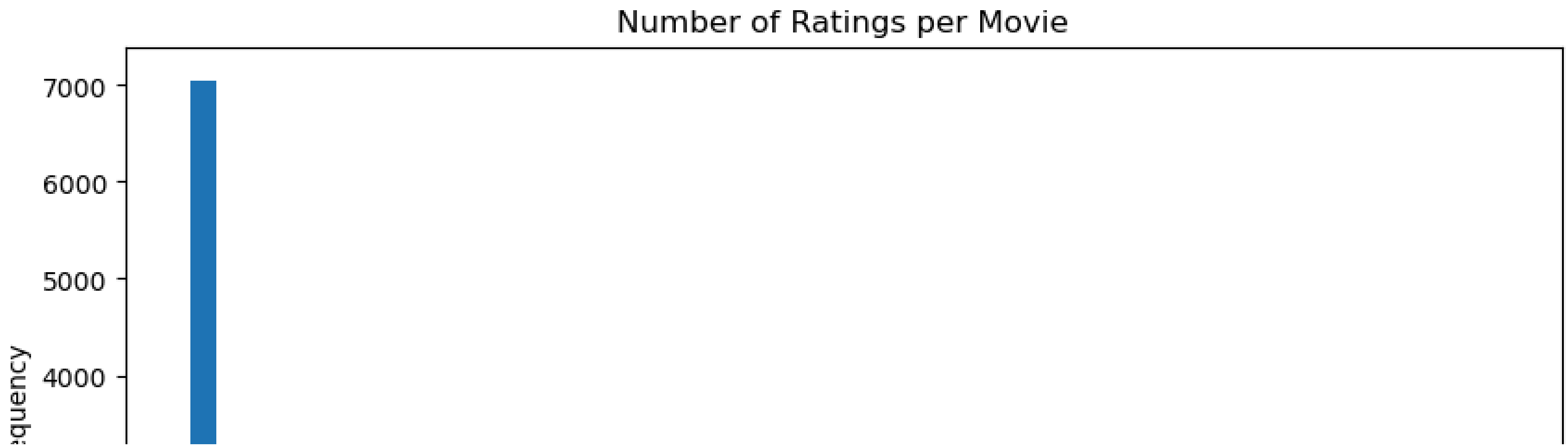
Exploratory Data Analysis

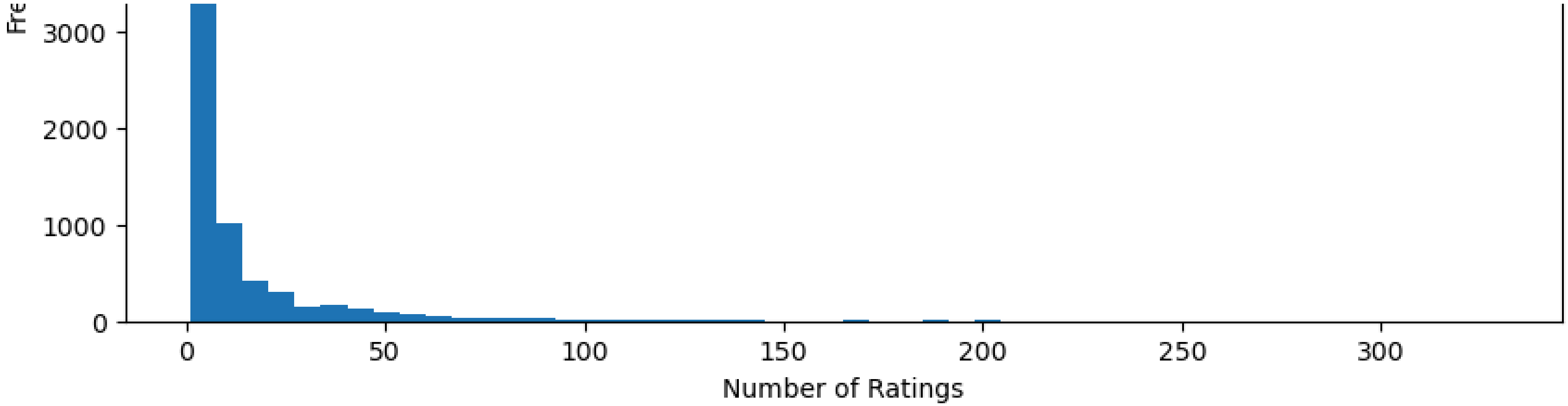
The code Below visualizes movie ratings data using Matplotlib and Seaborn with two different charts:

- Creates a bar chart showing the count of each rating value in the dataset.
- Uses Seaborn's countplot, which counts how many times each rating appears.
- Groups the dataset by movieId and counts how many ratings each movie has.
- Creates a histogram (with 50 bins) to show the distribution of the number of ratings per movie.

```
import matplotlib.pyplot as plt
import seaborn as sns

# Distribution of ratings
plt.figure(figsize=(10, 5))
sns.countplot(x='rating', data=df)
plt.title('Distribution of Ratings')
plt.show()

# Number of ratings per movie
ratings_per_movie = df.groupby('movieId')['rating'].count().reset_index()
plt.figure(figsize=(10, 5))
plt.hist(ratings_per_movie['rating'], bins=50)
plt.title('Number of Ratings per Movie')
plt.xlabel('Number of Ratings')
plt.ylabel('Frequency')
plt.show()
```


Distribution of Ratings
25000
20000
15000
10000
5000
0
count
0.5
1.0
1.5
2.0
2.5
3.0
3.5
4.0
4.5
5.0
rating


