Business Understanding

1) Overview

This project aims to develop a personalized movie recommendation system by leveraging a dataset containing movie information, user ratings, and interactions. The system will utilize content-based and collaborative filtering techniques to suggest movies to users based on their preferences and past interactions. Modules for movie and user profiling will be developed to analyze movie attributes and user preferences, respectively. Evaluation and optimization will be conducted to enhance the accuracy Furthermore, leveraging movie metadata, user ratings, and collaborative filtering algorithms, the system provides personalized movie recommendations to enhance the user's movie-watching experience.

1.1)Introduction

- TMDB is a popular database that provides comprehensive information about movies,that contains the following titles, release dates, genres,cast and crew information. Credit information is given as well about the cast and crew information whereby the cast and crew are invoved in each movie. With the combination of the datasets, we gain valuable insights and perform variious analyses related to the movie industry

1.2) Problem Statement

- The movie industry is vast and fast evolving , with countless movies and movie sequels released each year hence can be a challenge for the users to navigate through the vast amount of content and get to know which movies align with their preferences.
- To ease this, or rather improve the users' experience, we come up withh a recommendation system that provides personalized movie recommendations based on user preferences and similarities with other users, and also aim to improve user satisfaction, increase user engagement, which ultimately drive user's retention on the platform.

1.3) Objectives

1.3.1) General Objectives

- Develop a recommendation system that leverages user data and movie information to provide personalized movie recommendations. Incorporate user preferences, including movie genres, ratings, and historical interactions, to generate relevant and engaging recommendations.
- Implement different recommendation techniques, such as collaborative filtering and content-based filtering, to ensure a diverse and accurate set of movie recommendations.
- To develop a movie recommendation system based on movie attributes, user ratings, and user interactions. The dataset consists of movie information such as

title, cast, crew, budget, genres, keywords, language, revenue, and other relevant attributes. The objective is to leverage this data to build a recommendation system that can suggest movies to users based on their preferences and past interactions.

1.4 Data Understanding

- Columns Understanding:
- id: Unique identifier for each movie
- title: Title of the movie
- cast: List of actors/actresses in the movie
- crew: List of crew members involved in the movie
- budget: Budget of the movie
- genres: List of genres associated with the movie
- homepage: Website URL of the movie
- keywords: List of keywords associated with the movie
- original_language: Original language of the movie
- original_title: Original title of the movie
- production_companies: List of production companies involved in the movie
- production_countries: List of countries where the movie was produced
- release_date: Release date of the movie
- revenue: Revenue generated by the movie
- runtime: Duration of the movie in minutes
- spoken_languages: List of languages spoken in the movie
- status: Current status of the movie (e.g., Released, Post Production)
- tagline: Tagline or slogan of the movie
- vote_average: Average vote rating for the movie
- vote_count: Number of votes received by the movie
- tags: List of tags associated with the movie

Import/ Load the libraries required

```
import numpy as np
import pandas as pd
```

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

import ast
import json
from collections.abc import Iterable

from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.metrics.pairwise import linear_kernel
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.metrics.pairwise import cosine_similarity
from sklearn.metrics import PrecisionRecallDisplay,
mean_squared_error, precision_recall_fscore_support,
precision_recall_curve
from sklearn.pipeline import Pipeline

from wordcloud import WordCloud

from surprise import SVD, Reader, Dataset
from surprise.model_selection import cross_validate, train_test_split,
GridSearchCV
from surprise import KNNWithMeans
from surprise import accuracy

from nltk import PorterStemmer

from my_functions import DatasetInfo, movie_score,
get_user_recommendations, recommended_movies

import warnings
warnings.filterwarnings('ignore', category=UserWarning,
module='IPython')
```

Load the Datasets

- Movie Credits Dataset

```
tmdb_movie_credits = pd.read_csv(r".data/tmdb_5000_credits.csv")
tmdb_movie_credits
```

```
      movie_id                                     title  \
0        19995                                    Avatar
1          285  Pirates of the Caribbean: At World's End
2       206647                                   Spectre
3        49026                     The Dark Knight Rises
4        49529                               John Carter
...        ...                                       ...
4798      9367                               El Mariachi
4799     72766                                 Newlyweds
4800    231617                 Signed, Sealed, Delivered
```

```
4801    126186                             Shanghai Calling
4802     25975                            My Date with Drew

                                                  cast  \
0     [{"cast_id": 242, "character": "Jake Sully", "...
1     [{"cast_id": 4, "character": "Captain Jack Spa...
2     [{"cast_id": 1, "character": "James Bond", "cr...
3     [{"cast_id": 2, "character": "Bruce Wayne / Ba...
4     [{"cast_id": 5, "character": "John Carter", "c...
...                                                 ...
4798  [{"cast_id": 1, "character": "El Mariachi", "c...
4799  [{"cast_id": 1, "character": "Buzzy", "credit_...
4800  [{"cast_id": 8, "character": "Oliver O\u2019To...
4801  [{"cast_id": 3, "character": "Sam", "credit_id...
4802  [{"cast_id": 3, "character": "Herself", "credi...

                                                  crew
0     [{"credit_id": "52fe48009251416c750aca23", "de...
1     [{"credit_id": "52fe4232c3a36847f800b579", "de...
2     [{"credit_id": "54805967c3a36829b5002c41", "de...
3     [{"credit_id": "52fe4781c3a36847f81398c3", "de...
4     [{"credit_id": "52fe479ac3a36847f813eaa3", "de...
...                                                 ...
4798  [{"credit_id": "52fe44eec3a36847f80b280b", "de...
4799  [{"credit_id": "52fe487dc3a368484e0fb013", "de...
4800  [{"credit_id": "52fe4df3c3a36847f8275ecf", "de...
4801  [{"credit_id": "52fe4ad9c3a368484e16a36b", "de...
4802  [{"credit_id": "58ce021b9251415a390165d9", "de...

[4803 rows x 4 columns]
```

-Movies Dataset

```
tmdb_movies = pd.read_csv(r".data/tmdb_5000_movies.csv")
tmdb_movies
```

```
         budget                                             genres  \
0     237000000  [{"id": 28, "name": "Action"}, {"id": 12, "nam...
1     300000000  [{"id": 12, "name": "Adventure"}, {"id": 14, "...
2     245000000  [{"id": 28, "name": "Action"}, {"id": 12, "nam...
3     250000000  [{"id": 28, "name": "Action"}, {"id": 80, "nam...
4     260000000  [{"id": 28, "name": "Action"}, {"id": 12, "nam...
...         ...                                                ...
4798     220000  [{"id": 28, "name": "Action"}, {"id": 80, "nam...
4799       9000  [{"id": 35, "name": "Comedy"}, {"id": 10749, "...
4800          0  [{"id": 35, "name": "Comedy"}, {"id": 18, "nam...
4801          0                                                 []
4802          0                [{"id": 99, "name": "Documentary"}]

                                              homepage      id  \
0                          http://www.avatarmovie.com/   19995
```

```
1         http://disney.go.com/disneypictures/pirates/     285
2          http://www.sonypictures.com/movies/spectre/  206647
3                   http://www.thedarkknightrises.com/   49026
4                 http://movies.disney.com/john-carter   49529
...                                                ...     ...
4798                                               NaN    9367
4799                                               NaN   72766
4800  http://www.hallmarkchannel.com/signedsealeddel...  231617
4801                         http://shanghaicalling.com/  126186
4802                                               NaN   25975

                                               keywords
original_language  \
0     [{"id": 1463, "name": "culture clash"}, {"id":...
en
1     [{"id": 270, "name": "ocean"}, {"id": 726, "na...
en
2     [{"id": 470, "name": "spy"}, {"id": 818, "name...
en
3     [{"id": 849, "name": "dc comics"}, {"id": 853,...
en
4     [{"id": 818, "name": "based on novel"}, {"id":...
en
...                                                 ...
...
4798  [{"id": 5616, "name": "united states\u2013mexi...
es
4799                                                 []
en
4800  [{"id": 248, "name": "date"}, {"id": 699, "nam...
en
4801                                                 []
en
4802  [{"id": 1523, "name": "obsession"}, {"id": 224...
en

                                original_title  \
0                                       Avatar
1     Pirates of the Caribbean: At World's End
2                                      Spectre
3                        The Dark Knight Rises
4                                  John Carter
...                                        ...
4798                               El Mariachi
4799                                 Newlyweds
4800                 Signed, Sealed, Delivered
4801                          Shanghai Calling
4802                         My Date with Drew

                                               overview  popularity  \
```

```
0     In the 22nd century, a paraplegic Marine is di...  150.437577
1     Captain Barbossa, long believed to be dead, ha...  139.082615
2     A cryptic message from Bond’s past sends him o...  107.376788
3     Following the death of District Attorney Harve...  112.312950
4     John Carter is a war-weary, former military ca...   43.926995
...                                                 ...         ...
4798  El Mariachi just wants to play his guitar and ...   14.269792
4799  A newlywed couple's honeymoon is upended by th...    0.642552
4800  "Signed, Sealed, Delivered" introduces a dedic...    1.444476
4801  When ambitious New York attorney Sam is sent t...    0.857008
4802  Ever since the second grade when he first saw ...    1.929883

                                   production_companies  \
0     [{"name": "Ingenious Film Partners", "id": 289...
1     [{"name": "Walt Disney Pictures", "id": 2}, {"...
2     [{"name": "Columbia Pictures", "id": 5}, {"nam...
3     [{"name": "Legendary Pictures", "id": 923}, {"...
4           [{"name": "Walt Disney Pictures", "id": 2}]
...                                                 ...
4798           [{"name": "Columbia Pictures", "id": 5}]
4799                                                 []
4800  [{"name": "Front Street Pictures", "id": 3958}...
4801                                                 []
4802  [{"name": "rusty bear entertainment", "id": 87...

                                   production_countries
release_date  \
0     [{"iso_3166_1": "US", "name": "United States o...   2009-12-10

1     [{"iso_3166_1": "US", "name": "United States o...   2007-05-19

2     [{"iso_3166_1": "GB", "name": "United Kingdom"...   2015-10-26

3     [{"iso_3166_1": "US", "name": "United States o...   2012-07-16

4     [{"iso_3166_1": "US", "name": "United States o...   2012-03-07

...                                                 ...          ...

4798  [{"iso_3166_1": "MX", "name": "Mexico"}, {"iso...   1992-09-04

4799                                                 []   2011-12-26

4800  [{"iso_3166_1": "US", "name": "United States o...   2013-10-13

4801  [{"iso_3166_1": "US", "name": "United States o...   2012-05-03

4802  [{"iso_3166_1": "US", "name": "United States o...   2005-08-05
```

```
         revenue  runtime
spoken_languages  \
0     2787965087    162.0  [{"iso_639_1": "en", "name": "English"},
{"iso...
1      961000000    169.0           [{"iso_639_1": "en", "name":
"English"}]
2      880674609    148.0  [{"iso_639_1": "fr", "name": "Fran\
u00e7ais"},...
3     1084939099    165.0           [{"iso_639_1": "en", "name":
"English"}]
4      284139100    132.0           [{"iso_639_1": "en", "name":
"English"}]
...          ...      ...
...
4798     2040920     81.0      [{"iso_639_1": "es", "name": "Espa\
u00f1ol"}]
4799           0     85.0
[]
4800           0    120.0           [{"iso_639_1": "en", "name":
"English"}]
4801           0     98.0           [{"iso_639_1": "en", "name":
"English"}]
4802           0     90.0           [{"iso_639_1": "en", "name":
"English"}]

        status                                            tagline  \
0     Released                        Enter the World of Pandora.
1     Released     At the end of the world, the adventure begins.
2     Released                              A Plan No One Escapes
3     Released                                    The Legend Ends
4     Released               Lost in our world, found in another.
...        ...                                                ...
4798  Released  He didn't come looking for trouble, but troubl...
4799  Released  A newlywed couple's honeymoon is upended by th...
4800  Released                                                NaN
4801  Released                           A New Yorker in Shanghai
4802  Released                                                NaN

                                         title  vote_average
vote_count
0                                       Avatar           7.2
11800
1     Pirates of the Caribbean: At World's End           6.9
4500
2                                      Spectre           6.3
4466
3                        The Dark Knight Rises           7.6
9106
4                                  John Carter           6.1
```

```
2124
...                                              ...           ...          .
..
4798                                      El Mariachi          6.6
238
4799                                        Newlyweds          5.9
5
4800                         Signed, Sealed, Delivered          7.0
6
4801                                  Shanghai Calling          5.7
7
4802                                 My Date with Drew          6.3
16

[4803 rows x 20 columns]
```

Merge the Datasets

- To avoid overlapping of the tilte columns we drop because we already have the title in the movie dataset

```
# Drop the Title column in Movies Dataset
tmdb_movies.drop(['title'], axis = 1, inplace = True )

# Identify the columns that are common and need to be merged
tmdb_movie_credits.columns=['id', 'title', 'cast', 'crew']

movies_credits = pd.merge(tmdb_movie_credits, tmdb_movies, on = 'id')
movies_credits.head()
```

```
       id                                     title  \
0   19995                                    Avatar
1     285  Pirates of the Caribbean: At World's End
2  206647                                   Spectre
3   49026                     The Dark Knight Rises
4   49529                               John Carter

                                                cast  \
0  [{"cast_id": 242, "character": "Jake Sully", "...
1  [{"cast_id": 4, "character": "Captain Jack Spa...
2  [{"cast_id": 1, "character": "James Bond", "cr...
3  [{"cast_id": 2, "character": "Bruce Wayne / Ba...
4  [{"cast_id": 5, "character": "John Carter", "c...

                                                crew     budget  \
0  [{"credit_id": "52fe48009251416c750aca23", "de...  237000000
1  [{"credit_id": "52fe4232c3a36847f800b579", "de...  300000000
2  [{"credit_id": "54805967c3a36829b5002c41", "de...  245000000
3  [{"credit_id": "52fe4781c3a36847f81398c3", "de...  250000000
4  [{"credit_id": "52fe479ac3a36847f813eaa3", "de...  260000000

                                              genres  \
```

```
0  [{"id": 28, "name": "Action"}, {"id": 12, "nam...
1  [{"id": 12, "name": "Adventure"}, {"id": 14, "...
2  [{"id": 28, "name": "Action"}, {"id": 12, "nam...
3  [{"id": 28, "name": "Action"}, {"id": 80, "nam...
4  [{"id": 28, "name": "Action"}, {"id": 12, "nam...

                                       homepage  \
0                   http://www.avatarmovie.com/
1  http://disney.go.com/disneypictures/pirates/
2   http://www.sonypictures.com/movies/spectre/
3            http://www.thedarkknightrises.com/
4          http://movies.disney.com/john-carter

                                            keywords original_language
\
0  [{"id": 1463, "name": "culture clash"}, {"id":...               en

1  [{"id": 270, "name": "ocean"}, {"id": 726, "na...               en

2  [{"id": 470, "name": "spy"}, {"id": 818, "name...               en

3  [{"id": 849, "name": "dc comics"}, {"id": 853,...               en

4  [{"id": 818, "name": "based on novel"}, {"id":...               en


                             original_title  ...  \
0                                    Avatar  ...
1  Pirates of the Caribbean: At World's End  ...
2                                   Spectre  ...
3                     The Dark Knight Rises  ...
4                               John Carter  ...

