Movie Recommendation System

Business Understanding

1.1) Overview

The vast and fast growing movie industry may be overwhelming for a movie platform user to decide on which movie to watch and actually enjoy it. This project aims to curb this challenge by developing 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.

1.2) 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) Specific Objectives

- To develop a demographic recommendation system that suggests popular movies based on user demographic attributes.
- To implement a content-based recommendation system that recommends movies based on movie overviews, cast, and keywords.
- To build a collaborative filtering recommendation system that suggests movies based on user similarities and their ratings.
- To create a hybrid recommendation system that combines the techniques from content-based and collaborative filtering approaches to provide personalized movie recommendations.

Data Understanding

- 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

The dataset columns represent:

- `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 Preparation

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 0x0000023A07DC43D0>
```

```
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.convert)

# 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_companies'].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_directors)
```

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
```

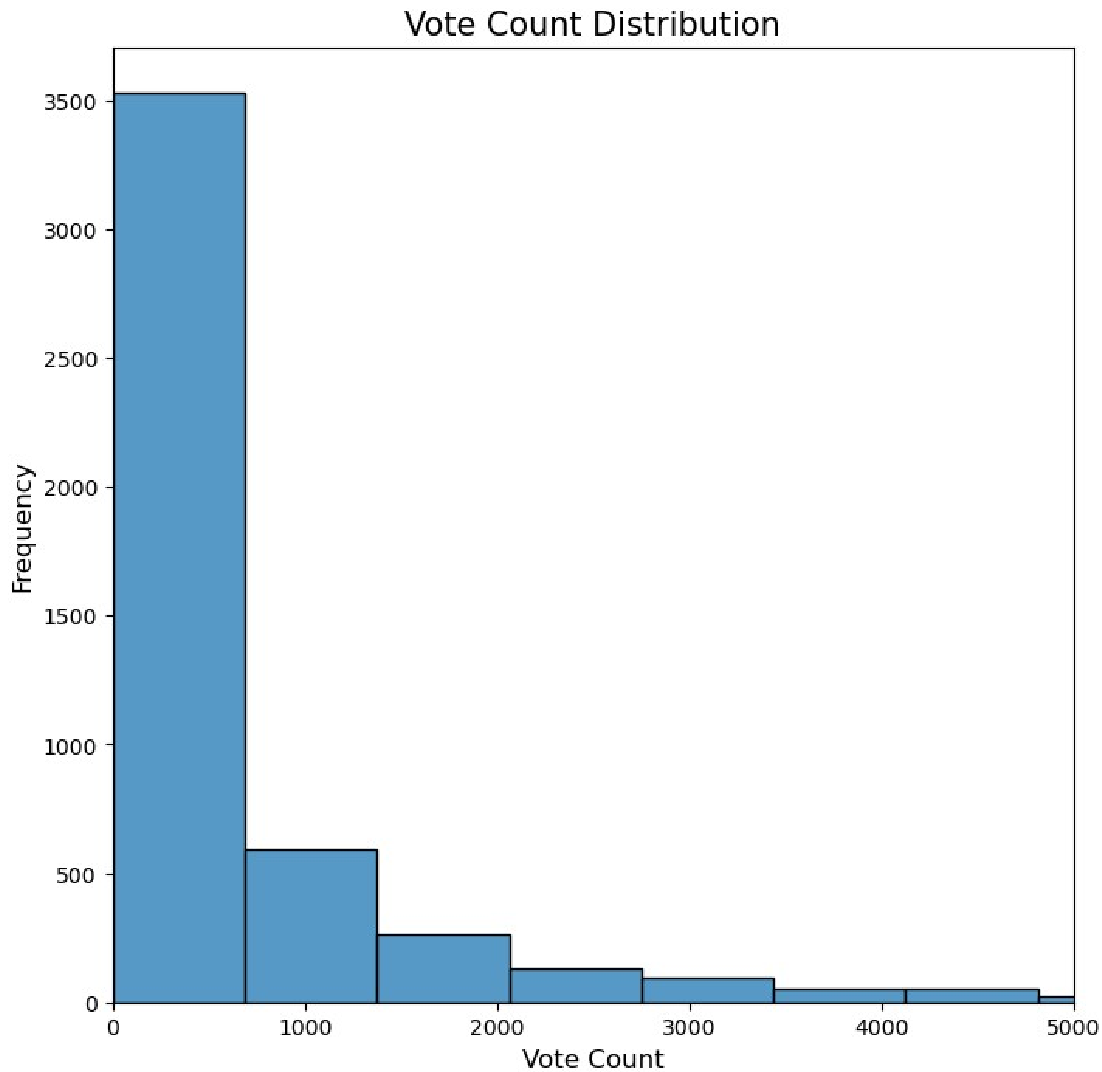
EDA

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
```

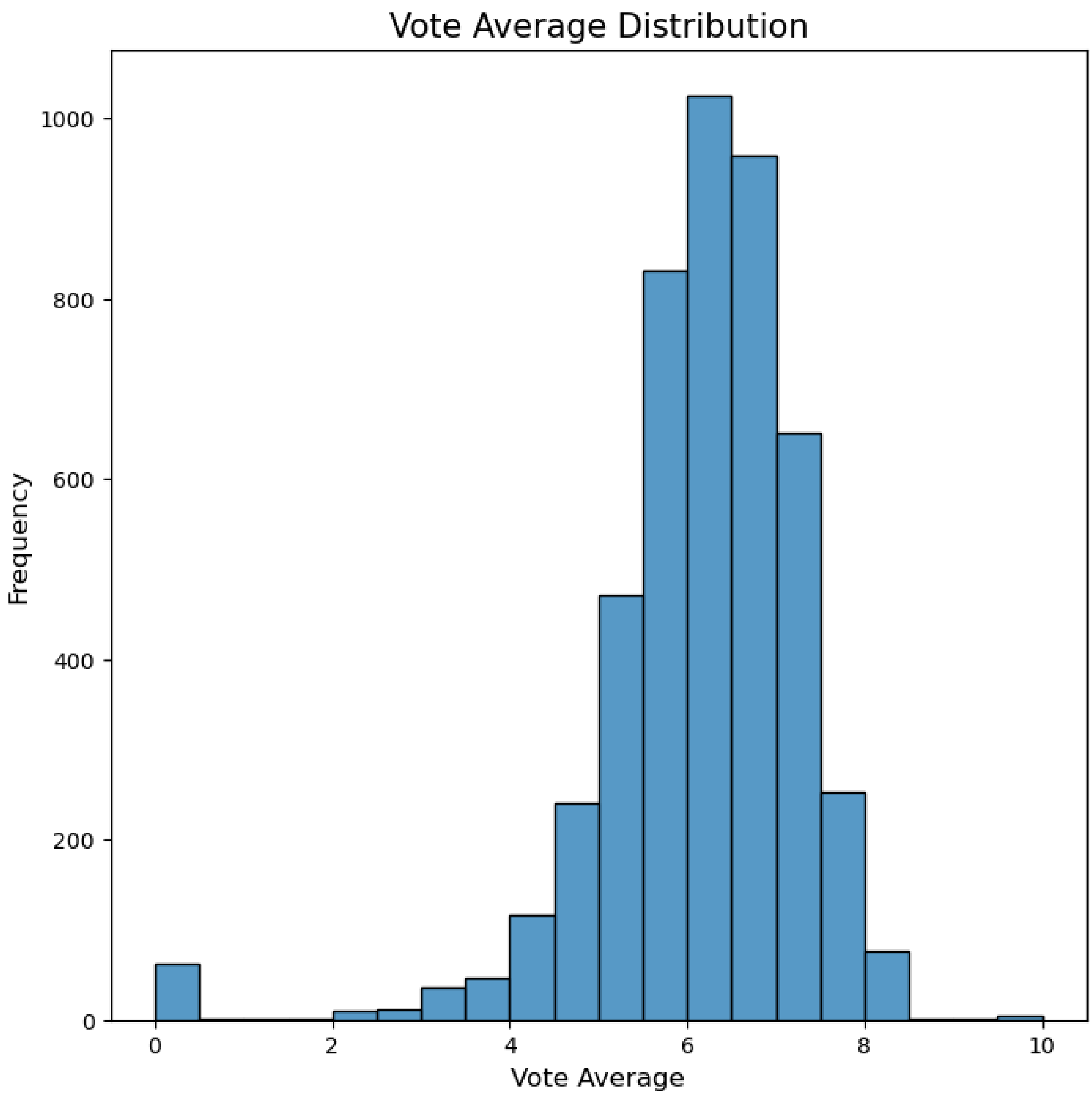


From the plot above we can determine that the vote count decreases hence a low concentarationtion for the vote counts

- Vote Average