Number of Ratings per Movie
7000
6000
5000
4000



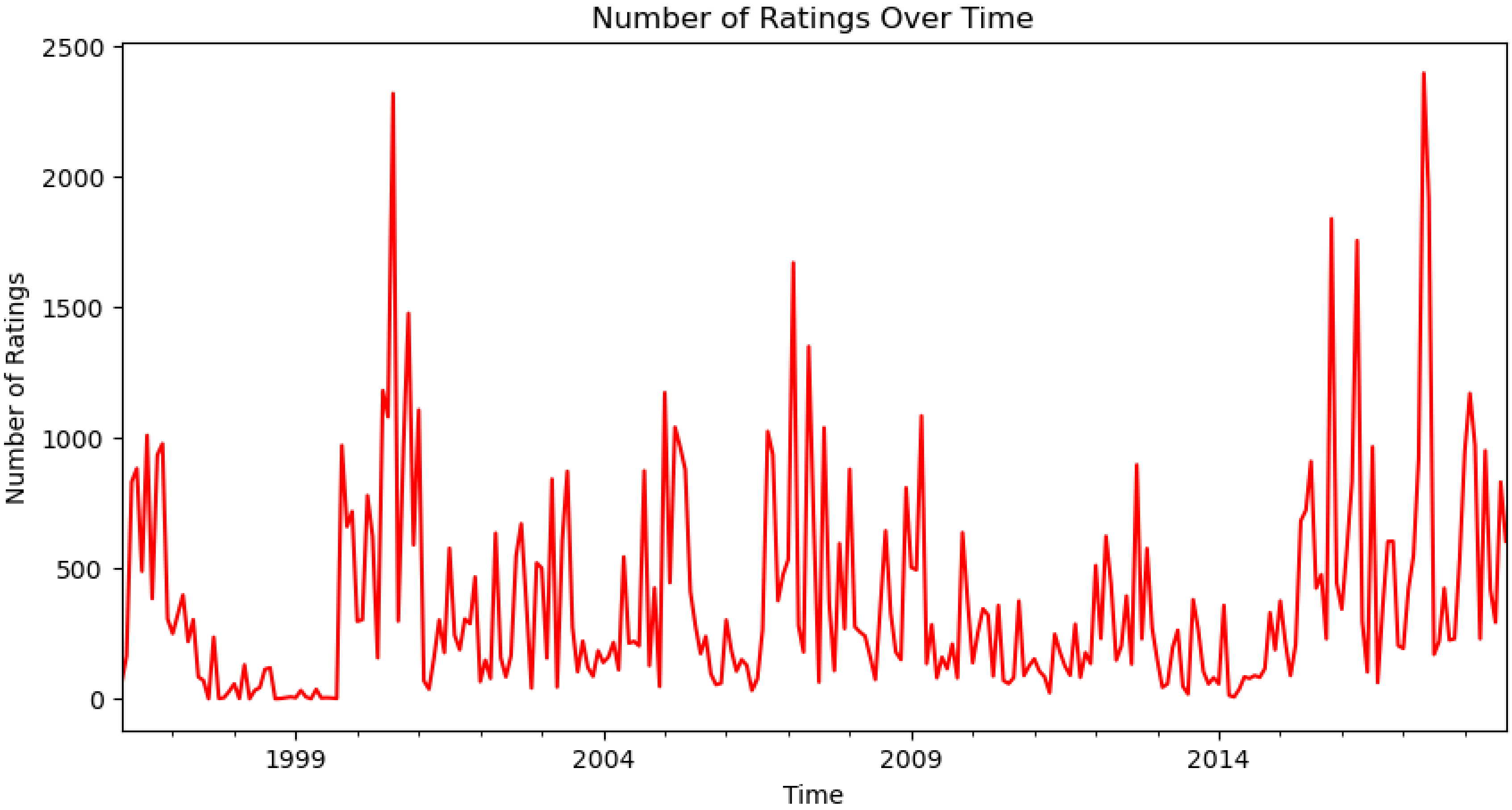
The code below:

Processes timestamped movie ratings and plots a time series chart to show the number of ratings over time.

- Imports Required Libraries
- Extracts the Ratings Data
- Converts Timestamps to Datetime Format
- Plotts the Number of Ratings Over Time
- Customizes the Plot

```
import datetime
import pandas as pd
import matplotlib.pyplot as plt

ratings = data["ratings"]

# Convert timestamp to datetime
ratings['timestamp'] = pd.to_datetime(ratings['timestamp'], unit='s')

# Plot the number of ratings over time
plt.figure(figsize=(10, 5))
```

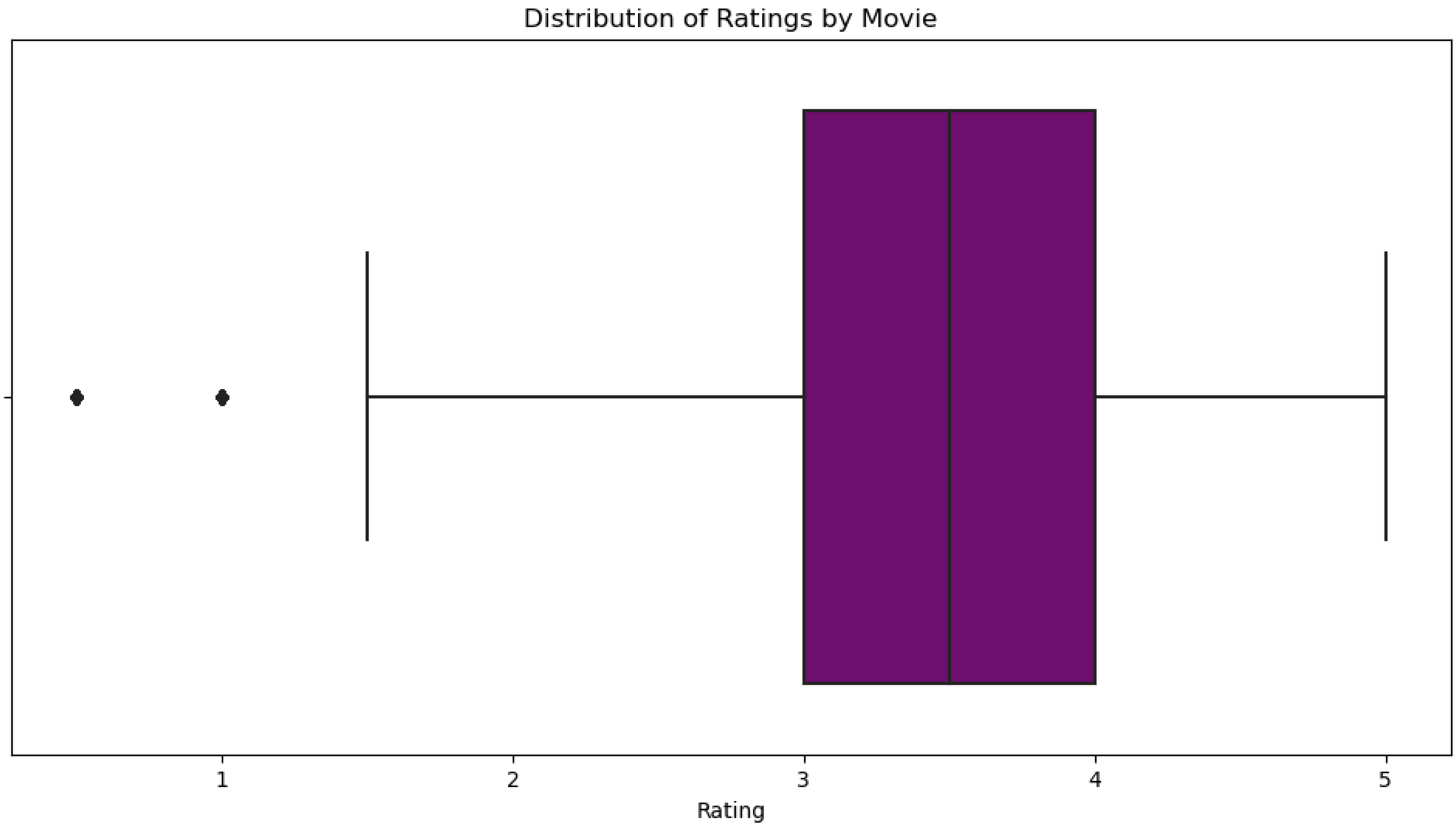
```
ratings.set_index('timestamp').resample('M').size().plot(color='red')  # Set line color to red
plt.title('Number of Ratings Over Time')
plt.xlabel('Time')
plt.ylabel('Number of Ratings')
plt.show()
```



The code below does the following:

Imports necessary libraries: Creates a figure with a specific size: Creates a box plot of movie ratings: Adds a title and label: Displays the plot:

```
import matplotlib.pyplot as plt
import seaborn as sns

# Boxplot of ratings by movie
plt.figure(figsize=(12, 6))
sns.boxplot(x='rating', data=df, color='purple')  # Set box color to purple
plt.title('Distribution of Ratings by Movie')
plt.xlabel('Rating')
plt.show()
```



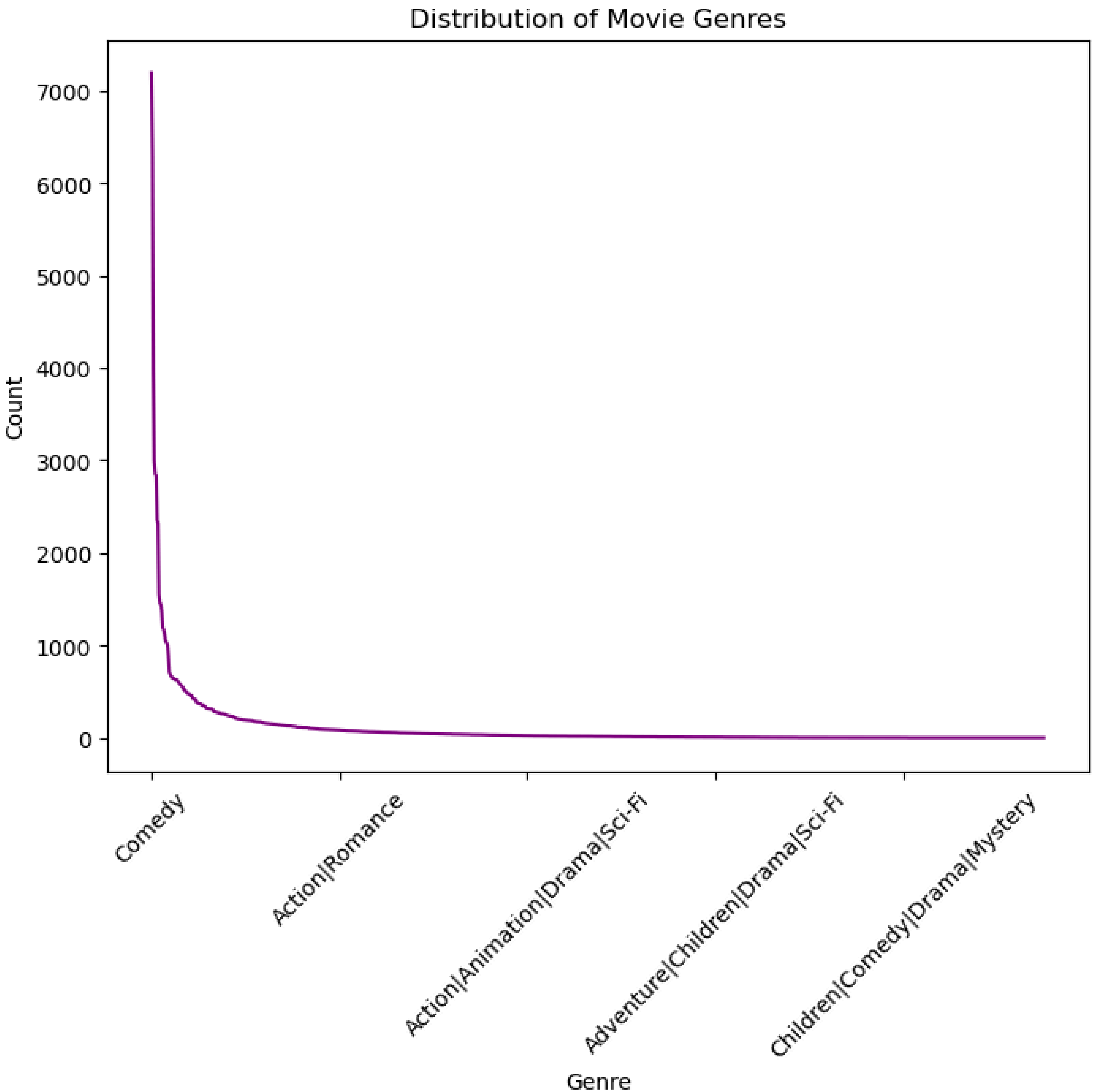
The code below:

This code creates a line plot that visualizes the distribution of movie genres based on how frequently they appear in the dataset.