                                production_companies  \
0  [{"name": "Ingenious Film Partners", "id": 289...
1  [{"name": "Walt Disney Pictures", "id": 2}, {"...
2  [{"name": "Columbia Pictures", "id": 5}, {"nam...
3  [{"name": "Legendary Pictures", "id": 923}, {"...
4        [{"name": "Walt Disney Pictures", "id": 2}]

                                production_countries release_date
revenue  \
0  [{"iso_3166_1": "US", "name": "United States o...   2009-12-10
2787965087
1  [{"iso_3166_1": "US", "name": "United States o...   2007-05-19
961000000
2  [{"iso_3166_1": "GB", "name": "United Kingdom"...   2015-10-26
880674609
3  [{"iso_3166_1": "US", "name": "United States o...   2012-07-16
```

```
1084939099
4  [{"iso_3166_1": "US", "name": "United States o...   2012-03-07
284139100

  runtime                                   spoken_languages    status
\
0   162.0  [{"iso_639_1": "en", "name": "English"}, {"iso...  Released

1   169.0           [{"iso_639_1": "en", "name": "English"}]  Released

2   148.0  [{"iso_639_1": "fr", "name": "Fran\u00e7ais"},...  Released

3   165.0           [{"iso_639_1": "en", "name": "English"}]  Released

4   132.0           [{"iso_639_1": "en", "name": "English"}]  Released


                                         tagline vote_average
vote_count
0                    Enter the World of Pandora.          7.2
11800
1  At the end of the world, the adventure begins.          6.9
4500
2                           A Plan No One Escapes          6.3
4466
3                                 The Legend Ends          7.6
9106
4             Lost in our world, found in another.          6.1
2124

[5 rows x 22 columns]
```

Data Cleaning and Exploration

In this section, we create functions to explore the following characteristics of our dataset

- Info
- Columns, Column Names
- Datatypes
- Statistcics

```
data_info = DatasetInfo(movies_credits)
print(data_info)
```

```
<my_functions.DatasetInfo object at 0x00000250BC29FE50>
```

```
data_info.check_dataset_info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4803 entries, 0 to 4802
Data columns (total 22 columns):
```

```
 #   Column                Non-Null Count  Dtype  
---  ------                --------------  -----  
 0   id                    4803 non-null   int64  
 1   title                 4803 non-null   object 
 2   cast                  4803 non-null   object 
 3   crew                  4803 non-null   object 
 4   budget                4803 non-null   int64  
 5   genres                4803 non-null   object 
 6   homepage              1712 non-null   object 
 7   keywords              4803 non-null   object 
 8   original_language     4803 non-null   object 
 9   original_title        4803 non-null   object 
 10  overview              4800 non-null   object 
 11  popularity            4803 non-null   float64
 12  production_companies  4803 non-null   object 
 13  production_countries  4803 non-null   object 
 14  release_date          4802 non-null   object 
 15  revenue               4803 non-null   int64  
 16  runtime               4801 non-null   float64
 17  spoken_languages      4803 non-null   object 
 18  status                4803 non-null   object 
 19  tagline               3959 non-null   object 
 20  vote_average          4803 non-null   float64
 21  vote_count            4803 non-null   int64  
dtypes: float64(3), int64(4), object(15)
memory usage: 825.6+ KB
```

```
data_info.check_dataset_shape()
```

```
Dataset shape: (4803, 22)
```

```
data_info.get_dataset_statistics_describe()
```

```
                  id        budget   popularity       revenue
runtime  \
count    4803.000000  4.803000e+03  4803.000000  4.803000e+03
4801.000000
mean    57165.484281  2.904504e+07    21.492301  8.226064e+07
106.875859
std     88694.614033  4.072239e+07    31.816650  1.628571e+08
22.611935
min         5.000000  0.000000e+00     0.000000  0.000000e+00
0.000000
25%      9014.500000  7.900000e+05     4.668070  0.000000e+00
94.000000
50%     14629.000000  1.500000e+07    12.921594  1.917000e+07
103.000000
75%     58610.500000  4.000000e+07    28.313505  9.291719e+07
118.000000
max    459488.000000  3.800000e+08   875.581305  2.787965e+09
338.000000
```

```
       vote_average    vote_count
count   4803.000000   4803.000000
mean       6.092172    690.217989
std        1.194612   1234.585891
min        0.000000      0.000000
25%        5.600000     54.000000
50%        6.200000    235.000000
75%        6.800000    737.000000
max       10.000000  13752.000000
```

```
movies_credits.duplicated().sum()
```

```
0
```

```
movies_credits.isnull().sum()
```

```
id                         0
title                      0
cast                       0
crew                       0
budget                     0
genres                     0
homepage                3091
keywords                   0
original_language          0
original_title             0
overview                   3
popularity                 0
production_companies       0
production_countries       0
release_date               1
revenue                    0
runtime                    2
spoken_languages           0
status                     0
tagline                  844
vote_average               0
vote_count                 0
dtype: int64
```

Some columns within our dataset contain a list of dictionaries. In the cells below, we apply the function from my_functions to extract the desired attribute from each element in the columns.

```
# For the genres column we have to convert it but first we have to
implement
movies_credits.iloc[0].genres
```

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

Here we will apply the functions from our python file to clean the dataset columns

```
# Cleaning the genres column
movies_credits['genres']=movies_credits['genres'].apply(data_info.conv
ert)

# Cleaning the keywords column
movies_credits['keywords']=movies_credits['keywords'].apply(data_info.
get_keywords)

# Cleaning the production companies column
movies_credits['production_companies']=movies_credits['production_comp
anies'].apply(data_info.convert)

# Cleaning the production countries column
movies_credits['production_countries'] =
movies_credits['production_countries'].apply(data_info.convert)

# Cleaning the cast column
movies_credits['cast']=movies_credits['cast'].apply(data_info.convert3
)

# Cleaning the crew column
movies_credits['crew']=movies_credits['crew'].apply(data_info.get_dire
ctors)
```

In the cell below, we split the text in the `overview` column into a list of words for each row where the value is a string. For rows where the value is not a string, it assigns `np.nan` to indicate a missing value.

```
movies_credits['overview'] = movies_credits['overview'].apply(lambda
x: x.split() if isinstance(x, str) else np.nan)

movies_credits.head()
```

```
       id                                      title  \
0   19995                                     Avatar
1     285   Pirates of the Caribbean: At World's End
2  206647                                    Spectre
3   49026                      The Dark Knight Rises
4   49529                                John Carter

                                                cast
crew  \
0  [Sam Worthington, Zoe Saldana, Sigourney Weave...      [James
Cameron]
1  [Johnny Depp, Orlando Bloom, Keira Knightley, ...     [Gore
```

```
Verbinski]
2  [Daniel Craig, Christoph Waltz, Léa Seydoux, R...         [Sam
Mendes]
3  [Christian Bale, Michael Caine, Gary Oldman, A...  [Christopher
Nolan]
4  [Taylor Kitsch, Lynn Collins, Samantha Morton,...     [Andrew
Stanton]

      budget                                          genres  \
0  237000000  [Action, Adventure, Fantasy, Science Fiction]
1  300000000                   [Adventure, Fantasy, Action]
2  245000000                     [Action, Adventure, Crime]
3  250000000               [Action, Crime, Drama, Thriller]
4  260000000           [Action, Adventure, Science Fiction]

                                          homepage  \
0                      http://www.avatarmovie.com/
1  http://disney.go.com/disneypictures/pirates/
2   http://www.sonypictures.com/movies/spectre/
3            http://www.thedarkknightrises.com/
4          http://movies.disney.com/john-carter

                                            keywords original_language
\
0  [culture clash, future, space war, space colon...                en

1  [ocean, drug abuse, exotic island, east india ...                en

2  [spy, based on novel, secret agent, sequel, mi...                en

3  [dc comics, crime fighter, terrorist, secret i...                en

4  [based on novel, mars, medallion, space travel...                en


                             original_title  ...  \
0                                    Avatar  ...
1  Pirates of the Caribbean: At World's End  ...
2                                   Spectre  ...
3                     The Dark Knight Rises  ...
4                               John Carter  ...

                                production_companies  \
0  [Ingenious Film Partners, Twentieth Century Fo...
1  [Walt Disney Pictures, Jerry Bruckheimer Films...
2                    [Columbia Pictures, Danjaq, B24]
3  [Legendary Pictures, Warner Bros., DC Entertai...
4                             [Walt Disney Pictures]
```

```
                        production_countries release_date     revenue  \
0  [United States of America, United Kingdom]   2009-12-10  2787965087

1                  [United States of America]   2007-05-19   961000000

2  [United Kingdom, United States of America]   2015-10-26   880674609

3                  [United States of America]   2012-07-16  1084939099

4                  [United States of America]   2012-03-07   284139100


  runtime                                   spoken_languages    status  \
0   162.0  [{"iso_639_1": "en", "name": "English"}, {"iso...  Released

1   169.0           [{"iso_639_1": "en", "name": "English"}]  Released

2   148.0  [{"iso_639_1": "fr", "name": "Fran\u00e7ais"},...  Released

3   165.0           [{"iso_639_1": "en", "name": "English"}]  Released

4   132.0           [{"iso_639_1": "en", "name": "English"}]  Released


                                          tagline vote_average
vote_count
0                      Enter the World of Pandora.          7.2
11800
1  At the end of the world, the adventure begins.          6.9
4500
2                            A Plan No One Escapes          6.3
4466
3                                  The Legend Ends          7.6
9106
4             Lost in our world, found in another.          6.1
2124

[5 rows x 22 columns]
```

The code below applies a lambda function to iterate over each element `i` (column value) in the input list `x` (column). It replaces any occurrence of whitespace (" ") in each element with an empty string, effectively removing any spaces.

```
# Remove spaces from the elements in the 'genres' column
movies_credits['genres'] = movies_credits['genres'].apply(lambda x:
[i.replace(" ","") for i in x])
```

```
# Remove spaces from the elements in the 'keywords' column
movies_credits['keywords'] = movies_credits['keywords'].apply(lambda
x: [i.replace(" ","") for i in x])

# Remove spaces from the elements in the 'crew' column
movies_credits['crew'] = movies_credits['crew'].apply(lambda x:
[i.replace(" ","") for i in x])

# Remove spaces from the elements in the 'cast' column
movies_credits['cast'] = movies_credits['cast'].apply(lambda x:
[i.replace(" ","") for i in x])
```

Concatenating the modified columns into one named `tags`

```
movies_credits['tags'] = movies_credits['overview'] +
movies_credits['genres'] + movies_credits['keywords'] +
movies_credits['cast'] + movies_credits['crew']

movies_credits['tags']

0       [In, the, 22nd, century,, a, paraplegic, Marin...
1       [Captain, Barbossa,, long, believed, to, be, d...
2       [A, cryptic, message, from, Bond’s, past, send...
3       [Following, the, death, of, District, Attorney...
4       [John, Carter, is, a, war-weary,, former, mili...
                              ...
4798    [El, Mariachi, just, wants, to, play, his, gui...
4799    [A, newlywed, couple's, honeymoon, is, upended...
4800    ["Signed,, Sealed,, Delivered", introduces, a,...
4801    [When, ambitious, New, York, attorney, Sam, is...
4802    [Ever, since, the, second, grade, when, he, fi...
Name: tags, Length: 4803, dtype: object
```

3) EDA:

Visualization

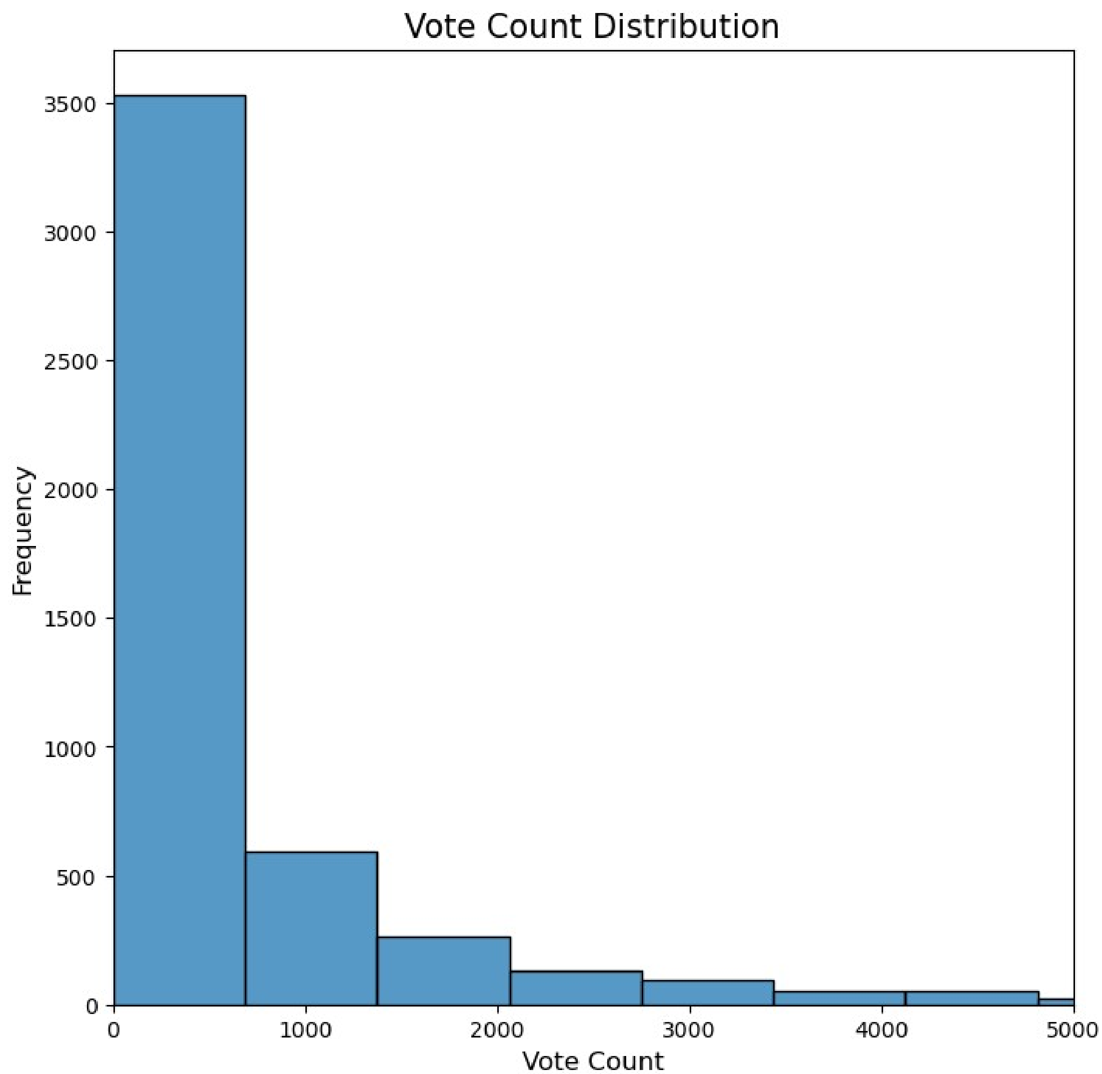
I. **Univariate Analysis**

- Vote Count

```
# Vote Count description
vote_count_univariate = movies_credits['vote_count'].describe()
print(vote_count_univariate)

# Plot vote count distribution
plt.figure(figsize=(8, 8))
sns.histplot(movies_credits['vote_count'], kde = False , bins = 20)
plt.xlabel("Vote Count", fontsize=12)
plt.ylabel("Frequency", fontsize=12)
plt.xlim(0, 5000)
plt.title("Vote Count Distribution", fontsize=15)
```

```
plt.savefig(".data/images/vote_count_plot")
plt.show()
```

```
count     4803.000000
mean       690.217989
std       1234.585891
min          0.000000
25%         54.000000
50%        235.000000
75%        737.000000
max      13752.000000
Name: vote_count, dtype: float64
```

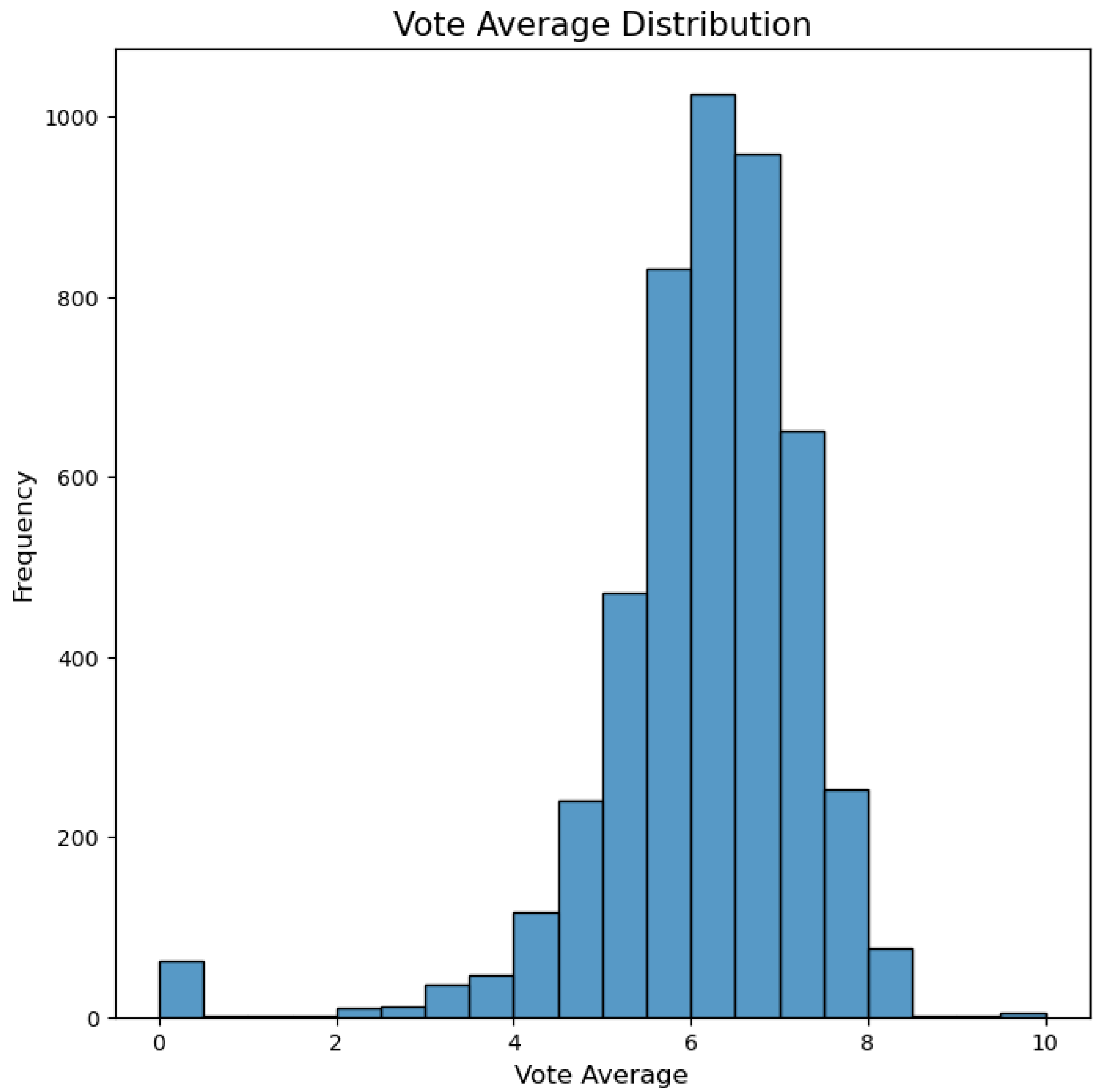


From the plot above we can determine that the vote count decreases hence a low concentarationtion for the vote counts

- Vote Average