```
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
```

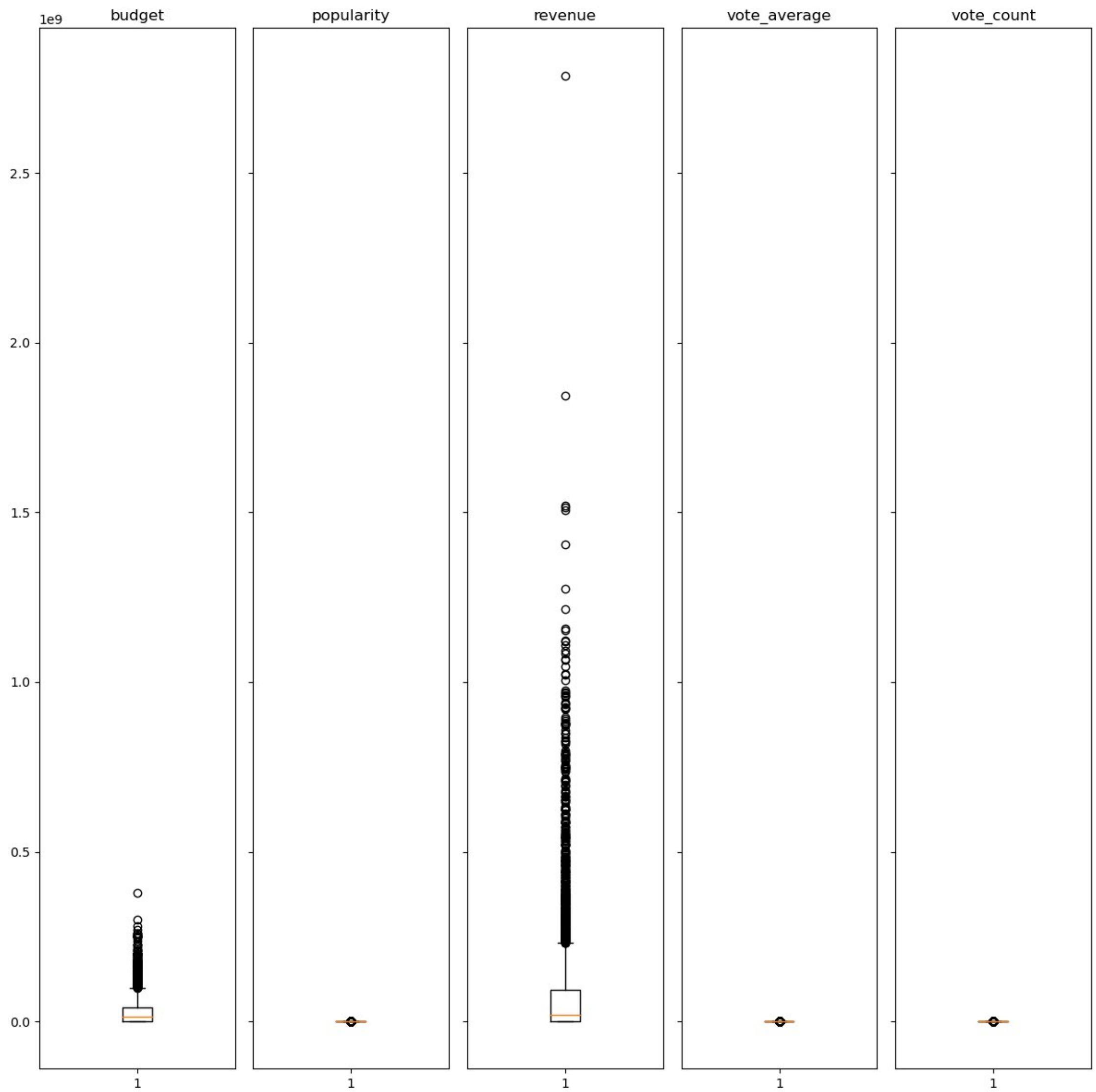


The vote average is normallly distributed with the majority of it being 6-8.

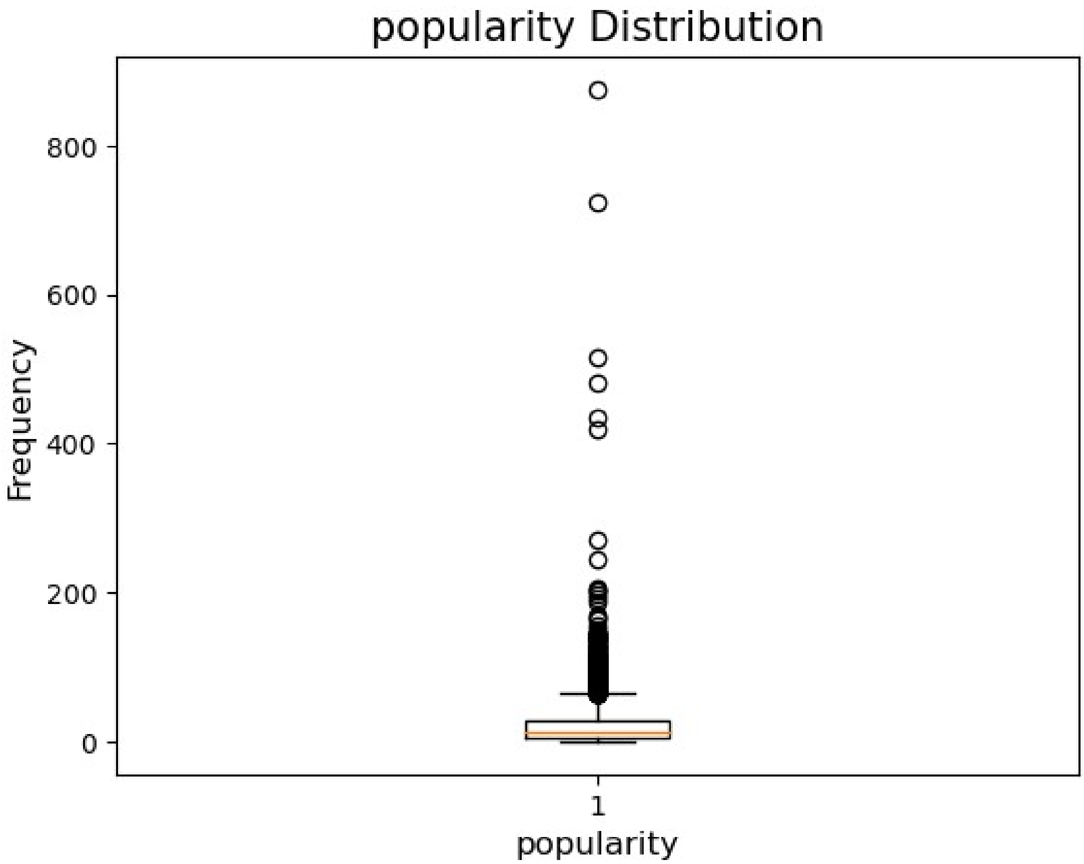
Check for existence of outliers

```
# Select the variables you want to plot

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