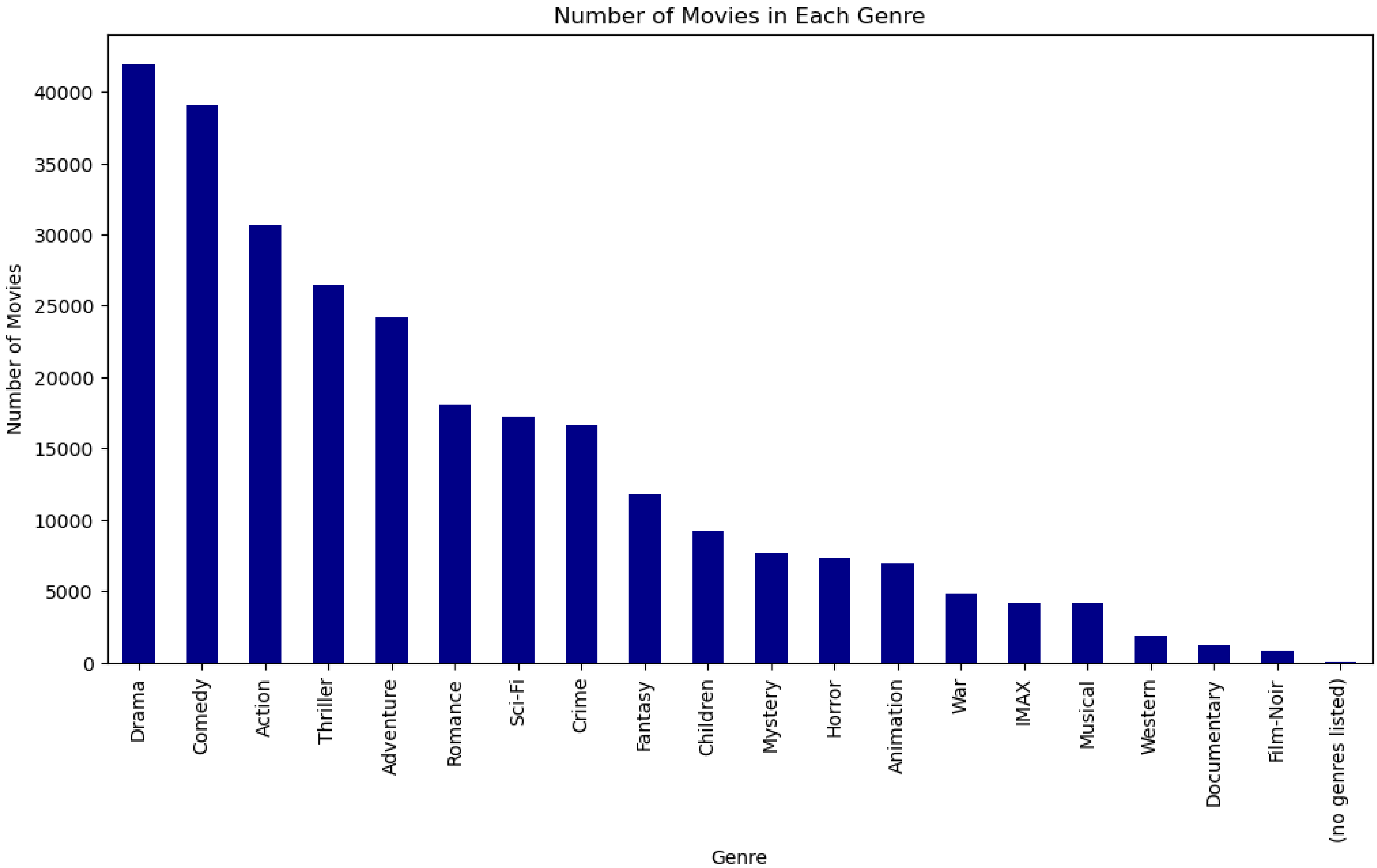
- Imports Matplotlib

- Sets Up the Figure & Axes
- Counts Movie Genres
- Plots the Data
- Customizes the X-Axis
- Adds Labels & Title

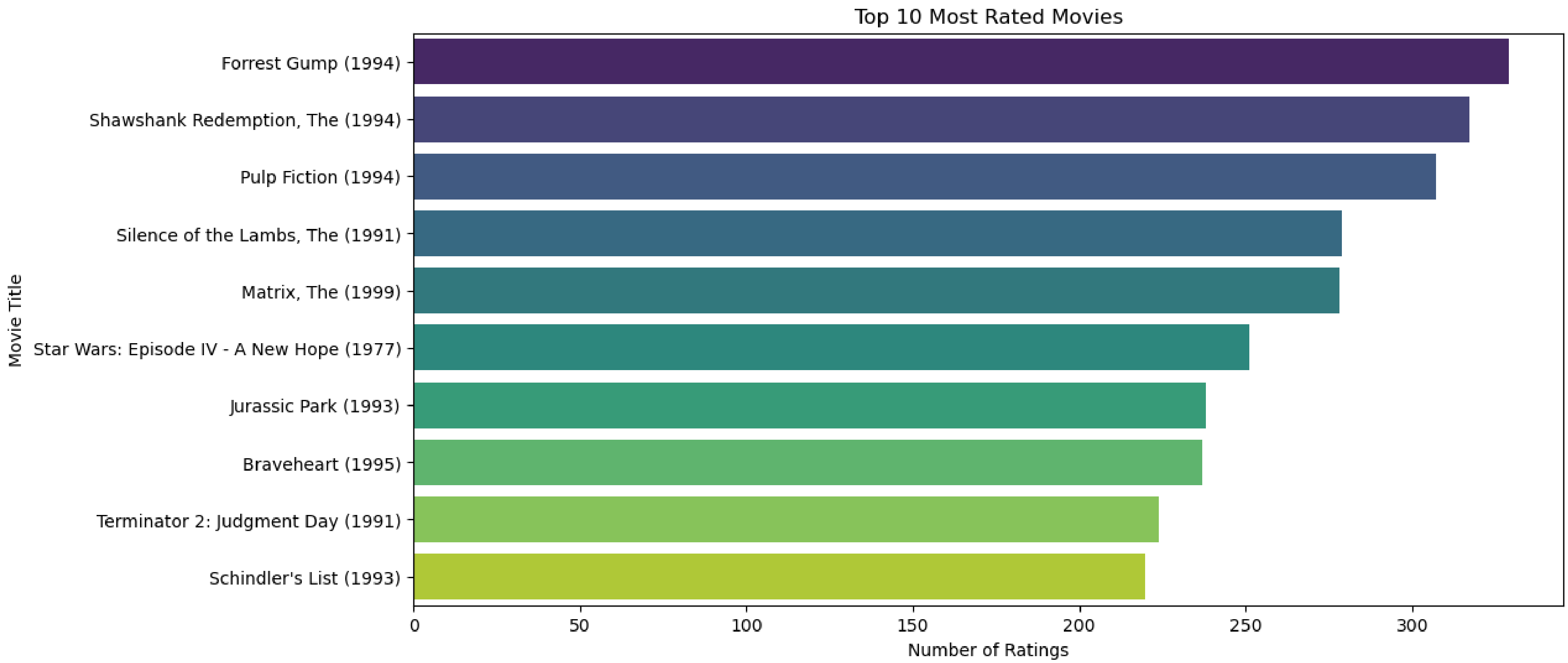
```
import matplotlib.pyplot as plt

# Creating a lineplot of the 'genre' column
fig, ax = plt.subplots(figsize=(8,6))

genre_counts = df['genres'].value_counts()

# Plot the lineplot and set the color to purple
genre_counts.plot(color='purple')

plt.xticks(rotation=45)

# Set the axis labels and title
plt.xlabel('Genre')
plt.ylabel('Count')
plt.title('Distribution of Movie Genres')

# Show the plot
plt.show()
```


Distribution of Movie Genres
Count
7000
6000
5000
4000
3000
2000
1000
0
Comedy
Action|Romance
Action|Animation|Drama|Sci-Fi
Adventure|Children|Drama|Sci-Fi
Children|Comedy|Drama|Mystery
Genre

```
import matplotlib.pyplot as plt

# Count of movies in each genre
genre_counts = df['genres'].str.split('|', expand=True).stack().value_counts()

plt.figure(figsize=(12, 6))

# Plot the bar chart with dark blue color
genre_counts.plot(kind='bar', color='darkblue')

plt.title('Number of Movies in Each Genre')
plt.xlabel('Genre')
plt.ylabel('Number of Movies')

# Show the plot
plt.show()
```


Number of Movies in Each Genre
Number of Movies
0
5000
10000
15000
20000
25000
30000
35000
40000
Drama
Comedy
Action
Thriller
Adventure
Romance
Sci-Fi
Crime
Fantasy
Children
Mystery
Horror
Animation
War
IMAX
Musical
Western
Documentary
Film-Noir
(no genres listed)
Genre

```
# Top N most rated movies.
top_rated_movies = df.groupby('movieId')['rating'].count().sort_values(ascending=False).head(10)
top_rated_movies = pd.merge(top_rated_movies, df[['movieId', 'title']], on='movieId', how='left')
plt.figure(figsize=(12, 6))
sns.barplot(x='rating', y='title', data=top_rated_movies, palette='viridis')
plt.title('Top 10 Most Rated Movies')
plt.xlabel('Number of Ratings')
plt.ylabel('Movie Title')
plt.show()
```



Generating the Recommender System

Two choices are to be considered while generating the recommender system

1. Unpersonalized:

- We could simply recommend the most popular movies for every use but that would throw away the desired user experience brought by personalized system.

2. Personalized:

- This leads us to use a personalized approach in this system, and for that, we have the choices below:

- Content-based filtering
- Collaborative filtering
- Memory/Neighbourhood based (KNN)
- Model based (Matrix factorization)
- Singular Value Decomposition
- Alternating Least Squares

The aim is try out all the systems and pick out the best recommmendation system.