```python
vote_average_univariate = movies_credits['vote_average'].describe()
print(vote_average_univariate)

# Plot the vote average distribution
plt.figure(figsize=(8, 8))
sns.histplot(movies_credits['vote_average'], kde = False , bins = 20)
plt.xlabel("Vote Average", fontsize=12)
plt.ylabel("Frequency", fontsize=12)
plt.title("Vote Average Distribution", fontsize=15)
# save the figure
plt.savefig(".data/images/vote_average_plot")
# show the figure
plt.show()
```

```
count    4803.000000
mean        6.092172
std         1.194612
min         0.000000
25%         5.600000
50%         6.200000
75%         6.800000
max        10.000000
Name: vote_average, dtype: float64
```

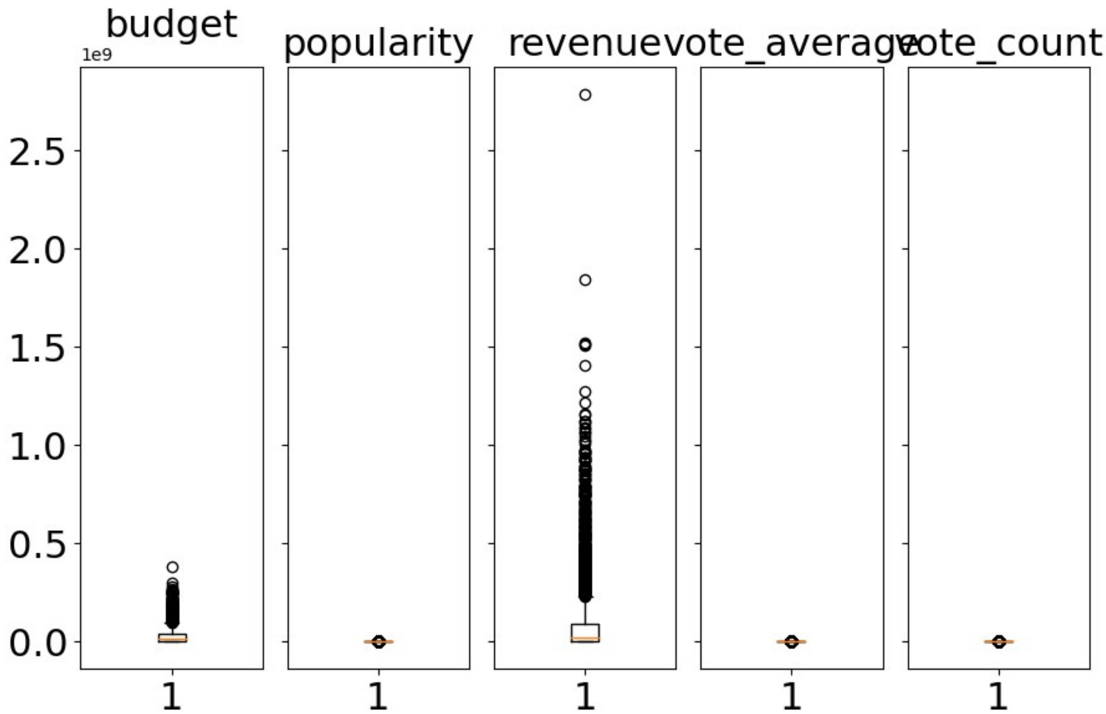


The vote average is normallly distributed with the majority of it being 6-8.

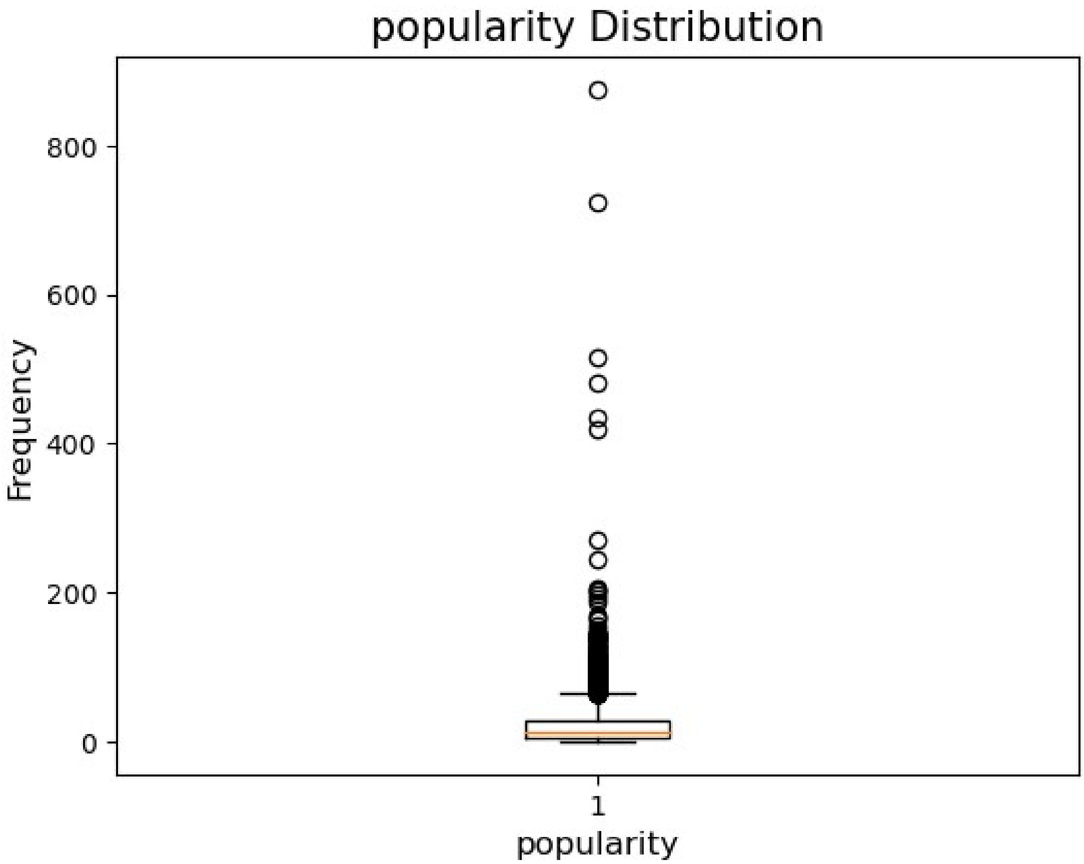
Check for existence of outliers

```
# Select the variables you want to plot

cols_to_plot = ['budget', 'popularity', 'revenue', 'vote_average',
'vote_count']

######## Create a subplot grid
fig, axes = plt.subplots(nrows=1, ncols=len(cols_to_plot), figsize=(9,
6), sharey=True)

####### Create a boxplot for each variable in a separate subplot
for i, col in enumerate(cols_to_plot):
    axes[i].boxplot(movies_credits[col])
    axes[i].set_title(col, fontsize=22)
```

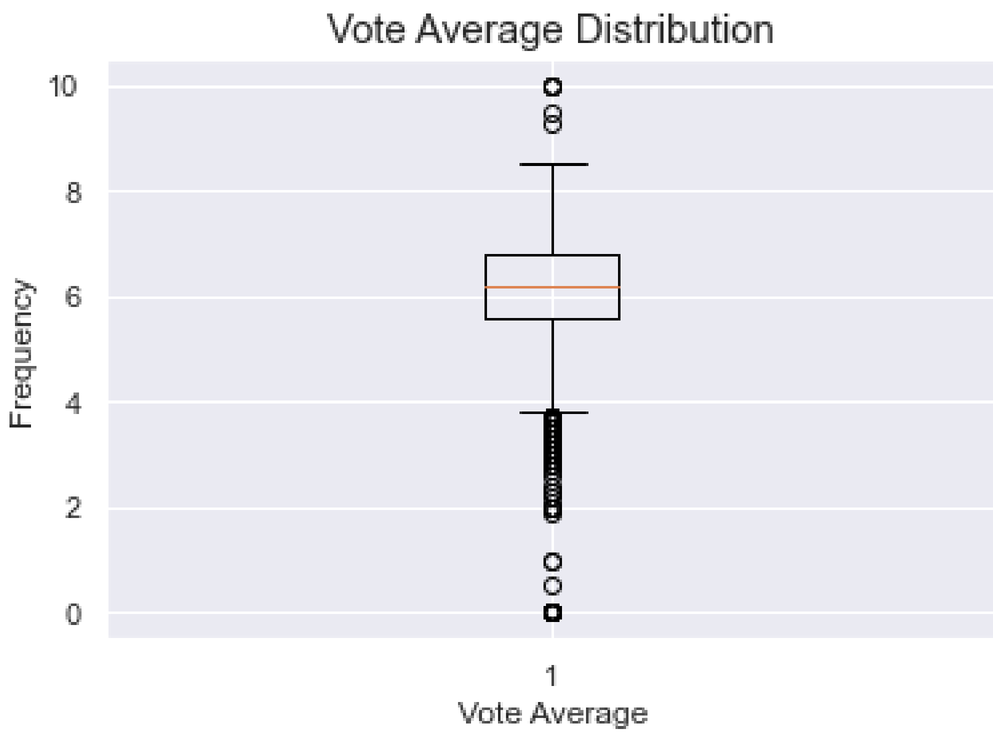
```
    axes[i].tick_params(axis='both', which='major', labelsize=22)

# Adjust spacing between subplots
plt.tight_layout()
# save te figure
plt.savefig(".data/images/Outliers")
# Show the figure
plt.show()
```




```
# Checking for outliers in the 'popularity' column
plt.boxplot(movies_credits['popularity'])
plt.xlabel("popularity", fontsize=12)
plt.ylabel("Frequency", fontsize=12)
plt.title("popularity Distribution", fontsize=15)
# save the figure
plt.savefig(".data/images/popularity_outliers_plot")
plt.show()
```




```
## Checking for outliers in the 'vote average' column
plt.boxplot(movies_credits['vote_average'])
plt.xlabel("Vote Average", fontsize=12)
plt.ylabel("Frequency", fontsize=12)
plt.title("Vote Average Distribution", fontsize=15)
# save the figure
#plt.savefig(".data/images/vote_average_outliers_plot")
plt.show()
```



There are outliers from 0-4 and 8-10, hence we remove them

```
movies_credits['popularity'].nlargest(10)
```

```
546    875.581305
95     724.247784
788    514.569956
94     481.098624
127    434.278564
28     418.708552
199    271.972889
82     243.791743
200    206.227151
88     203.734590
Name: popularity, dtype: float64
```

```
result = (movies_credits['popularity']  >= 200 ).value_counts()
```

```
movies_credits['popularity'].nsmallest(10)
```

```
4553    0.000000
3361    0.000372
4727    0.001117
4118    0.001186
4625    0.001389
4509    0.001586
4305    0.002386
4721    0.002388
```

```
4487    0.003142
4589    0.003352
Name: popularity, dtype: float64
```

```
# Define the lower and upper bounds for the outliers
lower_bound = 0
upper_bound = 400

# Remove outliers from the 'vote_average' column
movies_credits_filtered = movies_credits[(movies_credits['popularity']
>= lower_bound) & (movies_credits['popularity'] <= upper_bound)]

# Display the shape filtered dataset without outliers
movies_credits_filtered.shape
```

```
(4797, 23)
```

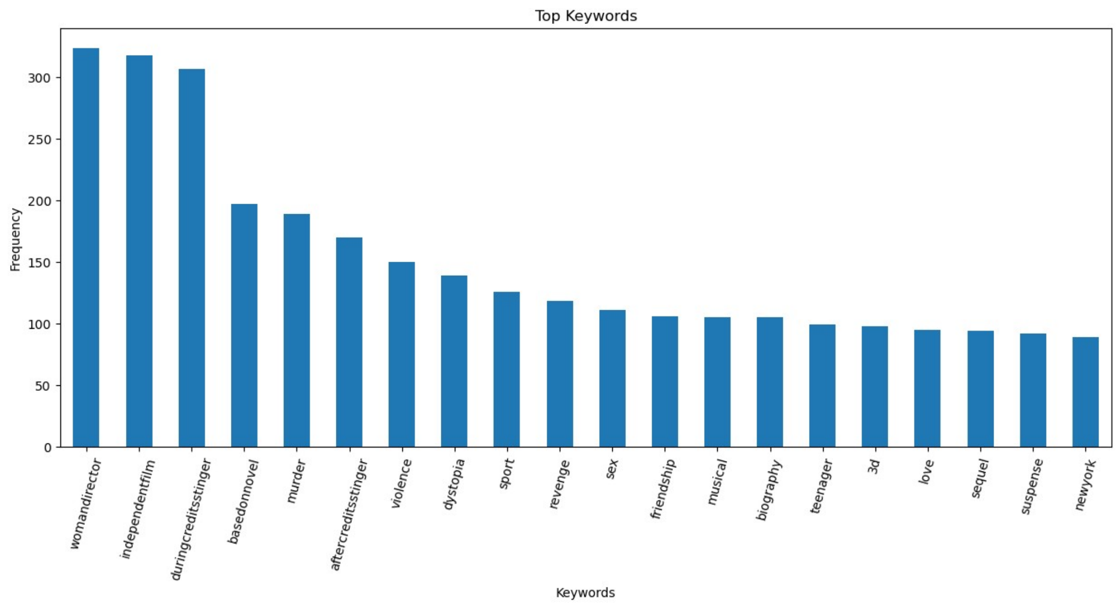
```
# Define the lower and upper bounds for the outliers
lower_bound = 2
upper_bound = 8

# Remove outliers from the 'vote_average' column
movies_credits_filtered =
movies_credits[(movies_credits['vote_average'] >= lower_bound) &
(movies_credits['vote_average'] <= upper_bound)]