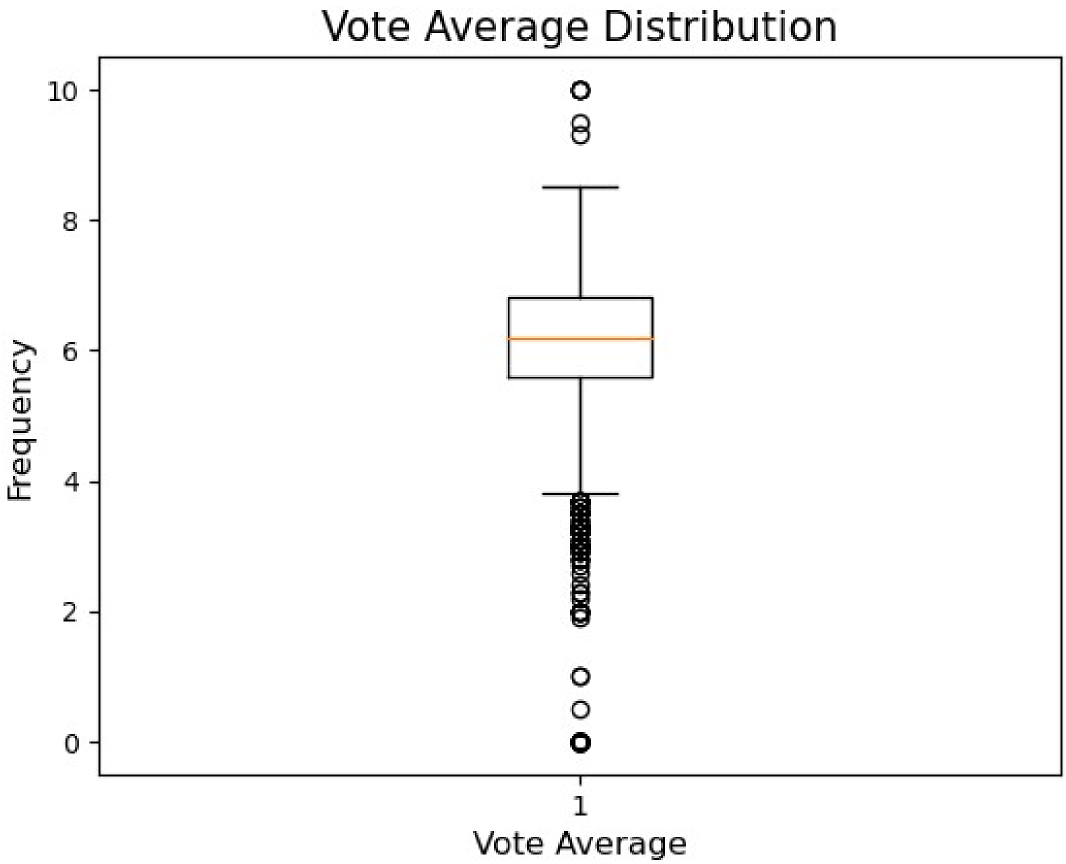
```python
######## Create a subplot grid
fig, axes = plt.subplots(nrows=1, ncols=len(cols_to_plot),
figsize=(12, 12), sharey=True)

####### 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)
    axes[i].tick_params(axis='both', which='major')

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