Content Based Filtering:

In our case, a content-based recommendation system is one where we recommend a movie similar to one a user likes. We will use the genres for the content-based filtering which is shown below:

```
# genres in the dataframe
df["genres"]
```

```
0       Adventure|Animation|Children|Comedy|Fantasy
0       Adventure|Animation|Children|Comedy|Fantasy
0       Adventure|Animation|Children|Comedy|Fantasy
0       Adventure|Animation|Children|Comedy|Fantasy
0       Adventure|Animation|Children|Comedy|Fantasy
                            ...
9737                Action|Animation|Comedy|Fantasy
9738                       Animation|Comedy|Fantasy
9739                                          Drama
9740                               Action|Animation
```

```
9741                                          Comedy
Name: genres, Length: 100823, dtype: object
```

Procedure:

- **SciKit Learn's TfidfVectorizer** will be used in this case which is a class from scikit-learn, a popular machine learning library in Python, used for converting a collection of raw text documents into a matrix of TF-IDF (Term Frequency-Inverse Document Frequency) features. TF-IDF is a numerical statistic that reflects the importance of a word in a document relative to a collection of documents.
- I shall then fit the **genres** into the TfidfVectorizer which yields a sparse matrix.
- To compute a similarity matrix, i then use a sigmoid kernel, which computes the similarity of movies given the index.

```
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.metrics.pairwise import sigmoid_kernel


tfv = TfidfVectorizer(min_df=3,  max_features=None,
            strip_accents='unicode', analyzer='word',token_pattern=r'\w{1,}',
            ngram_range=(1, 3),
            stop_words = 'english')

# Filling NaNs with empty string
merged_movies_links['genres'] = merged_movies_links['genres'].fillna('')
# replace the pipes '|' from the genres with 'commas'
merged_movies_links['genres'] = merged_movies_links['genres'].map(lambda x: ", ".join(x.split("|")))
# genres
merged_movies_links['genres'].head()
```

```
0    Adventure, Animation, Children, Comedy, Fantasy
1                      Adventure, Children, Fantasy
2                                   Comedy, Romance
3                            Comedy, Drama, Romance
4                                            Comedy
Name: genres, dtype: object
```

```
tfv_matrix = tfv.fit_transform(merged_movies_links['genres'])
tfv_matrix
```

```
<9742x402 sparse matrix of type '<class 'numpy.float64'>'
	with 42867 stored elements in Compressed Sparse Row format>
```

```
# Compute the sigmoid kernel
sig = sigmoid_kernel(tfv_matrix, tfv_matrix)

print("length of the similarity matrix:", len(sig))
print(sig[0])
```

```
length of the similarity matrix: 9742
[0.76263689 0.76180765 0.76164424 ... 0.76159416 0.76172628 0.76173151]
```

here i reate a reverse map of the movies titles, which helps us get a movie index just by the name as shown:

```
# reverse mapping of indices and movie titles
indices = pd.Series(merged_movies_links.index, index=merged_movies_links['title']).drop_duplicates()
indices
```

```
title
Toy Story (1995)                                0
Jumanji (1995)                                  1
Grumpier Old Men (1995)                         2
Waiting to Exhale (1995)                        3
Father of the Bride Part II (1995)              4
                                             ...
Black Butler: Book of the Atlantic (2017)    9737
No Game No Life: Zero (2017)                 9738
Flint (2017)                                 9739
Bungo Stray Dogs: Dead Apple (2018)          9740
Andrew Dice Clay: Dice Rules (1991)          9741
Length: 9742, dtype: int64
```

```
# Testing
indices['No Game No Life: Zero (2017)']
```

```
9738
```

```
list(enumerate(sig[indices['Toy Story (1995)']]))[:5]
```

```
[(0, 0.7626368906233343),
 (1, 0.7618076535093508),
 (2, 0.7616442356858768),
 (3, 0.7616291558555321),
 (4, 0.7617315097208257)]
```

This function get_title searches for a movie title in the dataframe df that contains the given text (case-insensitive, without regex), and if found, returns the first matching movie title along with its genres; otherwise, it prints an error message and returns None, None.

```
def get_title(text, df=df):
    """Gets movie title matching `text`
    returns:
        title - title of movie matching the input
        genres - the movie's genres
    """
    mask = df['title'].str.contains(text, case=False, regex=False)
    title = df.loc[mask, 'title'].head(1).values[0] if any(mask) else None

    if not title:
        print(f"\n'{text}' does not match any movies. Please try again")
        return None, None

    return title, df.loc[mask].head(1)["genres"].values[0]
```

This code tests the get_title function by attempting to find a movie titled "Superman (1978)" in the df dataframe (printing the title and genres if found) and then searches for a non-existent movie "NibK7Iv", which will trigger an error message and return None, None.

```
print(get_title("Superman (1978)", df))
print()
print(get_title("NibK7Iv", df))
```

```
('Superman (1978)', 'Action|Adventure|Sci-Fi')


'NibK7Iv' does not match any movies. Please try again
(None, None)
```

The give_rec function finds a movie by title, retrieves its index from a similarity matrix (sig), and returns the top 10 most similar movies from the merged_movies_links dataframe, while handling errors gracefully; the test call attempts to get recommendations for "superman".

```
def give_rec(title, sig=sig):
    """Get the index corresponding to title"""
    try:
        # get title
        title, genres = get_title(title, merged_movies_links)

        # print the movie title matching the text
        if title:
            print(f"Recommendation for {title}")
            print("Genres: ", genres)

        idx = indices[title]

        # Get the pairwsie similarity scores
        sig_scores = list(enumerate(sig[idx]))

        # Sort the movies
        sig_scores = sorted(sig_scores, key=lambda x: x[1], reverse=True)

        # Scores of the 10 most similar movies
        sig_scores = sig_scores[1:11]
```

```
        # Movie indices
        movie_indices = [i[0] for i in sig_scores]

        # Top 10 most similar movies
        return merged_movies_links.iloc[movie_indices].drop_duplicates()
    except Exception as _:
        print(_)
        return "⚠ Oops! Something went wrong!"
```

```
give_rec('superman')
```

```
Recommendation for Superman (1978)
Genres:  Action, Adventure, Sci-Fi
```

	movieId	title	genres	imdbId	tmdbId
224	260	Star Wars: Episode IV - A New Hope (1977)	Action, Adventure, Sci-Fi	76759	11.0
275	316	Stargate (1994)	Action, Adventure, Sci-Fi	111282	2164.0
385	442	Demolition Man (1993)	Action, Adventure, Sci-Fi	106697	9739.0
898	1196	Star Wars: Episode V - The Empire Strikes Back...	Action, Adventure, Sci-Fi	80684	1891.0
911	1210	Star Wars: Episode VI - Return of the Jedi (1983)	Action, Adventure, Sci-Fi	86190	1892.0
1058	1375	Star Trek III: The Search for Spock (1984)	Action, Adventure, Sci-Fi	88170	157.0
1346	1831	Lost in Space (1998)	Action, Adventure, Sci-Fi	120738	2157.0
1557	2094	Rocketeer, The (1991)	Action, Adventure, Sci-Fi	102803	10249.0
1567	2105	Tron (1982)	Action, Adventure, Sci-Fi	84827	97.0
1692	2275	Six-String Samurai (1998)	Action, Adventure, Sci-Fi	118736	24746.0

```
give_rec("Tron (1982)")
```

```
Recommendation for Tron (1982)
Genres:  Action, Adventure, Sci-Fi
```