# Display the shape filtered dataset without outliers
movies_credits_filtered.shape
```

```
(4686, 23)
```

- Keywords

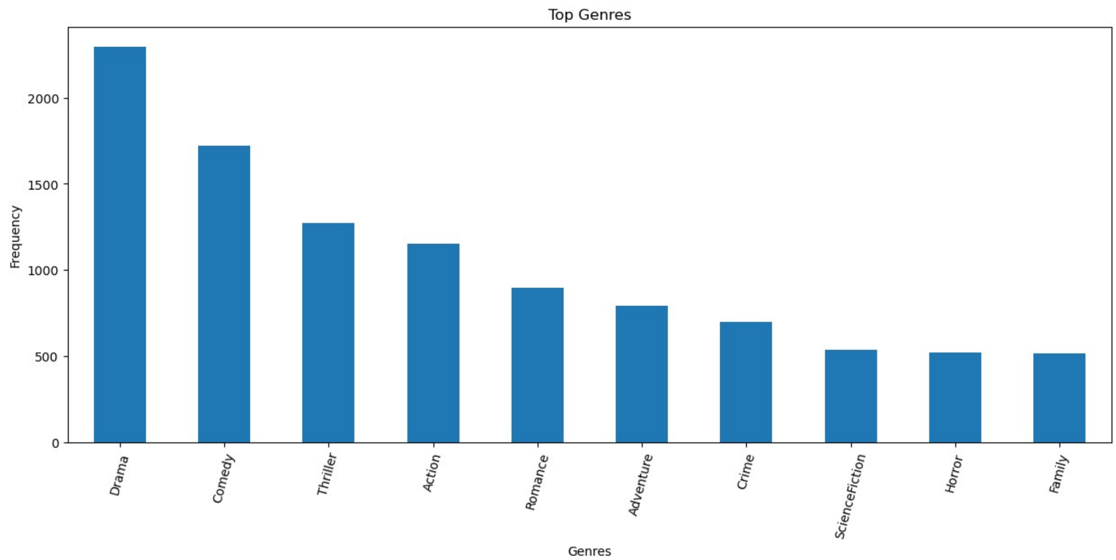
```
# Extract the 'keywords' column
keywords = movies_credits['keywords']

# Flatten the list of keywords
flat_keywords = [keyword for sublist in keywords for keyword in
sublist]

# Count the frequency of each keyword
keyword_counts = pd.Series(flat_keywords).value_counts()

# Select the top keywords
top_keywords = keyword_counts.head(20)

# Plot the top keywords
plt.figure(figsize=(15, 6))
top_keywords.plot(kind='bar')
plt.title('Top Keywords')
plt.xlabel('Keywords')
```

```
plt.ylabel('Frequency')
plt.xticks(rotation=75)
# save the figure
plt.savefig(".data/images/Keywords_plot")
plt.show()
```



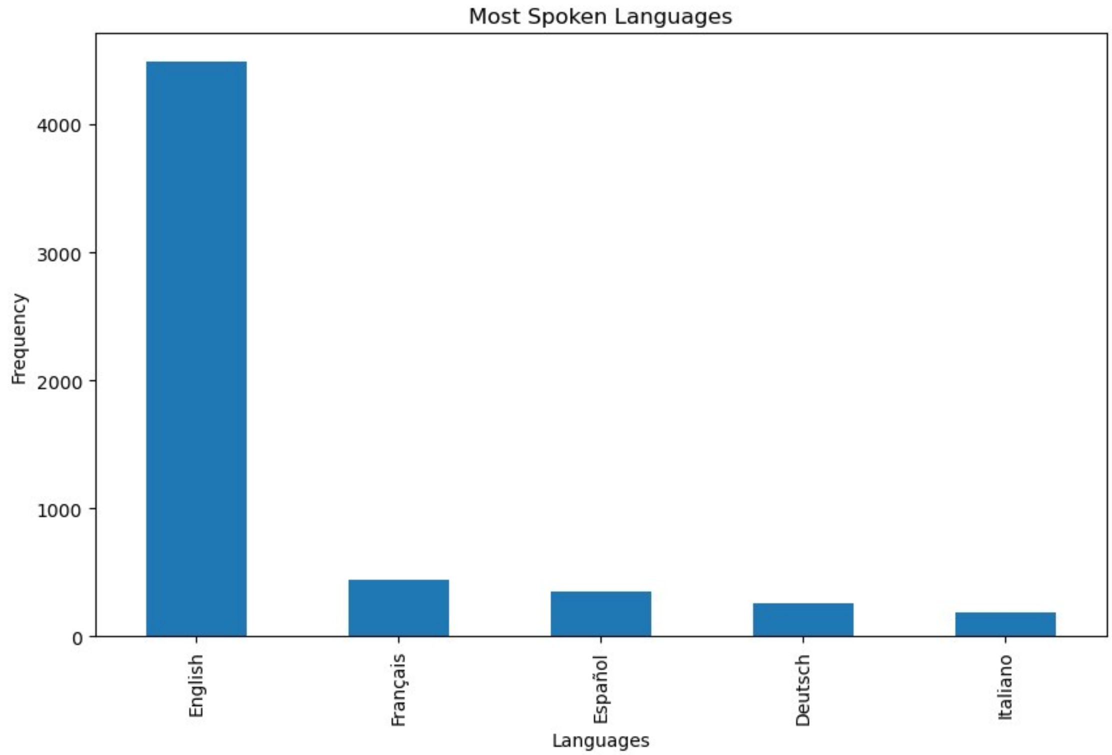
- Genres

```
# Extract the 'genres' column
genres = movies_credits['genres']

# Flatten the list of genres
flat_genres = [genre for sublist in genres for genre in sublist]

# Count the frequency of each genre
genre_counts = pd.Series(flat_genres).value_counts()

# Select the top genres
top_genres = genre_counts.head(10)

# Plot the top genres
plt.figure(figsize=(15, 6))
top_genres.plot(kind='bar')
plt.title('Top Genres')
plt.xlabel('Genres')
plt.ylabel('Frequency')
plt.xticks(rotation=75)
# save the figure
plt.savefig('.data/images/top_genres')
plt.show()
```



- Spoken Languages

```
# Extract the 'spoken_languages' column
spoken_languages = movies_credits['spoken_languages']

# Flatten the list of spoken languages
flat_languages = []
for sublist in spoken_languages:
    if isinstance(sublist, str):
        sublist = ast.literal_eval(sublist)
    for language in sublist:
        if isinstance(language, dict):
            flat_languages.append(language['name'])

# Count the frequency of each spoken language
language_counts = pd.Series(flat_languages).value_counts()

# Select the top spoken languages
top_languages = language_counts.head(5)  # Change the number to select
more or fewer top languages

# Plot the top spoken languages
plt.figure(figsize=(10, 6))
top_languages.plot(kind='bar')
plt.title('Most Spoken Languages')
plt.xlabel('Languages')
plt.ylabel('Frequency')
plt.savefig('.data/images/most_spoken_languages')
plt.show()
```



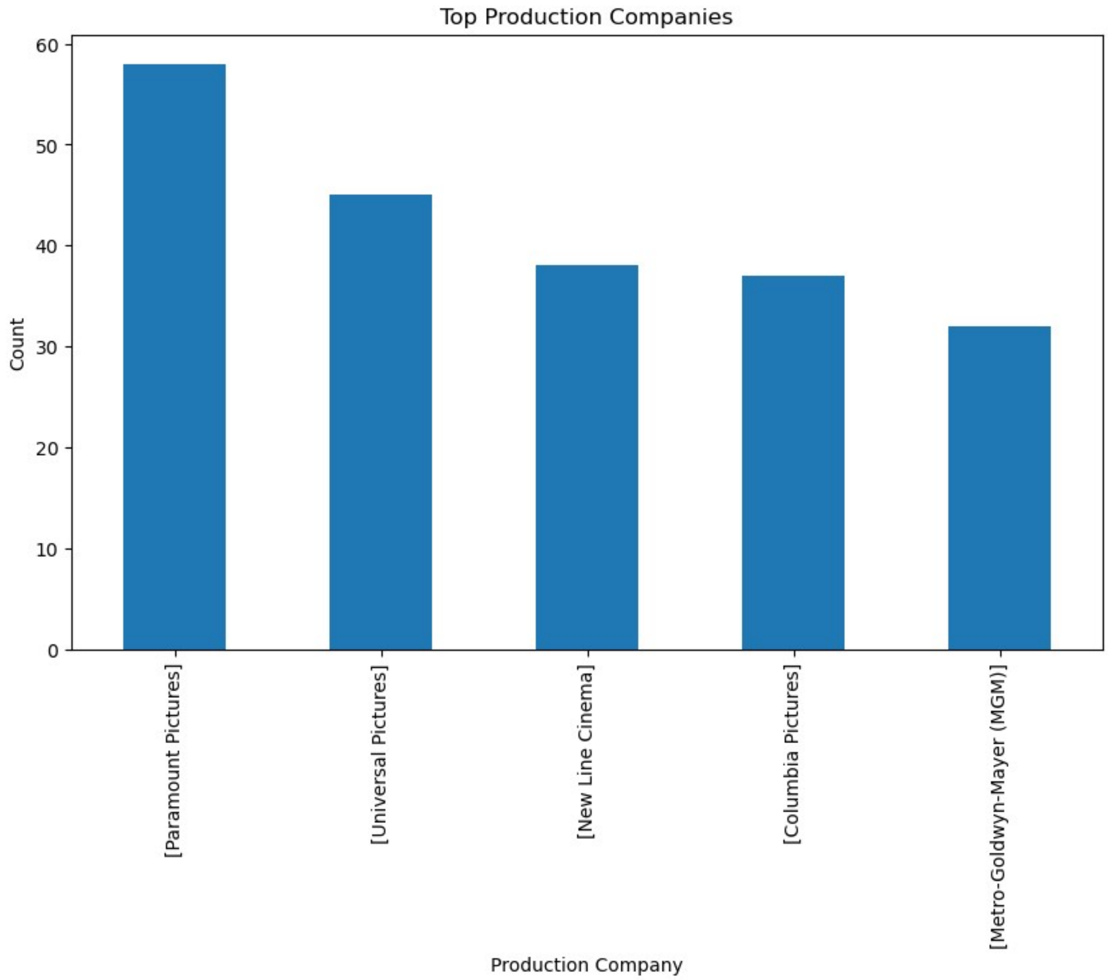
- Movie Status

```
movies_credits['status'].value_counts()
```

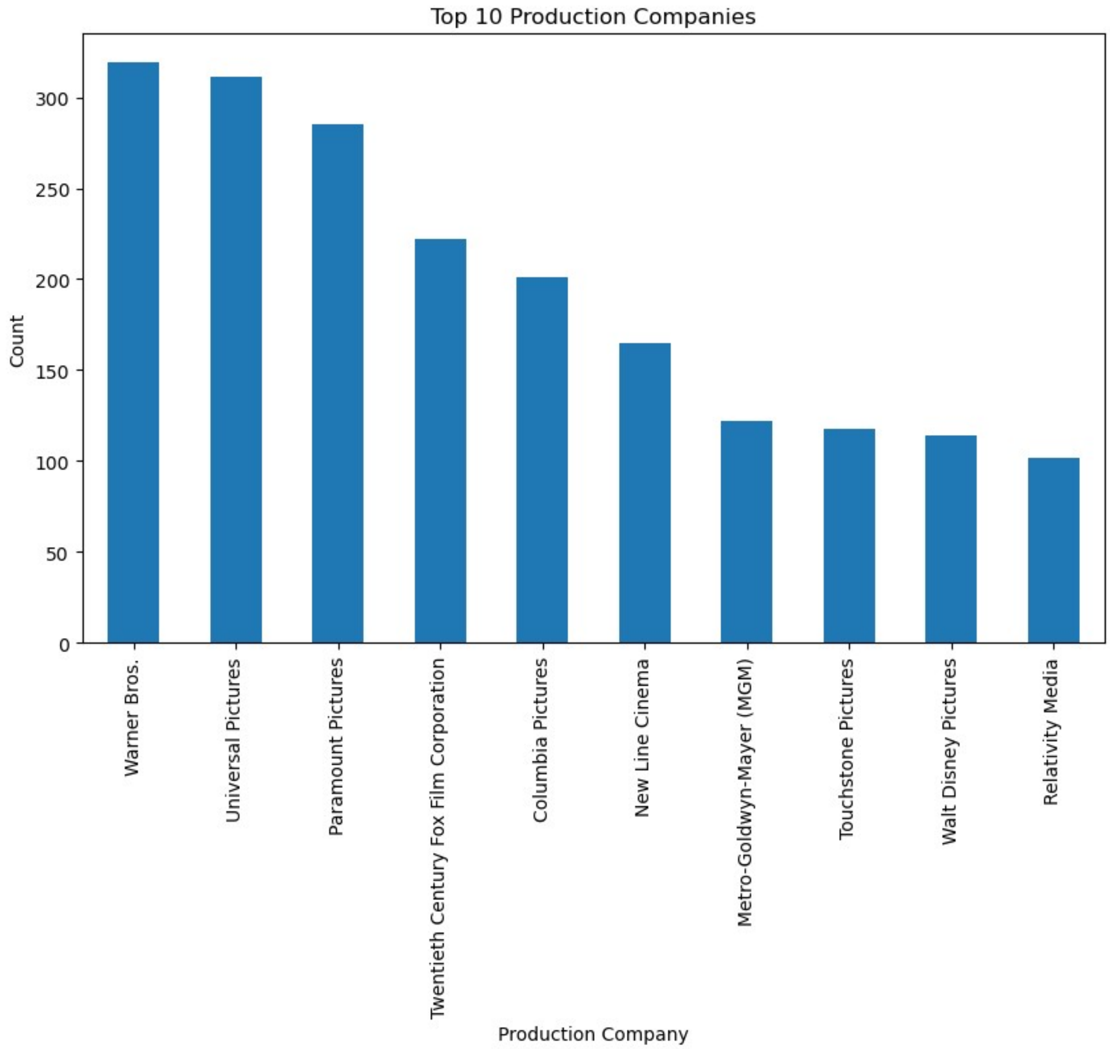
```
status
Released          4795
Rumored              5
Post Production      3
Name: count, dtype: int64
```

- Production Companies

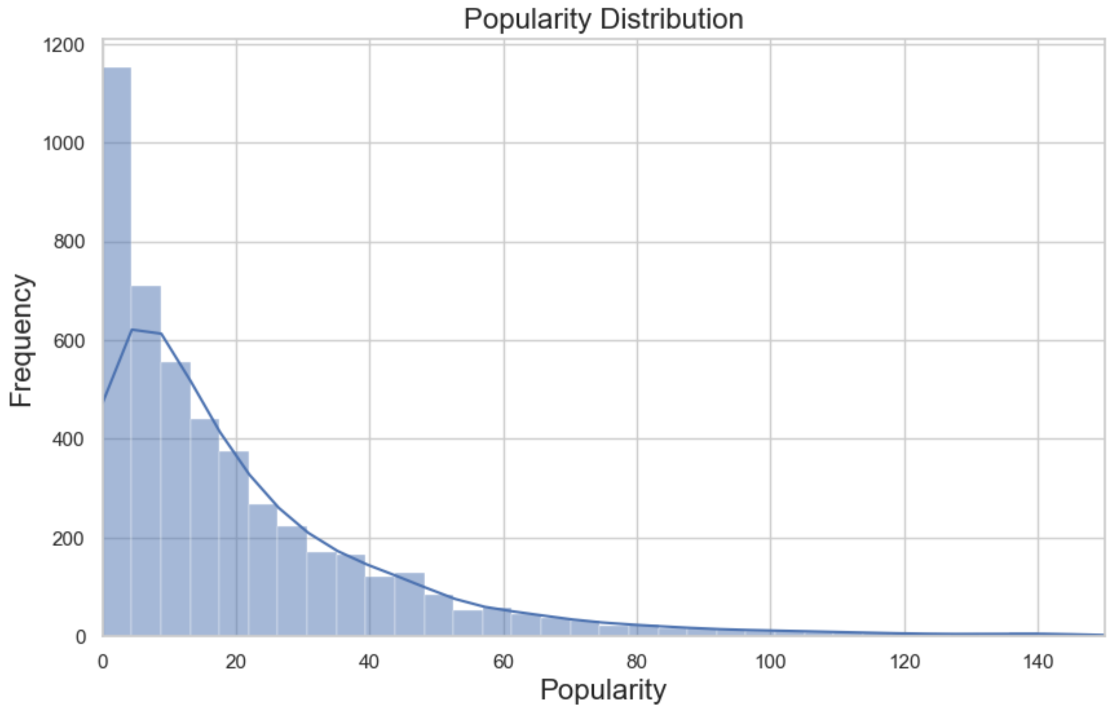
```
# Get value counts of production companies
production_company_counts =
movies_credits['production_companies'].value_counts()