```python
# 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
```

```python
# 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)
```

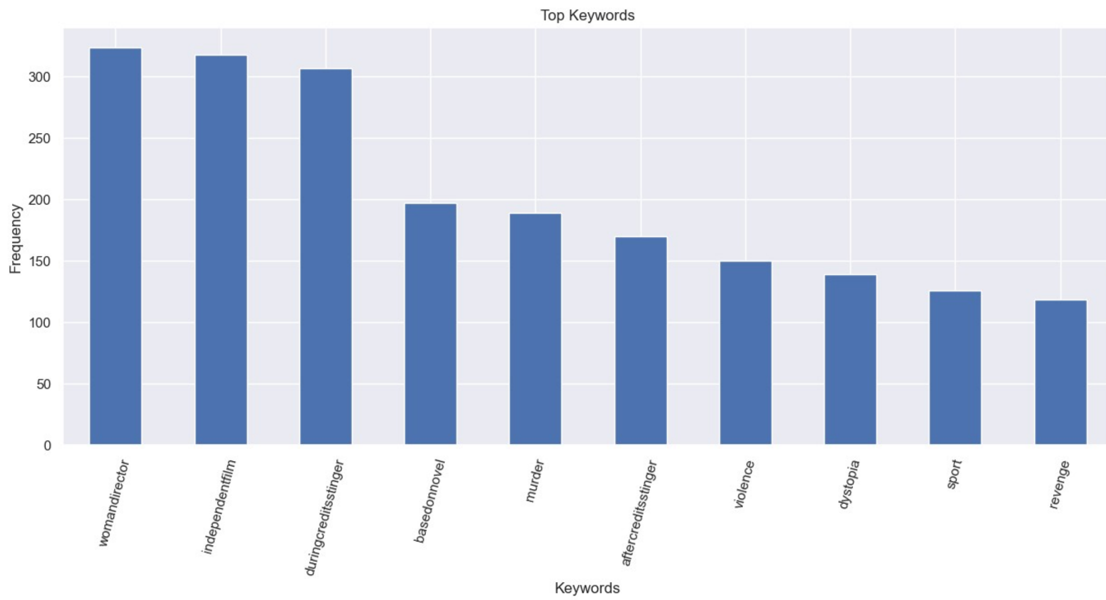
```python
# Define the lower and upper bounds for the outliers
lower_bound = 2
upper_bound = 8

# 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

```python
# 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().head(10)

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

# Plot the top keywords
```

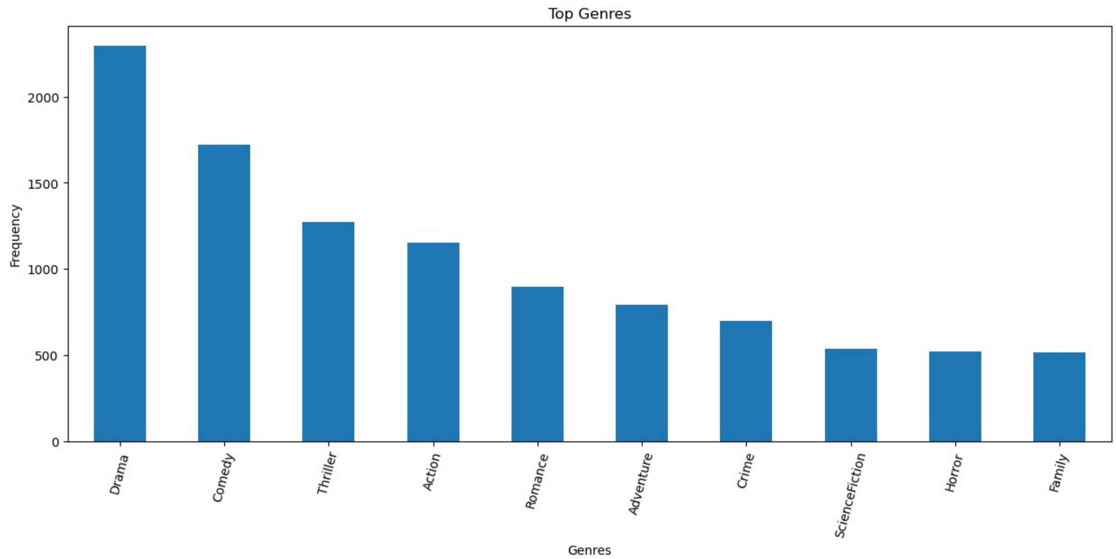
```
plt.figure(figsize=(15, 6))
top_keywords.plot(kind='bar')
plt.title('Top Keywords')
plt.xlabel('Keywords')
plt.ylabel('Frequency')
plt.xticks(rotation=75)
# save the figure
plt.savefig(".data/images/Keywords_plot")
plt.show()
```