	movieId	title	genres	imdbId	tmdbId
224	260	Star Wars: Episode IV - A New Hope (1977)	Action, Adventure, Sci-Fi	76759	11.0
275	316	Stargate (1994)	Action, Adventure, Sci-Fi	111282	2164.0
385	442	Demolition Man (1993)	Action, Adventure, Sci-Fi	106697	9739.0
898	1196	Star Wars: Episode V - The Empire Strikes Back...	Action, Adventure, Sci-Fi	80684	1891.0
911	1210	Star Wars: Episode VI - Return of the Jedi (1983)	Action, Adventure, Sci-Fi	86190	1892.0
1058	1375	Star Trek III: The Search for Spock (1984)	Action, Adventure, Sci-Fi	88170	157.0
1346	1831	Lost in Space (1998)	Action, Adventure, Sci-Fi	120738	2157.0
1557	2094	Rocketeer, The (1991)	Action, Adventure, Sci-Fi	102803	10249.0
1567	2105	Tron (1982)	Action, Adventure, Sci-Fi	84827	97.0
1692	2275	Six-String Samurai (1998)	Action, Adventure, Sci-Fi	118736	24746.0

Summary of the output:

As we can see, the system works for the most part, but it inherently has a few issues:

- It only recommends by genre, which is shallow and insufficient, as it doesn't scoop out the patterns deeply embedded in our dataset.
- Ratings, which are a high indicator of preference aren't used, so the system is to a degree, not as effective.
- Finally, as demonstrated above, the recommendation is somewhat 'rigid', meaning, if a movie's genre is Action, Adventure and Sci-fi, then one can only get a movie with the same exact genres.

For a more flexible system which goes deeper into the data-set, we have to use a collaborative filtering approach.

Collaborative filtering

Collaborative filtering can be user-based or item-based. User-based collaborative filtering recommends items based on the preferences of users with similar tastes, while item-based collaborative filtering recommends items similar to those the user has liked.

Memory/ Neighbourhood based:

- For this, i first create a pivot table, from which i will derive the sparse matrix:

```
## First lets create a Pivot matrix
knnrc_df=df.pivot_table(index='title',columns='userId',values='rating').fillna(0)
knnrc_df.head()
```

userId	1.0	2.0	3.0	4.0	5.0	6.0	7.0	8.0	9.0	10.0	...	601.0	602.0	603.0	604.0	605.0	606.0	607.0	608.0	6
title																				
'71 (2014)	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
'Hellboy': The Seeds of Creation (2004)	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
'Round Midnight	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	

```
knnrc_df.shape
```

```
(9713, 610)
```

```
from scipy.sparse import csr_matrix
from sklearn.neighbors import NearestNeighbors

movie_features_df_matrix = csr_matrix(knnrc_df.values)
```

```
model_knn = NearestNeighbors(metric = 'cosine', algorithm = 'brute')
model_knn.fit(movie_features_df_matrix)
```

```
NearestNeighbors(algorithm='brute', metric='cosine')
```

```
# reverse map using the pivot matrix
new_indices = {value: index for index, value in enumerate(knnrc_df.index)}


# test
query_index = new_indices['Tron (1982)']
distances, indices = model_knn.kneighbors(knnrc_df.iloc[query_index,:].values.reshape(1, -1), n_neighbors = 6)

for i in range(0, len(distances.flatten())):
    if i == 0:
        print('Recommendations for {0}:\n'.format(knnrc_df.index[query_index]))
    else:
        print('{0}: {1}, with distance of {2}:'.format(i, knnrc_df.index[indices.flatten()[i]], distances.flatten()[i]))
```

```
Recommendations for Tron (1982):

1: RoboCop (1987), with distance of 0.4333110059193197:
2: Logan's Run (1976), with distance of 0.5173426988364118:
3: Cocoon (1985), with distance of 0.5194918665320847:
4: Total Recall (1990), with distance of 0.5267681600937928:
5: Star Wars: Episode I - The Phantom Menace (1999), with distance of 0.5270073286035528:
```

Using **surprise** library aso as to be able to validate the models:

```
from surprise import Dataset, Reader
from surprise.model_selection import train_test_split
from surprise import accuracy
from surprise.prediction_algorithms import KNNWithMeans, KNNBasic, KNNBaseline
from surprise.prediction_algorithms import SVD
from surprise.model_selection import GridSearchCV, cross_validate
```

```
reader = Reader(rating_scale=(1, 5))

expected_column_names = ["userId", "movieId", "rating"]

# Load the data into a Surprise Dataset
data_surp = Dataset.load_from_df(df[expected_column_names], reader)


# cross validating with KNNBasic
knn_basic = KNNBasic(sim_options={'name':'pearson', 'user_based':True})
cv_knn_basic = cross_validate(knn_basic, data_surp, n_jobs=-1)



# cross validating with KNNBaseline
knn_baseline = KNNBaseline(sim_options={'name':'pearson', 'user_based':True})
cv_knn_baseline = cross_validate(knn_baseline, data_surp)
```

```
Estimating biases using als...
Computing the pearson similarity matrix...
Done computing similarity matrix.
Estimating biases using als...
Computing the pearson similarity matrix...
Done computing similarity matrix.
Estimating biases using als...
Computing the pearson similarity matrix...
Done computing similarity matrix.
Estimating biases using als...
Computing the pearson similarity matrix...
Done computing similarity matrix.
Estimating biases using als...
Computing the pearson similarity matrix...
Done computing similarity matrix.
```

```
for i in cv_knn_baseline.items():
    print(i)

print('----------------------')
```

```
# print validation results
np.mean(cv_knn_baseline['test_rmse'])
```

```
('test_rmse', array([0.88123987, 0.87103533, 0.88122198, 0.86745474, 0.87628082]))
('test_mae', array([0.67448283, 0.66480797, 0.67105828, 0.66408267, 0.66959848]))
('fit_time', (1.0844740867614746, 1.2472569942474365, 1.1685168743133545, 1.1000728607177734, 1.0998859405517578))
('test_time', (2.4182136058807373, 2.470033884048462, 2.6175668239593506, 2.4542808532714844, 2.5000932216644287))
-----------------------
0.8754465481123255
```

```
# print out the average RMSE score for the test set
for i in cv_knn_basic.items():
    print(i)
# print validation results
print('-----------------------')
print(np.mean(cv_knn_basic['test_rmse']))
```

```
('test_rmse', array([0.97853001, 0.96821609, 0.97072673, 0.96960788, 0.97196309]))
('test_mae', array([0.75519418, 0.74765207, 0.75051238, 0.75025736, 0.74961468]))
('fit_time', (1.0963311195373535, 1.0829288959503174, 1.1162476539611816, 1.0835578441619873, 0.962950468063354 5))
('test_time', (1.6501269340515137, 1.68666672706604, 1.6802098751068115, 1.6827118396759033, 1.5666980743408203))
-----------------------
0.9718087605226631
```

Summary of Surprise lib's KNN:

- The KNN Basic and KNN Baseline models exhibit similar RMSE, with the KNN Baseline slightly outperforming the KNN Basic model.
- Both KNN models have relatively low MAE, indicating good accuracy in predicting user ratings.
- The training time for the KNN models is relatively short, making them efficient for training.
- The SVD model has a slightly higher RMSE compared to the KNN models, but its overall performance is still competitive.