# Select the top 5 production companies
top_production_companies = production_company_counts[1:6]

# Plot the top production companies
plt.figure(figsize=(10, 6))
top_production_companies.plot(kind='bar')
plt.title('Top Production Companies')
plt.xlabel('Production Company')
plt.ylabel('Count')
plt.savefig('.data/images/top_production_companies')
plt.show()
```



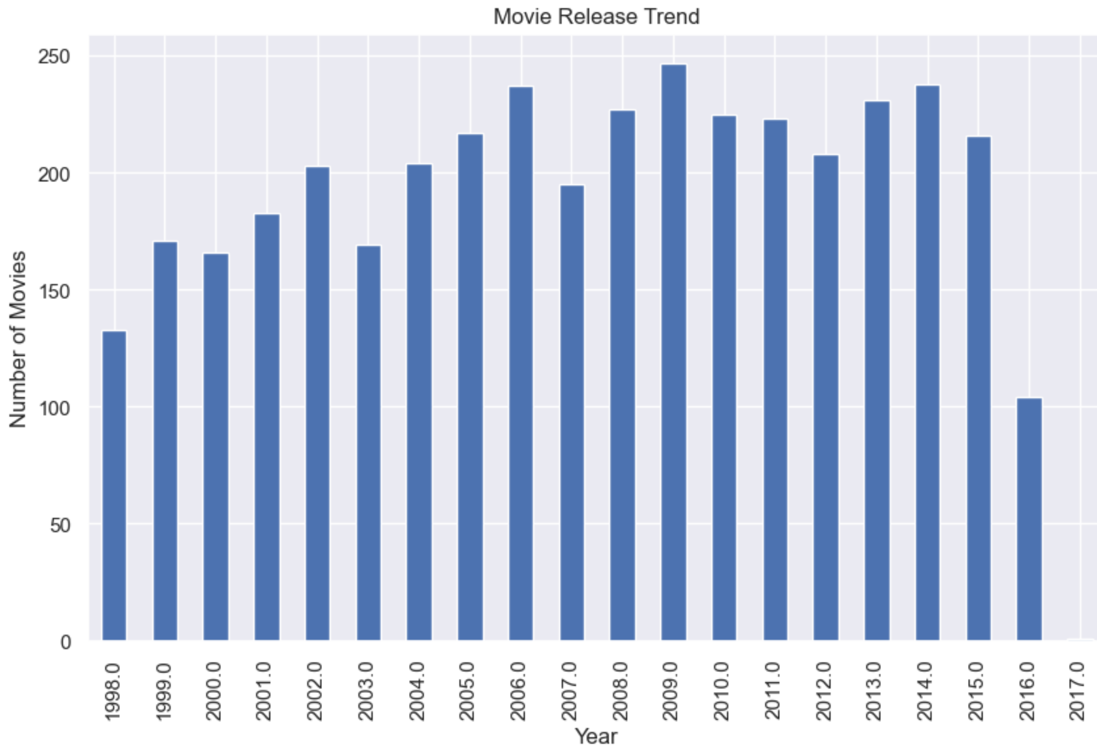

```
# Plotting 'production_companies' (top 10)
plt.figure(figsize=(10, 6))
top_10_production_companies =
movies_credits['production_companies'].explode().value_counts().head(1
0)
top_10_production_companies.plot(kind='bar')
plt.title('Top 10 Production Companies')
plt.xlabel('Production Company')
plt.ylabel('Count')
plt.savefig('.data/images/top_10_production_companies')
plt.show()
```



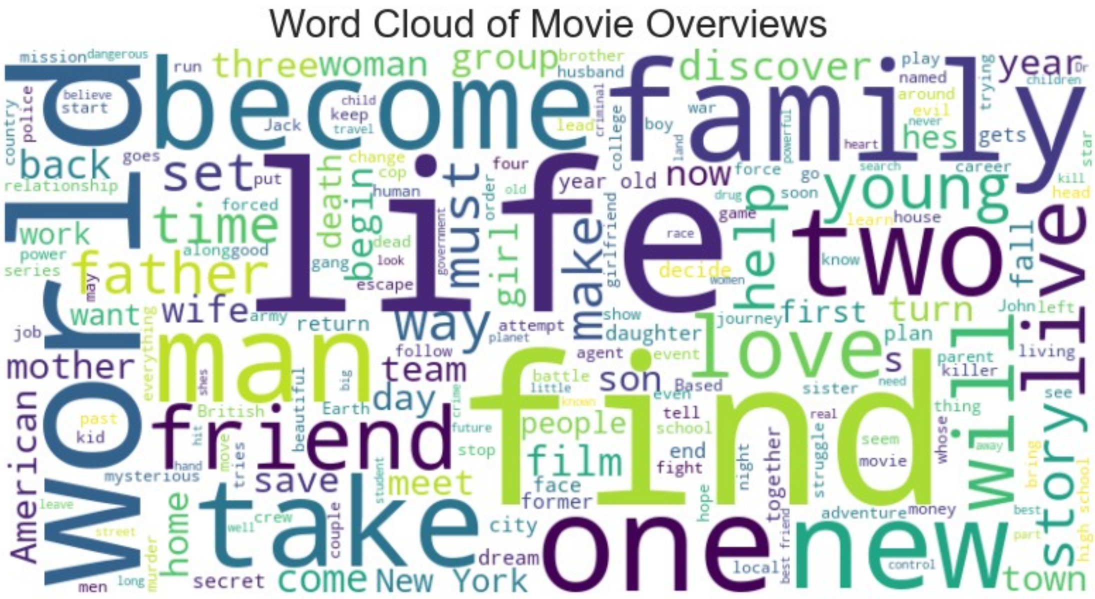

```python
# Set the style and context
sns.set(style='whitegrid')

# Histogram for popularity
plt.figure(figsize=(10, 6))
sns.histplot(data=movies_credits, x='popularity', bins=200, kde=True)
plt.title('Popularity Distribution', fontsize=16)
plt.xlabel('Popularity', fontsize=16)
plt.ylabel('Frequency', fontsize=16)
plt.xlim(0, 150)  # Set the x-axis limits
plt.show()
```




```
# Set the style and context for Seaborn
sns.set(style='darkgrid')

# Line plot for release_date
plt.figure(figsize=(10, 6))
movies_credits['release_date'] =
pd.to_datetime(movies_credits['release_date'], format='%Y-%m-%d',
errors='coerce')
movies_counts =
movies_credits.groupby(movies_credits['release_date'].dt.year)
['release_date'].count().tail(20)
movies_counts.plot(kind='bar')
plt.title('Movie Release Trend')
plt.xlabel('Year')
plt.ylabel('Number of Movies')

plt.savefig(".data/images/movies_Reease_year")
plt.show()
```



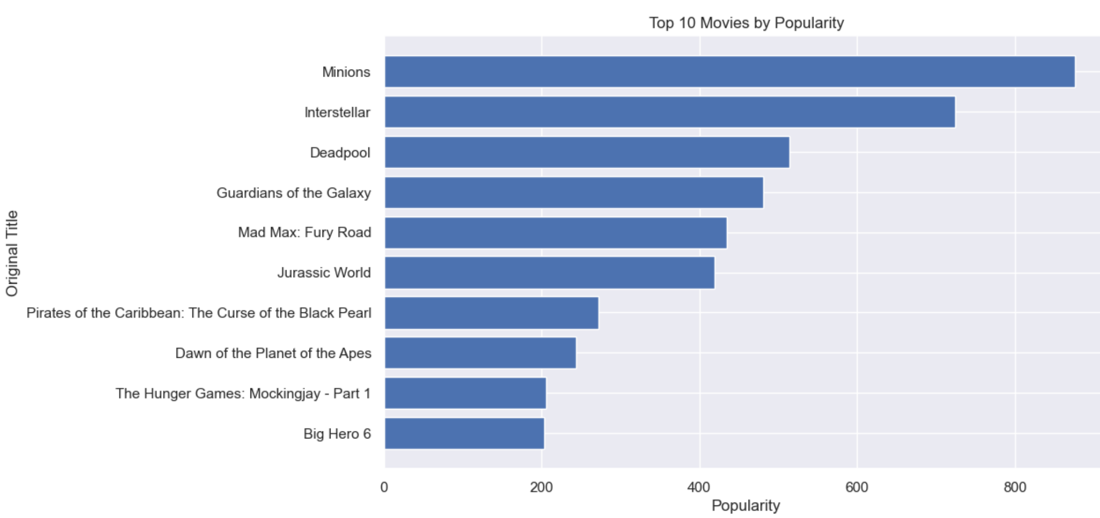

```
# Concatenate all overview strings into a single string and remove
single quotes
overview_text = ' '.join([str(overview).replace("'", "") for overview
in movies_credits['overview']])

# Word cloud for overview
plt.figure(figsize=(10, 6))
wordcloud = WordCloud(width=800, height=400,
background_color='white').generate(overview_text)
plt.imshow(wordcloud, interpolation='bilinear')
plt.title('Word Cloud of Movie Overviews', fontsize=20)
plt.axis('off')
plt.savefig(".data/images/wordcloud")
plt.show()
```



II. **Bivariate Analysis**

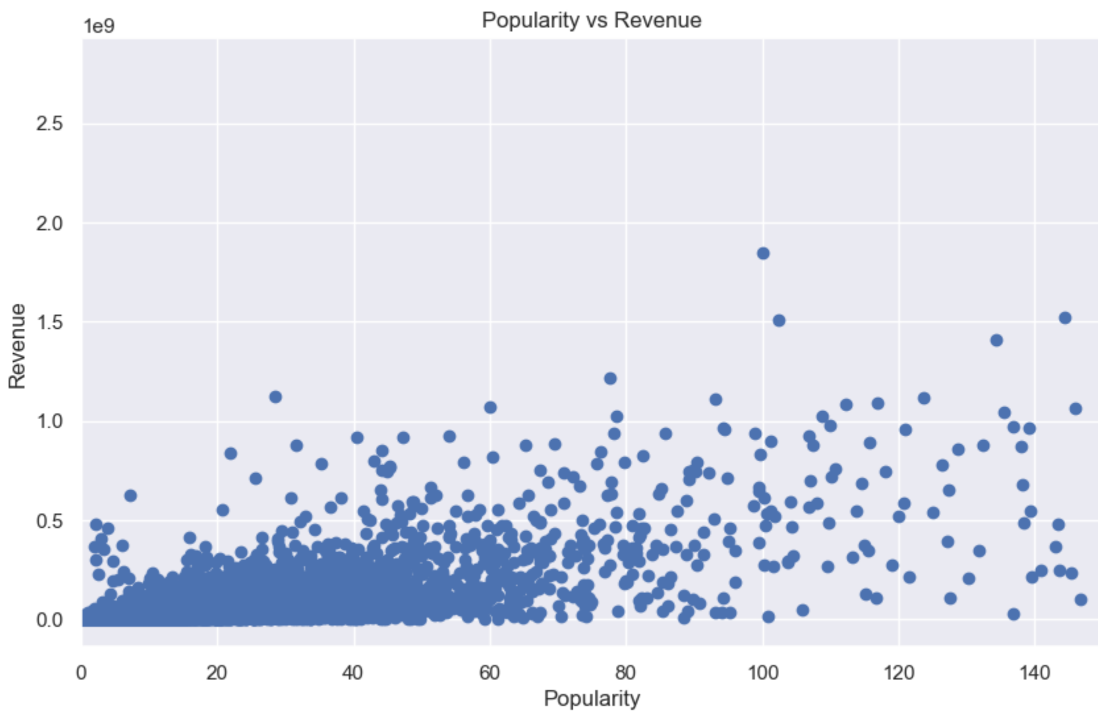
- Original Title vs Popularity

```
# Plotting 'original_title'against popularity (top 10 movies)
plt.figure(figsize=(10, 6))
top_10_movies = movies_credits.sort_values('popularity',
ascending=False).head(10)
plt.barh(top_10_movies['original_title'], top_10_movies['popularity'])
plt.title('Top 10 Movies by Popularity')
plt.xlabel('Popularity')
plt.ylabel('Original Title')
plt.gca().invert_yaxis()
plt.savefig('.data/images/top_10_movies_popularity')
plt.show()
```



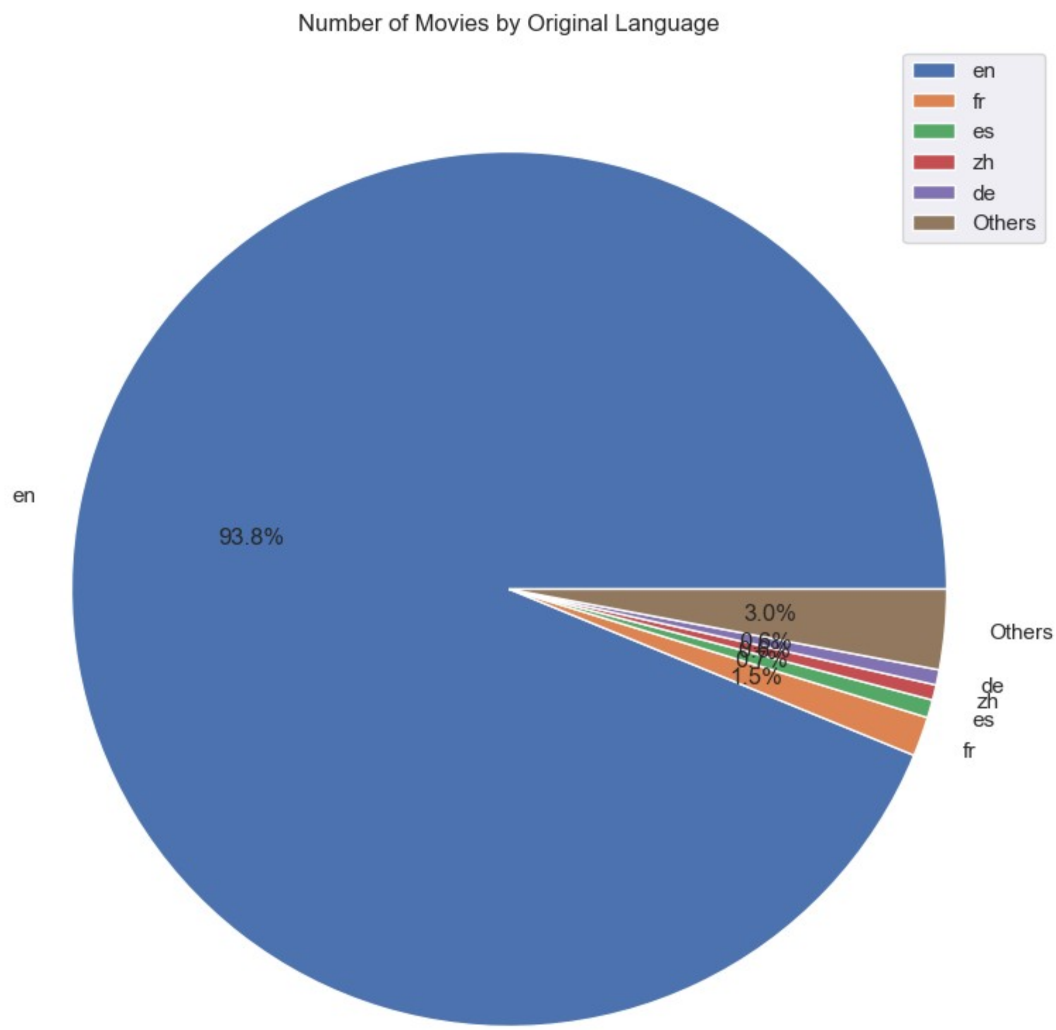
- Popularity vs Revenue