- Genres

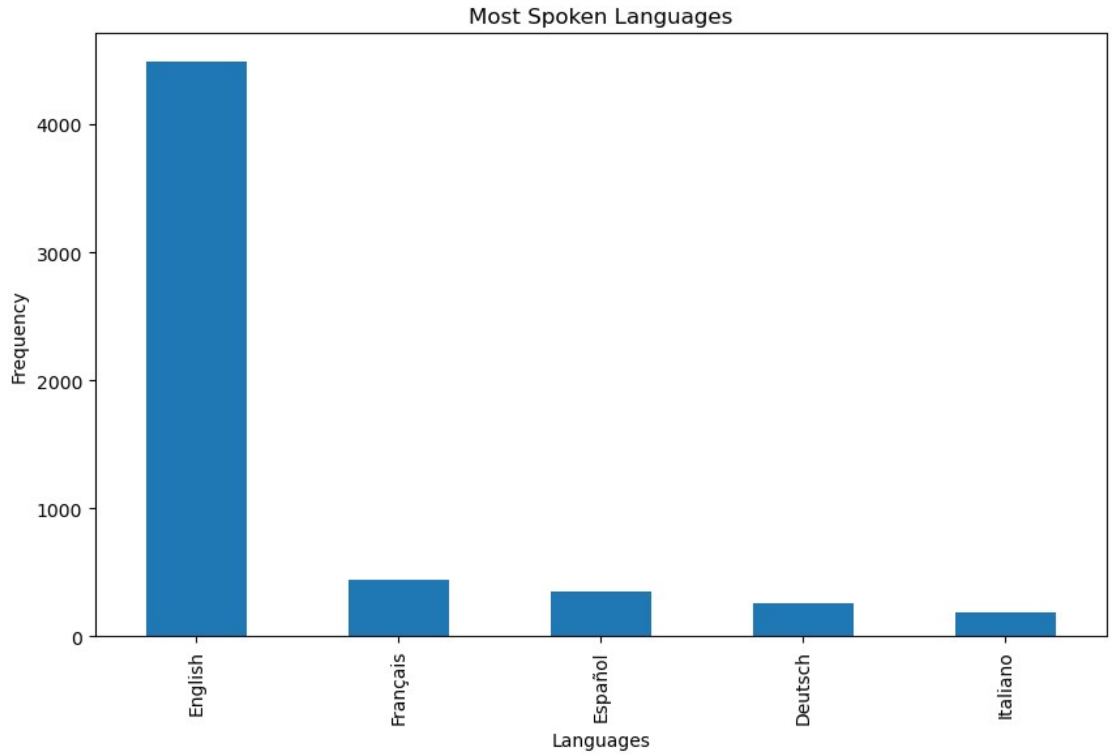
```
# Extract the 'genres' column
genres = movies_credits['genres']

# 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()
```

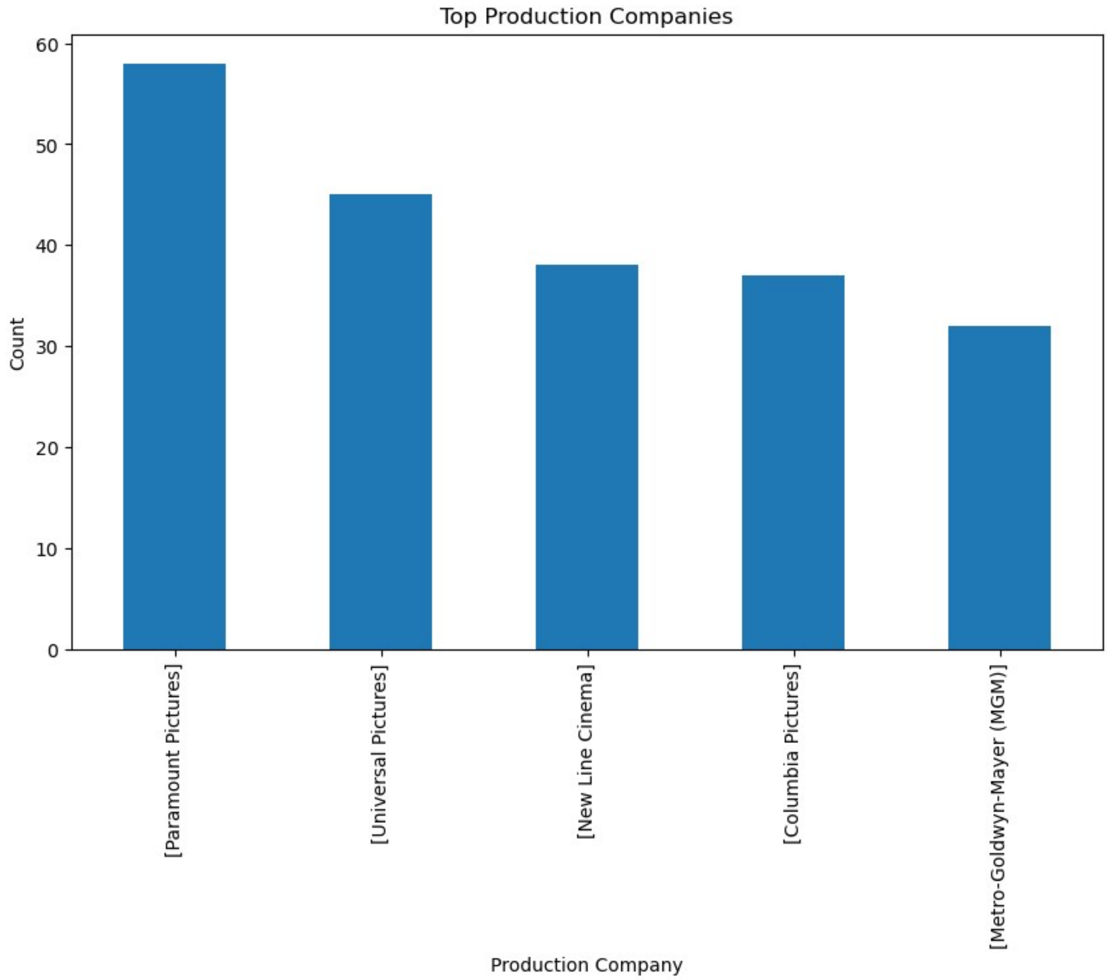
```
status
Released            4795
Rumored                5
Post Production        3
Name: count, dtype: int64
```