The choice between these models depends on specific use-case requirements, including the trade-off between accuracy and computational efficiency. Further analysis and potential hyperparameter tuning could refine the performance of these models.

Function to test out the KNN method

```
def knn_get_rec(title, rec=6, verbose=True):
    """Get recommendations for a movie using KNN
    """
    # create a return dataframe
    ret_df = pd.DataFrame()
    # initiate an empty list to fill the knn distances
    dists = []
    try:
        # get movie details and the pivot matrix index
        title, genres = get_title(title, df)
        idx = new_indices[title]

        # compute the knn distance and index
        distances, knn_indices = model_knn.kneighbors(knnrc_df.iloc[idx,:].values.reshape(1, -1), n_neighbors = rec + 1)

        if title and verbose:
            print(f'Recommendations for {title}:')
            print(f"Genres: {', '.join(genres.split('|'))}")

        for i in range(0, len(distances.flatten())):
            if i == 0:
                continue
            rec_movie = knnrc_df.index[knn_indices.flatten()[i]]
            movies_df = data['movies']
            mask = movies_df['title'].str.contains(rec_movie, case=False, regex=False)

            # fill in return dataframe
            ret_df = pd.concat([ret_df, movies_df[mask]])

            # fill in the knn distances in the df
            dists.append(distances.flatten()[i])

        ret_df["knn_distance"] = dists

        return ret_df
```

```
    except Exception as _:
        return "⚠ Oops! Something went wrong!"


# test
knn_get_rec('infinity war', 10)
```

```
Recommendations for Avengers: Infinity War - Part I (2018):
Genres: Action, Adventure, Sci-Fi
```

	movieId	title	genres	knn_distance
9709	187593	Deadpool 2 (2018)	Action|Comedy|Sci-Fi	0.197364
8694	122916	Thor: Ragnarok (2017)	Action|Adventure|Sci-Fi	0.218983
8699	122926	Untitled Spider-Man Reboot (2017)	Action|Adventure|Fantasy	0.303779
8688	122898	Justice League (2017)	Action|Adventure|Sci-Fi	0.395773
8695	122918	Guardians of the Galaxy 2 (2017)	Action|Adventure|Sci-Fi	0.408945
8696	122920	Captain America: Civil War (2016)	Action|Sci-Fi|Thriller	0.424481
8697	122922	Doctor Strange (2016)	Action|Adventure|Sci-Fi	0.450223
9604	176371	Blade Runner 2049 (2017)	Sci-Fi	0.454227
8692	122906	Black Panther (2017)	Action|Adventure|Sci-Fi	0.456780
9418	165639	While You Were Fighting: A Thor Mockumentary (...	Comedy|Fantasy|Sci-Fi	0.457608

```
# test 2
knn_get_rec('spider-man', 10)
```

```
Recommendations for Spider-Man (2002):
Genres: Action, Adventure, Sci-Fi, Thriller
```

	movieId	title	genres	knn_distance
5260	8636	Spider-Man 2 (2004)	Action|Adventure|Sci-Fi|IMAX	0.267842
3832	5378	Star Wars: Episode II - Attack of the Clones (...	Action|Adventure|Sci-Fi|IMAX	0.303643
3873	5445	Minority Report (2002)	Action|Crime|Mystery|Sci-Fi|Thriller	0.338738
4334	6333	X2: X-Men United (2003)	Action|Adventure|Sci-Fi|Thriller	0.361211
2836	3793	X-Men (2000)	Action|Adventure|Sci-Fi	0.370047
4427	6539	Pirates of the Caribbean: The Curse of the Bla...	Action|Adventure|Comedy|Fantasy	0.375362
3638	4993	Lord of the Rings: The Fellowship of the Ring,...	Adventure|Fantasy	0.379254
4351	6365	Matrix Reloaded, The (2003)	Action|Adventure|Sci-Fi|Thriller|IMAX	0.387891
4137	5952	Lord of the Rings: The Two Towers, The (2002)	Adventure|Fantasy	0.388087
3854	5418	Bourne Identity, The (2002)	Action|Mystery|Thriller	0.389831

Sumarry of the Neighbourhood based collaborative approach (SciKit's):

- This model works better than the content-based approach as it makes use of the user ratings, thereby reading more into the dataset.
    - However, neighbourhood-based collaborative filtering has some limitations, particularly in scenarios with sparse data, the cold start problem for new users or items, and scalability issues as the dataset grows. Therefore, it becomes essential to explore model-based approaches like Singular Value Decomposition (SVD) or Alternating Least Squares (ALS).

```
def surp_knn_get_rec(uid=1000, rec_count=10):
    # Load the dataset and create a train-test split
    reader = Reader(rating_scale=(1, 5))
    data_ = Dataset.load_from_df(df[expected_column_names], reader)
    trainset, _ = train_test_split(data_, test_size=0.2, random_state=42)
```

```
    # Train the KNN model
    sim_options = {'name': 'pearson', 'user_based': True}
    knn_model = KNNBasic(sim_options=sim_options)
    knn_model.fit(trainset)

    # Get the user's unrated items
    unrated_items = [item for item in trainset.all_items() if item not in trainset.ur[uid]]

    # Predict ratings for unrated items
    predictions = [knn_model.predict(uid, iid) for iid in unrated_items]

    # Sort the predictions by estimated rating in descending order
    sorted_predictions = sorted(predictions, key=lambda x: x.est, reverse=True)

    # Extract the top N recommended items
    top_recommendations = sorted_predictions[:rec_count]

    # Print or return the recommended items
    recommended_movie_ids = [prediction.iid for prediction in top_recommendations]
    movie_df = data['movies']
    recommended_movies = movie_df[movie_df['movieId'].isin(recommended_movie_ids)]

    return recommended_movies

# test
surp_knn_get_rec(uid=100, rec_count=10)
```

```
Computing the pearson similarity matrix...
Done computing similarity matrix.
```

	movieId	title	genres
36	40	Cry, the Beloved Country (1995)	Drama
107	123	Chungking Express (Chung Hing sam lam) (1994)	Drama|Mystery|Romance
265	305	Ready to Wear (Pret-A-Porter) (1994)	Comedy
346	389	Colonel Chabert, Le (1994)	Drama|Romance|War
467	534	Shadowlands (1993)	Drama|Romance
525	613	Jane Eyre (1996)	Drama|Romance
531	626	Thin Line Between Love and Hate, A (1996)	Comedy
536	633	Denise Calls Up (1995)	Comedy
548	650	Moll Flanders (1996)	Drama
557	670	World of Apu, The (Apur Sansar) (1959)	Drama

```
# test 2
surp_knn_get_rec(uid=300, rec_count=5)
```

```
Computing the pearson similarity matrix...
Done computing similarity matrix.
```

	movieId	title	genres
48	53	Lamerica (1994)	Adventure|Drama
202	236	French Kiss (1995)	Action|Comedy|Romance
245	283	New Jersey Drive (1995)	Crime|Drama
292	334	Vanya on 42nd Street (1994)	Drama
450	515	Remains of the Day, The (1993)	Drama|Romance