```
# Plotting 'popularity' vs 'revenue'
plt.figure(figsize=(10, 6))
plt.scatter(movies_credits['popularity'], movies_credits['revenue'])
plt.title('Popularity vs Revenue')
plt.xlabel('Popularity')
plt.xlim(0, 150)
plt.ylabel('Revenue')
plt.savefig('.data/images/popularity vs revenue')
plt.show()
```



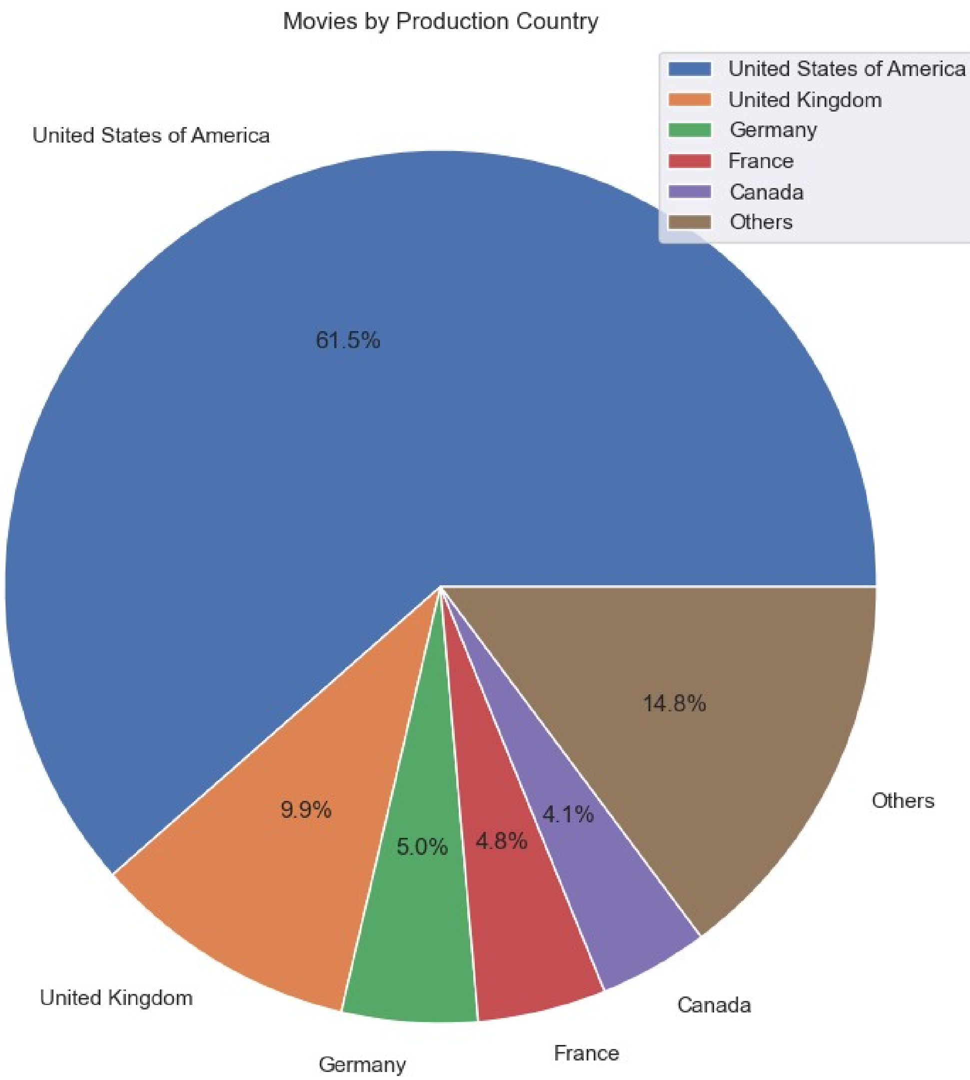

```
 #Get value counts of original languages
original_language_counts =
movies_credits['original_language'].value_counts()

# Get the top 5 languages
top_languages = original_language_counts[:5]

# Calculate the count for the "Others" category
others_count = original_language_counts[5:].sum()

# Create a new series with the top 5 languages and "Others"
languages_data = pd.concat([top_languages, pd.Series(others_count,
index=['Others'])])

# Plotting 'original_language'
plt.figure(figsize=(10, 12))
languages_data.plot(kind='pie', autopct='%1.1f%%')
plt.title('Number of Movies by Original Language')
```

```python
plt.ylabel('')

# Add labels to the pie chart
plt.legend(labels=languages_data.index)
plt.savefig('.data/images/no_movies by language')
plt.show()
```

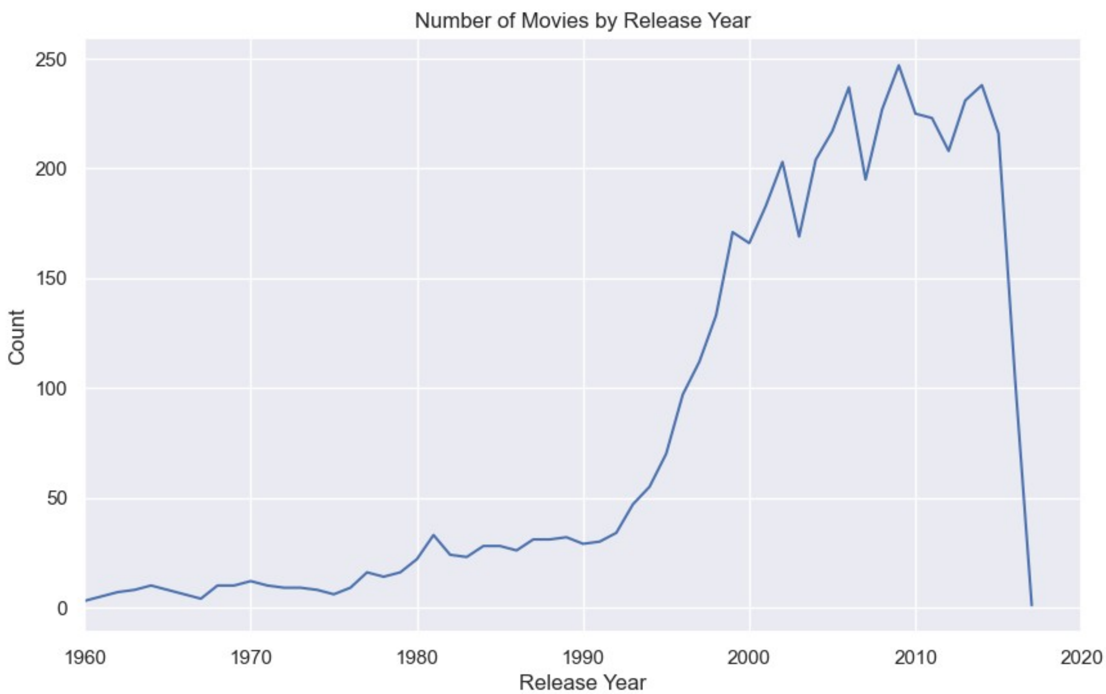



```python
# Get value counts of production countries
production_countries_counts =
movies_credits['production_countries'].explode().value_counts()

# Get the top five production countries
top_countries = production_countries_counts[:5]

# Calculate the count for the sixth slice ("others")
others_count = production_countries_counts[5:].sum()
```

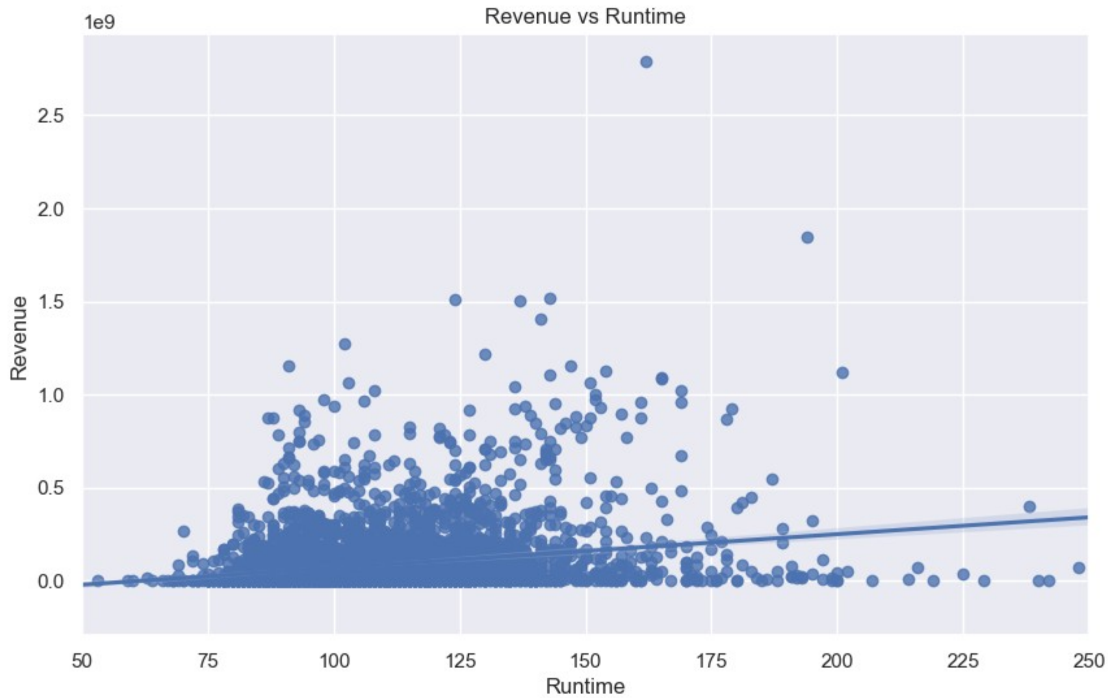
```python
# Create a new series with the top five countries and "others"
countries_data = pd.concat([top_countries, pd.Series(others_count,
index=['Others'])])

# Plotting 'production_countries'
plt.figure(figsize=(20, 10))
countries_data.plot(kind='pie', autopct='%1.1f%%')
plt.title('Movies by Production Country')
plt.ylabel('')

# Labeling the countries
plt.legend(labels=countries_data.index, loc='best')
plt.savefig('.data/images/movies_countries')
plt.show()
```



```python
# Plotting 'release_date' (yearly distribution)
movies_credits['release_year'] =
pd.to_datetime(movies_credits['release_date']).dt.year

plt.figure(figsize=(10, 6))
movies_credits['release_year'].value_counts().sort_index().plot(kind='
line')
plt.title('Number of Movies by Release Year')
plt.xlabel('Release Year')
plt.xlim(1960, 2020 )
plt.ylabel('Count')
plt.savefig('.data/images/movies_by_release_year')
plt.show()
```




```python
# Plotting 'revenue' and 'runtime' (scatter plot with regression line)
plt.figure(figsize=(10, 6))
sns.regplot(x='runtime', y='revenue', data=movies_credits)
plt.title('Revenue vs Runtime')
plt.xlabel('Runtime')
plt.xlim(50, 250)
plt.ylabel('Revenue')
plt.savefig('.data/images/revenue_vs_runtime')
plt.show()
```



Recommendation System

i) Demographic Recommendation based on Popularity

Sort The movie/credits based on ratings and display the top movies: Improve accuracy of the recommendations

- Create a metric to score or rate the movies.
- Calculate the score for each movie.
- Sort the scores and recommend the highest-rated movie to the users.

Implement the following Formula

Weighted Rating (WR) = (vv+m.R) / (v+m)

Where:

v is the number of votes for the movie. m is the minimum votes required to be listed in the chart. R is the average rating of the movie.

```
movies_credits['vote_average'].mean()
```

```
6.092171559442016
```

```
# Determine the appropriate value of M
movies_credits['vote_count'].quantile(q=0.9)
```

```
1838.4000000000015
```

```
# Filter and put them in a new dataframe
new_dataframe_filtered=movies_credits[movies_credits['vote_count']>mov
ies_credits['vote_count'].quantile(q=0.9)]

# Check the shape of the new dataframe
new_dataframe_filtered.shape

(481, 24)

# Calculate score for each qualified movie
def movie_score(x):
    v=x['vote_count']
    m=movies_credits['vote_count'].quantile(q=0.9)
    R=x['vote_average']
    C=movies_credits['vote_average'].mean()
    return ((R*v)/(v+m))+((C*m)/(v+m))

new_dataframe_filtered['score'] =
new_dataframe_filtered.apply(movie_score, axis=1)

C:\Users\rianm\AppData\Local\Temp\ipykernel_3360\2943978004.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_dataframe_filtered['score'] =
new_dataframe_filtered.apply(movie_score, axis=1)
```

- The warning above is raised when you are trying to set a value on a copy of a slice from the Pandas Dataframe
- As such we have .loc explicitly and one can set the values in the 'score column for the rows of the new dataframe

```
# We  solve the above warning by using the '.loc and set the new
values
new_dataframe_filtered.loc[:, 'score'] =
new_dataframe_filtered.apply(movie_score, axis=1)

# We sort the filtered dataframe based on the score feature
new_highscore=new_dataframe_filtered.sort_values(by='score',
ascending=False).head()
new_highscore[['title', 'vote_count','vote_average','popularity',
'score']]

                         title  vote_count  vote_average  popularity
score
1881  The Shawshank Redemption        8205           8.5  136.747729
8.059258
662                 Fight Club        9413           8.3  146.757391
```

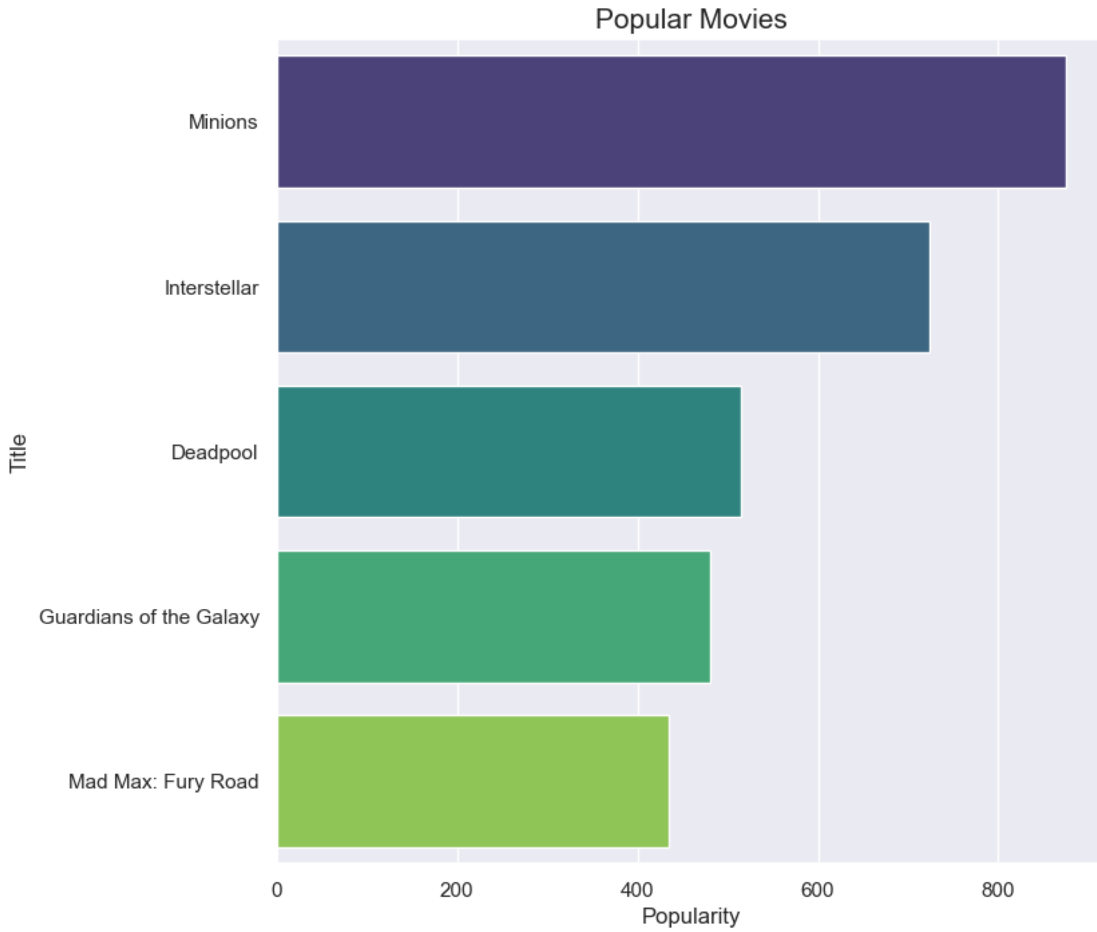
```
7.939256
65            The Dark Knight       12002           8.2  187.322927
7.920020
3232             Pulp Fiction        8428           8.3  121.463076
7.904645
96                  Inception       13752           8.1  167.583710
7.863239
```

Finding movie popularity

```
# Sort by the popularity column
popular_movies = movies_credits.sort_values('popularity', ascending =
False).head()
popular_movies[['title', 'vote_count','vote_average','popularity']]
```

```
                       title  vote_count  vote_average  popularity
546                  Minions        4571           6.4  875.581305
95              Interstellar       10867           8.1  724.247784
788                 Deadpool       10995           7.4  514.569956
94   Guardians of the Galaxy        9742           7.9  481.098624
127       Mad Max: Fury Road        9427           7.2  434.278564
```