- Production Companies

Top company collaborations

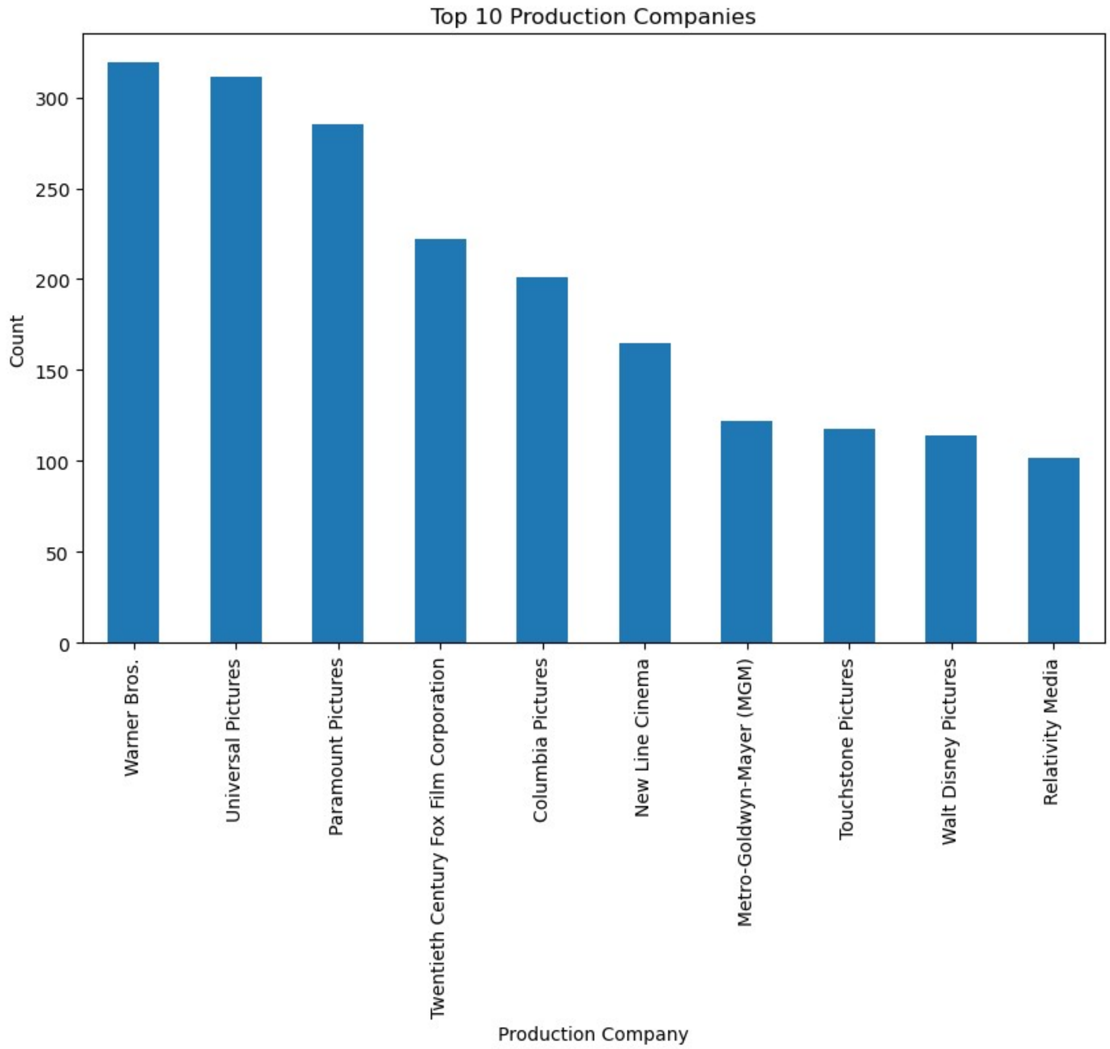
```
# Get value counts of production companies
production_company_counts =
movies_credits['production_companies'].value_counts()

# 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()
```



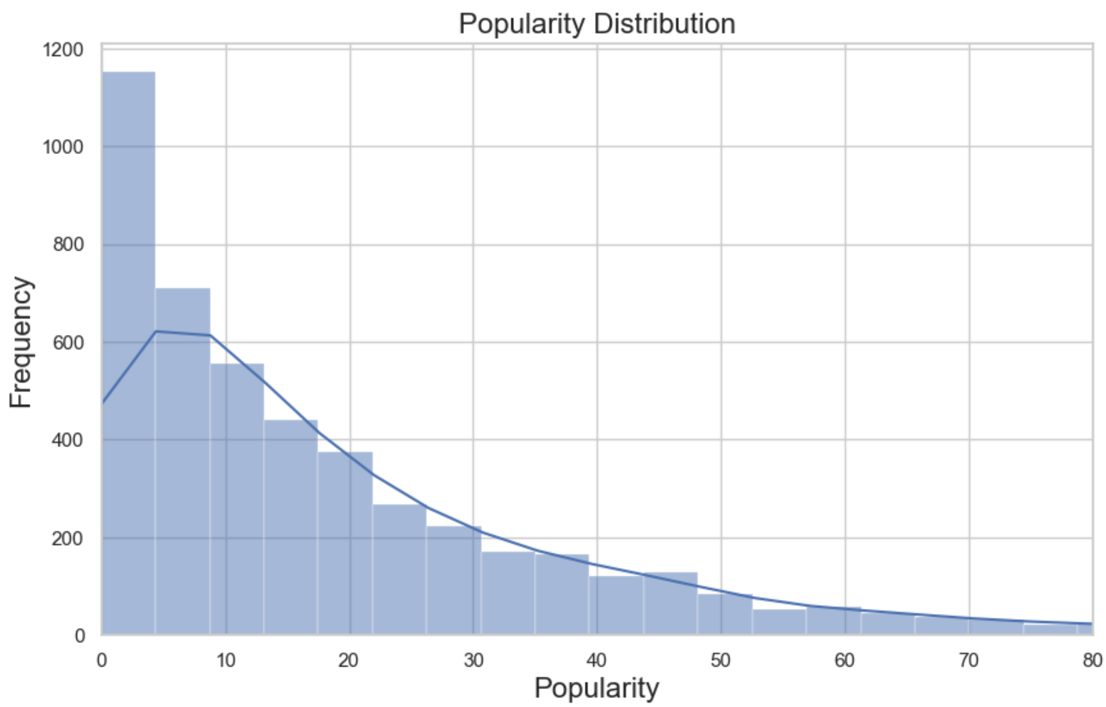
Top companies individually

```
# 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()
```