Model-Based Methods - Matrix Factorization using SVD:

Let's try out a matric factorization technique on the data, by singular value decomposition:

```
param_grid = {'n_factors':[20, 100],'n_epochs': [5, 10], 'lr_all': [0.002, 0.005],
              'reg_all': [0.4, 0.6]}

gs_model = GridSearchCV(SVD, param_grid=param_grid, n_jobs = -1, joblib_verbose=5)

gs_model.fit(data_surp)
```

```
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 4 concurrent workers.
[Parallel(n_jobs=-1)]: Done  10 tasks      | elapsed:    3.7s
[Parallel(n_jobs=-1)]: Done  64 tasks      | elapsed:   27.0s
[Parallel(n_jobs=-1)]: Done  80 out of  80 | elapsed:   41.3s finished
```

```
best_params = gs_model.best_params["rmse"]
```

```
trainset, testset = train_test_split(data_surp, test_size=0.2)

svd = SVD(**best_params)
svd.fit(trainset)
predictions = svd.test(testset)
print(accuracy.rmse(predictions))
```

```
RMSE: 0.8886
0.8886296625779166
```

A value of 0.8925 suggests that, on average, the predicted ratings deviate by approximately 0.8925 from the true ratings. Lower RMSE values indicate better predictive accuracy.

```
# test
svd.predict(uid="230", iid=23)
```

```
Prediction(uid='230', iid=23, r_ui=None, est=3.3293095948532123, details={'was_impossible': False})
```

```
def svd_get_rec(uid=1000, rec_count=0):
    """Returns top 10 movies using SVD
    Parameters:
    ===========
    uid - user id
    rec_count - movie recommendation count
    """
    trainset, testset = train_test_split(data_surp, test_size=0.2)
    # Get the user's unrated items
    unrated_items = [item for item in trainset.all_items() if item not in trainset.ur[uid]]

    # Predict ratings for unrated items
    predictions = [svd.predict(uid, iid) for iid in unrated_items]

    # Sort the predictions by estimated rating in descending order
    sorted_predictions = sorted(predictions, key=lambda x: x.est, reverse=True)

    # Extract the top N recommended items
    top_recommendations = sorted_predictions[:rec_count]

    # Print or return the recommended items
    recommended_movie_ids = [prediction.iid for prediction in top_recommendations]
    movie_df = data['movies']
    recommended_movies = movie_df[movie_df['movieId'].isin(recommended_movie_ids)]

    return recommended_movies

# test
svd_get_rec(uid=100, rec_count=10)
```

	movieId	title	genres
46	50	Usual Suspects, The (1995)	Crime|Mystery|Thriller
277	318	Shawshank Redemption, The (1994)	Crime|Drama
602	750	Dr. Strangelove or: How I Learned to Stop Worr...	Comedy|War
659	858	Godfather, The (1972)	Crime|Drama
686	904	Rear Window (1954)	Mystery|Thriller
694	912	Casablanca (1942)	Drama|Romance
901	1199	Brazil (1985)	Fantasy|Sci-Fi
906	1204	Lawrence of Arabia (1962)	Adventure|Drama|War
909	1208	Apocalypse Now (1979)	Action|Drama|War
2226	2959	Fight Club (1999)	Action|Crime|Drama|Thriller

Summary of the models:

Final Recommender System:

For the final recommender system, we decided to go with SciKit Learn's recommender system (which is a neighbourhood based (KNN) system).

> The main reason for this is because, it is easy to test out an item-item based movie system more than a user-user, after running the recommender functions, because the items are familiar more than the users.

How the final system works:

1. take in a user id.
2. randomly select movies they highly rated.

3. return 10 recommendations based on the movies liked.
4. If no id given, use the unpersonalized recommender.

```
def top_ten_highly_rated(uid, rec=10):
    """returns a list of movies highly rated by a user"""
    mask = data["ratings"]['userId'] == uid
    user_movies = data["ratings"][mask].sort_values(by=['rating'], ascending=False).head(rec)
    user_movies = pd.merge(data["movies"], user_movies, how="inner", on="movieId")

    if len(user_movies) < 1:
        raise ValueError(f"User denoted by id: '{uid}' does not exist!")

    return list(user_movies["title"])

# test for user-id: 100
top_ten_highly_rated(100)
```

```
['Top Gun (1986)',
 'When Harry Met Sally... (1989)',
 'Joy Luck Club, The (1993)',
 'Sliding Doors (1998)',
 'Wedding Singer, The (1998)',
 'Out of Sight (1998)',
 'Terms of Endearment (1983)',
 "Christmas Vacation (National Lampoon's Christmas Vacation) (1989)",
 'Officer and a Gentleman, An (1982)',
 'Sweet Home Alabama (2002)']
```

```
def unpersonalized_recomm(count=10):
    """Returns a randomlist of highly ranked movies movies"""
    unique_genres = list(set(df['genres'].str.split('|', expand=True).stack()))

    recomms = pd.DataFrame()
    for genre in unique_genres:
        # select top 5 of each genre
        mask = df["genres"].str.contains(genre, regex=False, case=False)
        top_5 = df[mask].sort_values(by="rating", ascending=False).head()
```

```
        top_5["year_of_release"] = top_5["title"].map(lambda x: x[-5:].strip(")"))
        recomms = pd.concat([recomms, top_5])

    # return shuffled
    print("Unpersonalized recommendation:")
    return recomms.sample(frac=1).drop_duplicates().head(count)

# test
unpersonalized_recomm()
```

Unpersonalized recommendation:

	movieId	title	genres	imdbId	tmdbId	userId	rating	timestamp	year_of_release
5248	8607	Tokyo Godfathers (2003)	Adventure|Animation|Drama	388473	13398	483	5.0	1.204278e+09	2003
508	590	Dances with Wolves (1990)	Adventure|Drama|Western	99348	581	565	5.0	8.465332e+08	1990
136	163	Desperado (1995)	Action|Romance|Western	112851	8068	1	5.0	9.649836e+08	1995
413	475	In the Name of the Father (1993)	Drama	107207	7984	239	5.0	1.221159e+09	1993
5200	8464	Super Size Me (2004)	Comedy|Documentary|Drama	390521	9372	51	5.0	1.230930e+09	2004
691	909	Apartment, The (1960)	Comedy|Drama|Romance	53604	284	177	5.0	1.435536e+09	1960
8687	122896	Pirates of the Caribbean: Dead Men Tell No Tal...	(no genres listed)	1790809	166426	586	5.0	1.529900e+09	2017
607	762	Striptease (1996)	Comedy|Crime	117765	9879	492	5.0	8.639761e+08	1996

```
import random

random.seed(555)

def final_recommender(uid=None, rec=10):
    """Get recommendations for a movie using KNN
    params:
```

```
    =======
    uid - user id
    rec - recommendation movie count
    """
    if not uid:
        return unpersonalized_recomm(rec)
    # create a return dataframe
    ret_df = pd.DataFrame()
    # initiate an empty list to fill the knn distances
```