```
plt.figure(figsize=(8, 8))
sns.barplot(x='popularity', y='title', data=popular_movies,
palette='viridis')
plt.xlabel("Popularity", fontsize=12)
plt.ylabel("Title", fontsize=12)
plt.title("Popular Movies", fontsize=15)
plt.savefig(".data/images/popular movies")
plt.show()
```



- From the plot above we can see that the most popular movie is minions with a popularity rate of > 800; hence being highly recommended to be watched by the user/ rather recommend users to watch

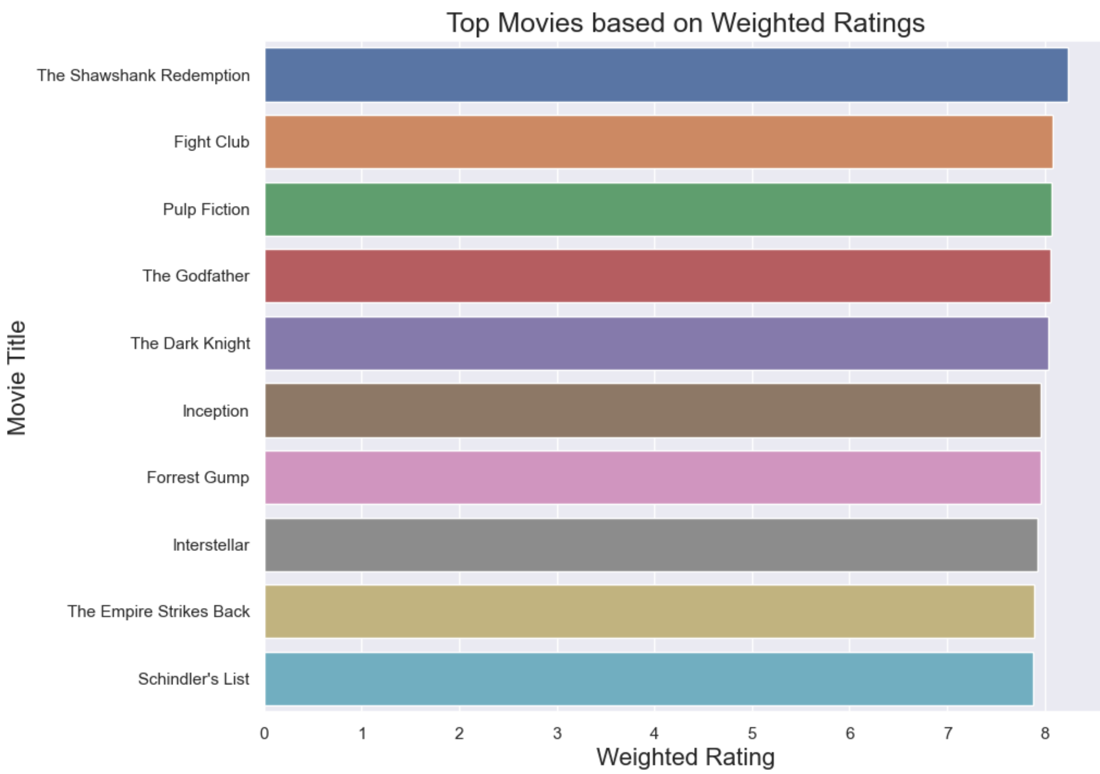
```
movie_rating= pd.read_csv(r".data/ratings.csv")
movie_rating.head()
```

```
   userId  movieId  rating  timestamp
0       1        1     4.0  964982703
1       1        3     4.0  964981247
2       1        6     4.0  964982224
3       1       47     5.0  964983815
4       1       50     5.0  964982931
```

```
# Step 1: Calculate values for the formula
v = movies_credits['vote_count']
R = movies_credits['vote_average']
m = 1000  # Choose a minimum vote threshold

# Step 2: Compute weighted rating (WR)
C = movies_credits['vote_average'].mean()
WR = (v / (v + m) * R) + (m / (v + m) * C)
```

```
# Step 3: Add 'Weighted_Rating' column to DataFrame
movies_credits['Weighted_Rating'] = WR

# Step 4: Sort the DataFrame based on 'Weighted_Rating' column
sorted_movies = movies_credits.sort_values('Weighted_Rating',
ascending=False)

# Step 5: Display top movies based on sorted results
top_movies = sorted_movies[['title', 'vote_average','genres',
'Weighted_Rating']].head(10)
top_movies

                         title  vote_average  \
1881  The Shawshank Redemption           8.5
662                 Fight Club           8.3
3232              Pulp Fiction           8.3
3337             The Godfather           8.4
65             The Dark Knight           8.2
96                   Inception           8.1
809                Forrest Gump           8.2
95                Interstellar           8.1
1990   The Empire Strikes Back           8.2
1818          Schindler's List           8.3

                                                 genres
Weighted_Rating
1881                                    [Drama, Crime]
8.238422
662                                            [Drama]
8.087974
3232                                 [Thriller, Crime]
8.065822
3337                                    [Drama, Crime]
8.065192
65                    [Drama, Action, Crime, Thriller]
8.037884
96    [Action, Thriller, ScienceFiction, Mystery, Ad...
7.963894
809                           [Comedy, Drama, Romance]
7.963882
95                  [Adventure, Drama, ScienceFiction]
7.930806
1990               [Adventure, Action, ScienceFiction]
7.893585
1818                             [Drama, History, War]
7.885696

# Step 6: Plot the data
fig, ax = plt.subplots(figsize=(10, 8))
sns.barplot(x=top_movies['Weighted_Rating'], y=top_movies['title'],
```

```
ax=ax)
ax.set_xlabel('Weighted Rating', fontsize=16)
ax.set_ylabel('Movie Title', fontsize=16)
ax.set_title('Top Movies based on Weighted Ratings', fontsize=18)
plt.savefig(".data/images/Top weighted movies")
plt.show()
```



ii) Content Based

For this recommendation system we build an engine that shows the similarity between movie based and the metrics new_dataframe_filtered. Secondly, this will be in two segments :

- Movie Overview
- Movie Cast , Keywords and Genre
- 1.ii)Movie Overview Recommendation
- We use this because provides a concise description of its storyline, theme, and main elements. It offers insights into the narrative and helps to understand the central idea or premise of the movie.

We pair the similar scores of the movies based on the overview

```
movies_credits ['overview'].head()

# Finding the Nan values(missing values) with an empty string
```

```
movies_credits['overview'].isnull().sum()# We know there 3 missing values hence we replace them

# Replacing the missing values
movies_credits['overview'].fillna('', inplace = True)

# Confirm if there are Missing values
movies_credits['overview'].isnull().sum()

0

# Convert the 'overview' column to string type
movies_credits['overview'] = movies_credits['overview'].apply(lambda x: ' '.join(x) if isinstance(x, list) else '')
```

In this case we implement the use of 'Term frequency-Inverse Documnet Frequency which is a numerical representation used to evaluate the key importance of the collection of documents.

- It calculates the ratio of the number of times a term appears in a text

```
movie_rating

        userId  movieId  rating   timestamp
0            1        1     4.0   964982703
1            1        3     4.0   964981247
2            1        6     4.0   964982224
3            1       47     5.0   964983815
4            1       50     5.0   964982931
...        ...      ...     ...         ...
100831     610   166534     4.0  1493848402
100832     610   168248     5.0  1493850091
100833     610   168250     5.0  1494273047
100834     610   168252     5.0  1493846352
100835     610   170875     3.0  1493846415

[100836 rows x 4 columns]

# Construct the TF-IDF Matrix
tfidfv=TfidfVectorizer(analyzer='word', stop_words='english')
tfidfv_matrix=tfidfv.fit_transform(movies_credits['overview'])
print(tfidfv_matrix.todense())
tfidfv_matrix.todense().shape

[[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.]]

(4803, 20978)
```

Computing the same Score based on the movie Similiarities

```
cosine_sim = cosine_similarity(tfidfv_matrix, tfidfv_matrix)

cosine_sim.shape

(4803, 4803)

indices = pd.Series(data = list(movies_credits.index), index =
movies_credits['title'])
indices

title
Avatar                                         0
Pirates of the Caribbean: At World's End       1
Spectre                                        2
The Dark Knight Rises                          3
John Carter                                    4
                                            ...
El Mariachi                                 4798
Newlyweds                                   4799
Signed, Sealed, Delivered                   4800
Shanghai Calling                            4801
My Date with Drew                           4802
Length: 4803, dtype: int64

def recommended_movies(title, cosine_sim):

    # Get the index of the movie that matches the title
    idx = indices[title]

    # Get the pairwsie similarity scores of all movies with that movie
    sim_scores = list(enumerate(cosine_sim[idx]))

    # Sort the movies based on the similarity scores
    sim_scores.sort(key=lambda x: x[1], reverse=True)

    # Get the scores of the 10 most similar movies
    sim_scores=sim_scores[1:11]

    # Get the movie indices
    ind=[]
    for (x,y) in sim_scores:
        ind.append(x)

    # Return the top 10 most similar movies
    tit=[]
    for x in ind:
        tit.append(movies_credits.iloc[x]['title'])
    return pd.Series(data=tit, index=ind)
```

```
recommended_movies('My Date with Drew', cosine_sim)
```

```
4100              Captive
868         Elizabethtown
2586          Firestarter
204             Fast Five
1685    Keeping the Faith
4532         Lonesome Jim
2156           Nancy Drew
3753              Boyhood
3623                 Made
3245                50/50
dtype: object
```

Movie Cast , Keywords and Genre Recommender

```
def update_crew_with_director(data):
    data['Directors'] = data['crew']
    return data

movies_credits = update_crew_with_director(movies_credits)

movies_credits['Director_clean'] =
movies_credits['Directors'].apply(lambda x: x[0].strip('[]') if x else
None)

movies_credits[['title', 'Directors', 'keywords', 'genres']]
```

```
                                         title  \
0                                       Avatar
1     Pirates of the Caribbean: At World's End
2                                      Spectre
3                        The Dark Knight Rises
4                                  John Carter
...                                        ...
4798                               El Mariachi
4799                                 Newlyweds
4800                 Signed, Sealed, Delivered
4801                          Shanghai Calling
4802                         My Date with Drew

                                Directors  \
0                           [JamesCameron]
1                          [GoreVerbinski]
2                              [SamMendes]
3                       [ChristopherNolan]
4                          [AndrewStanton]
...                                   ...
4798                     [RobertRodriguez]
4799                         [EdwardBurns]
4800                          [ScottSmith]
```

```
4801                              [DanielHsia]
4802  [BrianHerzlinger, JonGunn, BrettWinn]

                                               keywords  \
0     [cultureclash, future, spacewar, spacecolony, ...
1     [ocean, drugabuse, exoticisland, eastindiatrad...
2     [spy, basedonnovel, secretagent, sequel, mi6, ...
3     [dccomics, crimefighter, terrorist, secretiden...
4     [basedonnovel, mars, medallion, spacetravel, p...
...                                                 ...
4798  [unitedstates–mexicobarrier, legs, arms, paper...
4799                                                 []
4800  [date, loveatfirstsight, narration, investigat...
4801                                                 []
4802           [obsession, camcorder, crush, dreamgirl]

                                          genres
0     [Action, Adventure, Fantasy, ScienceFiction]
1                     [Adventure, Fantasy, Action]
2                       [Action, Adventure, Crime]
3                  [Action, Crime, Drama, Thriller]
4               [Action, Adventure, ScienceFiction]
...                                            ...
4798                     [Action, Crime, Thriller]
4799                             [Comedy, Romance]
4800              [Comedy, Drama, Romance, TVMovie]
4801                                            []
4802                                 [Documentary]

[4803 rows x 4 columns]
```

```
def create_soup(x):
    return ' '.join(x['keywords']) + ' ' + ' '.join(x['Directors']) +
' ' + ' '.join(x['genres'])

movies_credits['soup'] = movies_credits.apply(create_soup, axis=1)

cv = CountVectorizer(stop_words='english')
cv_matrix = cv.fit_transform(movies_credits['soup'])

cosine_sim2 = cosine_similarity(cv_matrix, cv_matrix)

recommended_movies('Minions', cosine_sim2)
```

```
506                                      Despicable Me 2
359                 Alvin and the Chipmunks: The Road Chip
418            Cats & Dogs 2 : The Revenge of Kitty Galore
1580                                         The Nut Job
848          The Pirates! In an Adventure with Scientists!
2464                                 The Master of Disguise
3403    Alpha and Omega: The Legend of the Saw Tooth Cave
```

```
86                                     Shrek Forever After
173                                        Happy Feet Two
837                                            Free Birds
dtype: object
```

```
recommended_movies('The Godfather', cosine_sim2)
```

```
1018            The Cotton Club
1209              The Rainmaker
3293                10th & Wolf
867      The Godfather: Part III
2731      The Godfather: Part II
877                  Black Mass
1464         Black Water Transit
3112     Blood Done Sign My Name
4184           Deadline - U.S.A.
4502              Water & Power
dtype: object
```

iii) Collaborative Based Recommendation

This allows for coincidental recommendations; that is, collaborative filtering models can recommend an item to user A based on the interests of a similar user B. Furthermore, the embeddings can be learned automatically, without relying on hand-engineering of features.

steps to implement collaborative recommendation

1. Data collection and preprocessing collect data that includes user-item interactions. It may include: user reviews, ratings, or explicit feedback.
1. User-item interactions matrix. this involves creating a user-item matrix where each row in the matrix corresponds to a user, and each column corresponds to an item.
1. Similarity calculations We will calculate similarity between user or items based on their interactions by employing similarity measures like cosine similarity or Pearson correlation coefficient.thus getting users or items similarity in terms of preference.
1. Neighborhood selection We will select the neighborhood of users or items based on their similarity.
1. Recommendation generation We will generate recommendations based on the preference neighborhood of users or items. we will aggregate the preferences of similar users/items and suggest items that have high ratings or interactions from the neighborhood.
1. Evaluation We will evaluate performance of the recommendation system using metrics suc as precision, recall, or mean average precision.

data selection.

Ratings Data File Structure (ratings.csv)

All ratings are contained in the file *ratings.csv*. Each line of this file after the header row represents one rating of one movie by one user, and has the following format:

`userId,movieId,rating,timestamp`

The lines within this file are ordered first by userId, then, within user, by movieId.

Ratings are made on a 5-star scale, with half-star increments (0.5 stars - 5.0 stars).

Timestamps represent seconds since midnight Coordinated Universal Time (UTC) of January 1, 1970.

We will use this dataset because it has the columns that we need to create the recommendation system. the column UserId represent each individual user, while that of MovieId represents the item.

```
movie_rating.head()
```

```
   userId  movieId  rating  timestamp
0       1        1     4.0  964982703
1       1        3     4.0  964981247
2       1        6     4.0  964982224
3       1       47     5.0  964983815
4       1       50     5.0  964982931
```

Split the data

```
# create train and test sets
data_df = movie_rating.drop(columns='timestamp')
data = Dataset.load_from_df(data_df,Reader(rating_scale=(1,5)))

# create train and test sets
trainset, testset = train_test_split(data, test_size=0.2)

actual_ratings = [true_rating for (_, _, true_rating) in testset]

# By default the surprise library creates the trainset as a user-item
matrix.
trainset
```

```
<surprise.trainset.Trainset at 0x250ce176050>
```

step 3 Similarity calculations

```
# Using KNNWithMeans algorithm with cosine similarity
sim_options = {'name': 'cosine', 'user_based': True}
knnmeans = KNNWithMeans(sim_options=sim_options, random_state=42)
# train the model
knnmeans.fit(trainset)
```

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

```
<surprise.prediction_algorithms.knns.KNNWithMeans at 0x250c84281d0>
```

While applying the surprise model. we do not need to explicitly define the neighborhood selection and therefore we skip directly to step five of building the recommmendation. we will apply the surprise model KNNWithMeans

```
# Getting the top-N recomendations
user_id = 243
top_n = 5

user_items = trainset.ur[trainset.to_inner_uid(user_id)]
predicted_ratings = []
for item_id, rating in user_items:
    predicted_rating = knnmeans.predict(user_id, 
trainset.to_raw_iid(item_id)).est
    predicted_ratings.append((trainset.to_raw_iid(item_id), 
predicted_ratings))

# Sort the predicted ratings in descending order
predicted_ratings.sort(key=lambda x: x[1], reverse=True)

# Get the top_n recomendations
top_n_recomendations = predicted_ratings[:top_n]

# Print the top-N recommendations
for item_id, predicted_ratings in top_n_recomendations:
    print(f"Item ID: {item_id}, Predicted Rating: {predicted_rating}")
```

```
Item ID: 485, Predicted Rating: 3.905481471229577
Item ID: 420, Predicted Rating: 3.905481471229577
Item ID: 44, Predicted Rating: 3.905481471229577
Item ID: 227, Predicted Rating: 3.905481471229577
Item ID: 376, Predicted Rating: 3.905481471229577
```