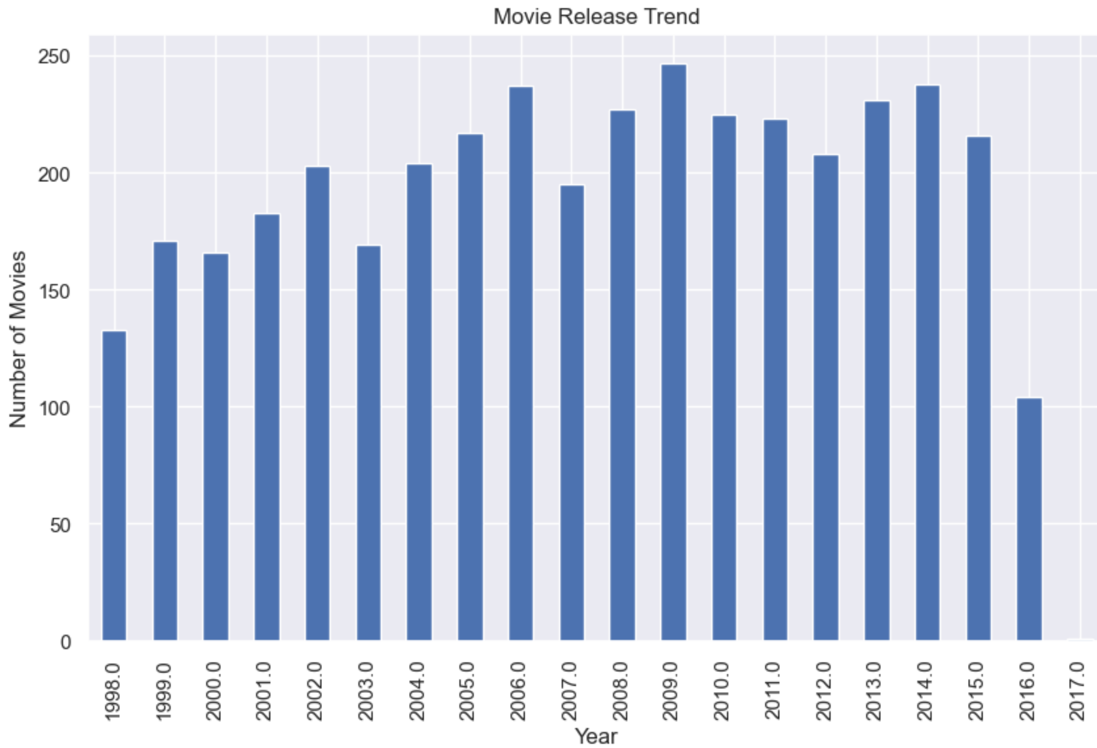
- Popularity

```
# 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, 80)  # Set the x-axis limits
plt.show()
```



- Release date

```
# 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()
```



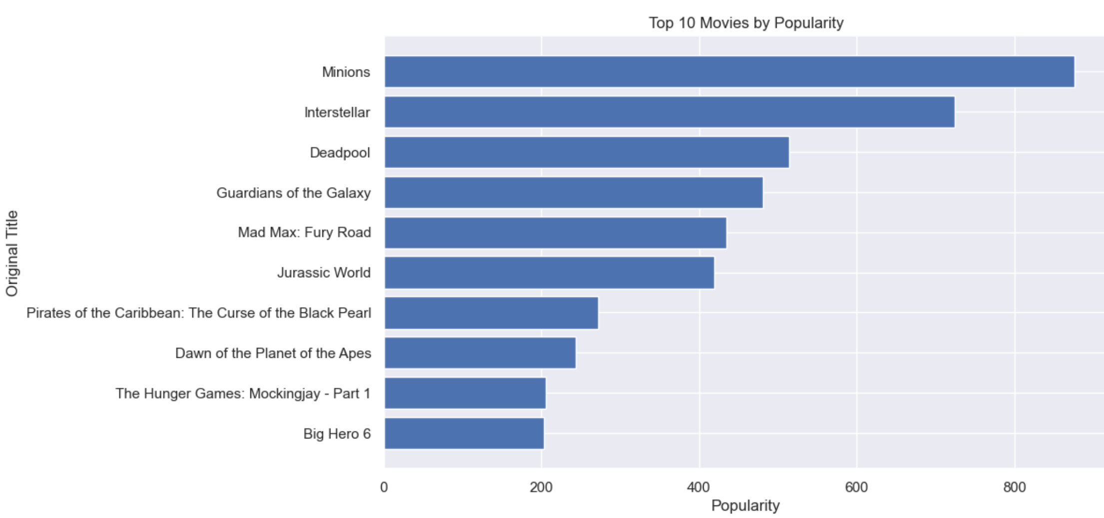
- Word Cloud of Movie Overviews

```
# 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**

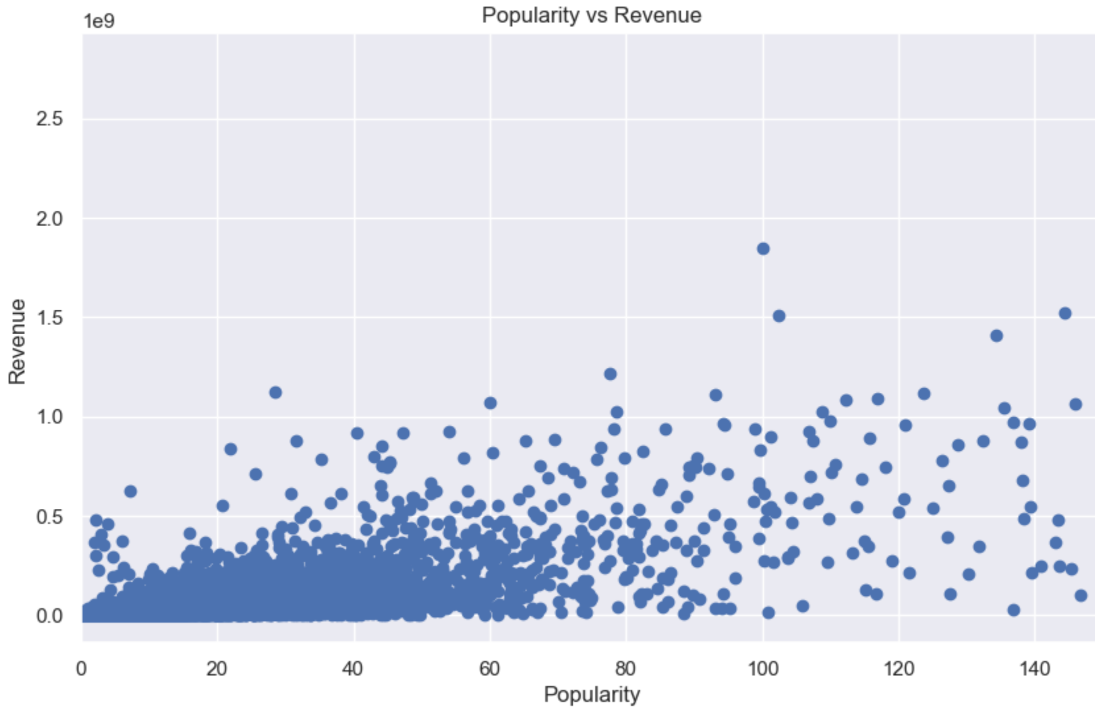
- Original Title vs Popularity