```
# Step 6: Evaluation

# Evaluate the model on the testing set
predictions = knnmeans.test(testset)
rmse = accuracy.rmse(predictions)
```

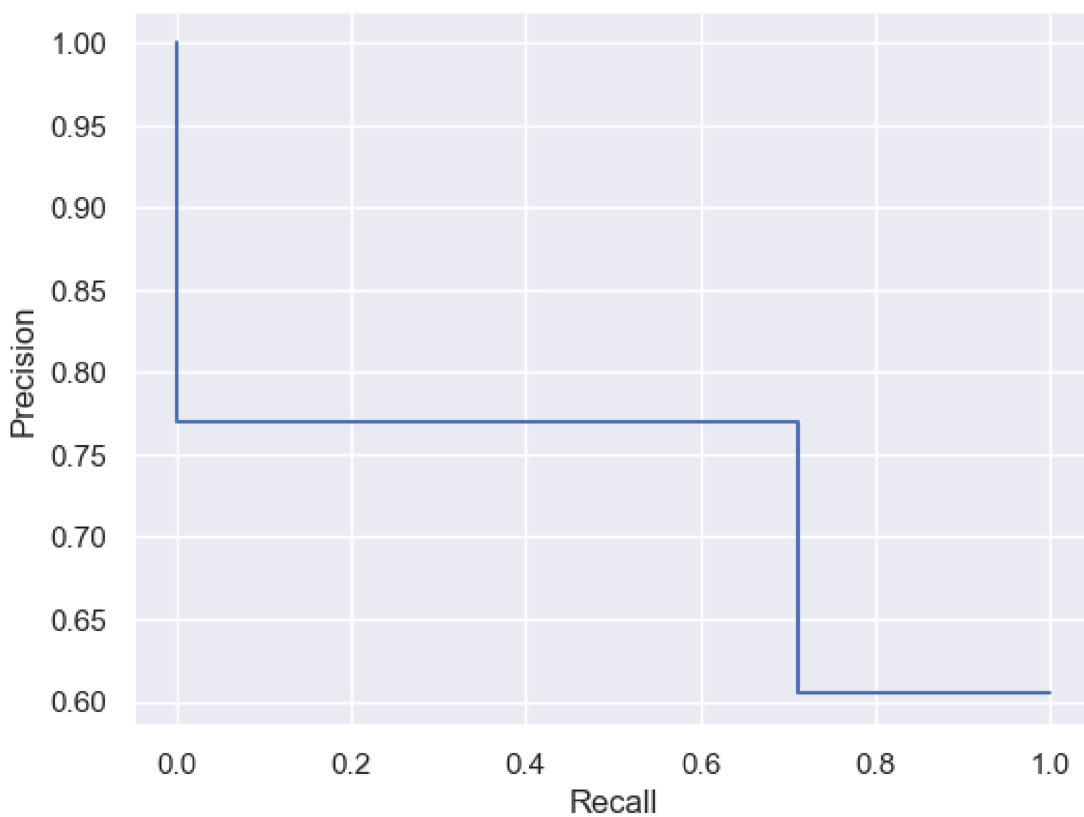
```
RMSE: 0.9081
```

The Root Mean Square Error (RMSE) value indicates the average prediction error of the recommendation system. It is a measure of the difference between the predicted ratings and the actual ratings provided by users.

A lower RMSE value indicates better accuracy and performance of the recommendation system. In this case, an RMSE suggests that, on average, the predictions of the recommendation system deviate from the actual ratings by approximately those units.

```
threshold = 3.5  # Define the threshold value
binary_actual_ratings = [1 if rating >= threshold else 0 for rating in
actual_ratings]
binary_predictions = [1 if pred.est >= threshold else 0 for pred in
predictions]
# compute precsion and recall
precision, recall, threshhold = precision_recall_curve(
    binary_actual_ratings, binary_predictions
)

print(f"Precision: {precision}")
print(f"Recall: {recall}")

# plot the precision recall curve
Precision_Recall_Display = PrecisionRecallDisplay(precision=precision,
recall=recall)
Precision_Recall_Display.plot();
```

```
Precision: [0.60476993 0.76963954 1.        ]
Recall: [1.         0.71247028 0.        ]
```



Precision:

At the first threshold level, the precision is 0.6125. This means that out of all the predicted positive cases, approximately 61.25% were true positive cases. At the second threshold level, the precision increases to 0.7779. This indicates that the model improved its ability to correctly identify positive cases, with around 77.79% precision. At the third threshold level, the precision reaches 1.0, indicating perfect precision. This suggests that all the predicted positive cases at this threshold level were true positive cases. Recall:

At the first threshold level, the recall is 1.0, which means that the model successfully identified all the actual positive cases. At the second threshold level, the recall decreases to 0.7084. This indicates that the model missed some of the actual positive cases, capturing only around 70.84% of them. At the third threshold level, the recall drops to 0.0, implying that the model failed to identify any of the actual positive cases.

Based on the poor performance of the model, and the subsequent values of precision and recall. it is best to employ some sort of model finetuning and optimization.

```
new_movies = movies_credits[["id" , "title", "tags"]]
new_movies.head()
```

```
       id                                     title  \
0   19995                                    Avatar   
1     285  Pirates of the Caribbean: At World's End   
2  206647                                   Spectre   
3   49026                     The Dark Knight Rises   
4   49529                               John Carter   

                                                tags  
0  [In, the, 22nd, century,, a, paraplegic, Marin...  
1  [Captain, Barbossa,, long, believed, to, be, d...  
2  [A, cryptic, message, from, Bond’s, past, send...  
3  [Following, the, death, of, District, Attorney...  
4  [John, Carter, is, a, war-weary,, former, mili...  
```

```
# Lambda function to remove the brackets
new_movies.loc[:, "tags"] = new_movies['tags'].apply(lambda x: " ".join(map(str, x)) if isinstance(x, Iterable) else str(x))
```

```
new_movies['tags'].head()
```

```
0    In the 22nd century, a paraplegic Marine is di...
1    Captain Barbossa, long believed to be dead, ha...
2    A cryptic message from Bond’s past sends him o...
3    Following the death of District Attorney Harve...
4    John Carter is a war-weary, former military ca...
Name: tags, dtype: object
```

```
new_movies["tags"][6]
```

```
"When the kingdom's most wanted-and most charming-bandit Flynn Rider
hides out in a mysterious tower, he's taken hostage by Rapunzel, a
beautiful and feisty tower-bound teen with 70 feet of magical, golden
hair. Flynn's curious captor, who's looking for her ticket out of the
tower where she's been locked away for years, strikes a deal with the
handsome thief and the unlikely duo sets off on an action-packed
escapade, complete with a super-cop horse, an over-protective
chameleon and a gruff gang of pub thugs. Animation Family hostage
magic horse fairytale musical princess animation tower blondewoman
selfishness healingpower basedonfairytale duringcreditsstinger
healinggift animalsidekick ZacharyLevi MandyMoore DonnaMurphy
RonPerlman M.C.Gainey ByronHoward NathanGreno"
```

```
# Lambda Function to turn the strings to lower case.
new_movies.loc[:, "tags"] = new_movies["tags"].apply(lambda
X:X.lower())
```

Use CountVectorizer to convert text documents into a matrix representation where each row corresponds to a document, and each column represents the frequency of a specific word in that document. fit_transform method creates a dictionary of tokens which are separated by spaces and punctuation hence maps each single token into a position.

```
cv = CountVectorizer(max_features = 5000, stop_words="english")

cv.fit_transform(new_movies["tags"]).toarray()

vectors = cv.fit_transform(new_movies["tags"]).toarray()

vectors[7]

array([0, 0, 0, ..., 0, 0, 0], dtype=int64)

len(cv.get_feature_names_out())

5000

# We will use the famous SVD algorithm.
svd = SVD()

reader = Reader()

# Load the ratings_small dataset (download it if needed),
data = Dataset.load_from_df(movie_rating[['userId', 'movieId',
'rating']], reader)

# Run 5-fold cross-validation and print the results
cross_validate(svd, data, measures=['RMSE', 'MAE'], cv=6,
verbose=True)

Evaluating RMSE, MAE of algorithm SVD on 6 split(s).

                  Fold 1  Fold 2  Fold 3  Fold 4  Fold 5  Fold 6  Mean
```

```
Std
RMSE (testset)    0.8734  0.8683  0.8672  0.8832  0.8685  0.8740
0.8724  0.0055
MAE (testset)     0.6717  0.6663  0.6668  0.6763  0.6670  0.6719
0.6700  0.0036
Fit time          2.13    1.91    1.73    1.81    1.74    1.68    1.83
0.15
Test time         0.18    0.17    0.17    0.34    0.16    0.16    0.20
0.06

{'test_rmse': array([0.87338536, 0.86831246, 0.86719835, 0.88322982,
0.86852095,
        0.87397903]),
 'test_mae': array([0.67171329, 0.66629101, 0.66682736, 0.67630696,
0.66696895,
        0.67189488]),
 'fit_time': (2.125659942626953,
  1.910017728805542,
  1.7289955615997314,
  1.8050041198730469,
  1.736999273300171,
  1.6789968013763428),
 'test_time': (0.1849968433380127,
  0.17498421669006348,
  0.16800379753112793,
  0.33700060844421387,
  0.1569995880126953,
  0.15500617027282715)}
```

```
#sample full trainset
trainset = data.build_full_trainset()

# Train the algorithm on the trainset
svd.fit(trainset)
```

```
<surprise.prediction_algorithms.matrix_factorization.SVD at
0x250c84197d0>
```

```
movie_rating[movie_rating['userId'] == 1]
```

	userId	movieId	rating	timestamp
0	1	1	4.0	964982703
1	1	3	4.0	964981247
2	1	6	4.0	964982224
3	1	47	5.0	964983815
4	1	50	5.0	964982931
..	...	...	...	...
227	1	3744	4.0	964980694
228	1	3793	5.0	964981855
229	1	3809	4.0	964981220
230	1	4006	4.0	964982903

```
231       1     5060     5.0  964984002

[232 rows x 4 columns]
```

```
reader = Reader(rating_scale=(0.5, 5.0))
data = Dataset.load_from_df(movie_rating[['userId', 'movieId',
'rating']], reader)

trainset, testset = train_test_split(data, test_size=0.2)

model = SVD()
model.fit(trainset)
```

```
<surprise.prediction_algorithms.matrix_factorization.SVD at
0x250cf856850>
```

```
uid = 3
iid = 302
prediction = model.predict(uid, iid)
print(f"Estimated rating for user {uid} and item {iid}:
{prediction.est}")
```

```
Estimated rating for user 3 and item 302: 2.2425165984833053
```

Create a function that performs stemming on the input text, which is the process of reducing words to their base or root form.

```
ps = PorterStemmer()
def stem(text):
    y=[]
    for i in text.split():
        y.append(ps.stem(i))
    return" ".join(y)

new_movies.loc[:, "tags"] = new_movies["tags"].apply(stem)

cosine_similarity(vectors)
```

```
array([[1.        , 0.08458258, 0.05812382, ..., 0.02478408,
0.02739983,
        0.        ],
       [0.08458258, 1.        , 0.06063391, ..., 0.02585438, 0.
,
        0.        ],
       [0.05812382, 0.06063391, 1.        , ..., 0.02665009, 0.
,
        0.        ],
       ...,
       [0.02478408, 0.02585438, 0.02665009, ..., 1.        ,
0.07537784,
```

```
        0.04828045],
       [0.02739983, 0.        , 0.        , ..., 0.07537784, 1.
,
        0.05337605],
       [0.        , 0.        , 0.        , ..., 0.04828045,
0.05337605,
        1.        ]])
```

```
cosine_similarity(vectors).shape
```

```
(4803, 4803)
```

```
similarity = cosine_similarity(vectors)
```

```
similarity[2]
```

```
array([0.05812382, 0.06063391, 1.        , ..., 0.02665009,
0.        ,
       0.        ])
```

```
similarity[2].shape
```

```
(4803,)
```

```
sorted(list(enumerate(similarity[2])), reverse= True, key=lambda
x:x[1])[1:7]
```

```
[(11, 0.36336104634371585),
 (1343, 0.34521548171187133),
 (29, 0.3217979514674191),
 (4071, 0.28097574347450816),
 (3162, 0.27695585470349865),
 (1717, 0.23717082451262844)]
```

```
def recommend(movie):
    movie_index = new_movies[new_movies["title"]==movie].index[0]
    distances = similarity[movie_index]
    movies_list = sorted(list(enumerate(distances)), reverse = True,
key = lambda x:x[1])[1:7]

    for i in movies_list:
        print(new_movies.iloc[i[0]].title)
```

```
recommend("Avatar")
```

```
Titan A.E.
Independence Day
Aliens vs Predator: Requiem
Small Soldiers
Battle: Los Angeles
Krull
```

Hybrid Recommender¶

In this section, we try to build a simple hybrid recommender that brings together techniques we have implemented in the content-based and collaborative filter based engines. This is how it works:

Input: User ID and the Title of a Movie

Output: Similar movies sorted on the basis of expected ratings by that particular user.

```
movies_credits.columns=['movieId', 'title', 'cast', 'crew', 'budget', 
'genres', 'homepage',
       'keywords', 'original_language', 'original_title', 'overview',
       'popularity', 'production_companies', 'production_countries',
       'release_date', 'revenue', 'runtime', 'spoken_languages', 
'status',
       'tagline', 'vote_average', 'vote_count', 'director', 'actor', 
'soup','userId','rating','timestamp']

# Function that takes in movie title as input and outputs most similar 
movies
def hybrid_recommendations(userId, title):

    # Get the index of the movie that matches the title
    idx = indices[title]

    # Get the pairwsie similarity scores of all movies with that movie
    sim_scores = list(enumerate(cosine_sim2[idx]))

    # Sort the movies based on the similarity scores
    sim_scores.sort(key=lambda x: x[1], reverse=True)

    # Get the scores of the 10 most similar movies
    sim_scores=sim_scores[1:11]

    # Get the movie indices
    ind=[]
    for (x,y) in sim_scores:
        ind.append(x)

    # Grab the title,movieid,vote_average and vote_count of the top 10 
most similar movies
    tit=[]
    movieid=[]
    vote_average=[]
    vote_count=[]
    for x in ind:
        tit.append(movies_credits.iloc[x]['title'])
        movieid.append(movies_credits.iloc[x]['movieId'])
        vote_average.append(movies_credits.iloc[x]['vote_average'])
        vote_count.append(movies_credits.iloc[x]['vote_count'])
```

```
    # Predict the ratings a user might give to these top 10 most 
similar movies
    est_rating=[]
    for a in movieid:
        est_rating.append(svd.predict(userId, a, r_ui=None).est)

    return pd.DataFrame({'index': ind, 'title':tit, 'movieId':movieid, 
'vote_average':vote_average, 
'vote_count':vote_count,'estimated_rating':est_rating}).set_index('ind
ex').sort_values(by='estimated_rating', ascending=False)

hybrid_recommendations(1,'Avatar')

                                       title  movieId  vote_average  \
index                                                                  
466                         The Time Machine     2135           5.8   
2327                                Predator      106           7.3   
2403                                  Aliens      679           7.7   
47                    Star Trek Into Darkness    54138           7.4   
61                         Jupiter Ascending    76757           5.2   
83                                The Lovers    79698           4.8   
1201                               Predators    34851           6.0   
260                             Ender's Game    80274           6.6   
2372                               Megaforce    27380           3.5   
71     The Mummy: Tomb of the Dragon Emperor     1735           5.2   

       vote_count  estimated_rating  
index                                
466           631          4.671496  
2327         2093          4.303260  
2403         3220          4.244681  
47           4418          4.234051  
61           2768          4.234051  
83             34          4.234051  
1201         1206          4.234051  
260          2303          4.234051  
2372           15          4.234051  
71           1387          4.112555  

hybrid_recommendations(4,'Avatar')

                                       title  movieId  vote_average  \
index                                                                  
466                         The Time Machine     2135           5.8   
2327                                Predator      106           7.3   
2403                                  Aliens      679           7.7   
71     The Mummy: Tomb of the Dragon Emperor     1735           5.2   
47                    Star Trek Into Darkness    54138           7.4   
61                         Jupiter Ascending    76757           5.2   
```

```
83                                        The Lovers    79698           4.8
1201                                       Predators    34851           6.0
260                                     Ender's Game    80274           6.6
2372                                       Megaforce    27380           3.5

       vote_count  estimated_rating
index
466           631          3.637135
2327         2093          3.636922
2403         3220          3.498574
71           1387          3.349678
47           4418          3.312889
61           2768          3.312889
83             34          3.312889
1201         1206          3.312889
260          2303          3.312889
2372           15          3.312889
```

Exporting to Create GUI

```python
import pickle

with open('movies.pkl','wb') as f:
    pickle.dump(movies_credits.to_dict(), f)

with open('.similarity.pkl','wb') as f:
    pickle.dump(similarity,f)

with open('hybrid_recommendations.pkl', 'wb') as f:
    pickle.dump(hybrid_recommendations, f)

with open('recommend.pkl', 'wb') as f:
    pickle.dump(recommend, f)
```