```
# 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

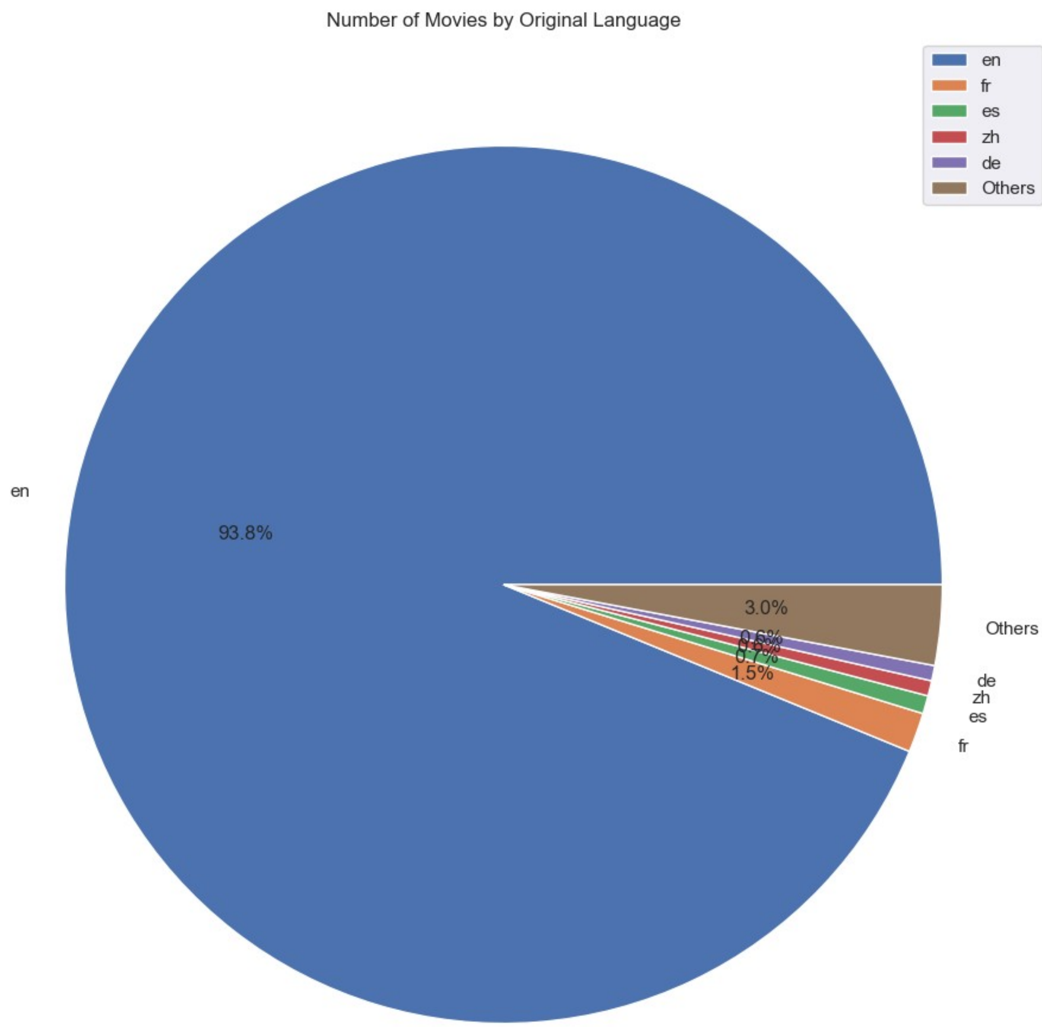
```python
# Plotting 'popularity' vs 'revenue'
plt.figure(figsize=(10, 6))
plt.scatter(movies_credits['popularity'], movies_credits['revenue'])
plt.title('Popularity vs Revenue')
plt.xlabel('Popularity')
plt.xlim(0, 150)
plt.ylabel('Revenue')
plt.savefig('.data/images/popularity vs revenue')
plt.show()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



- Number of Movies by original language of production

```python
#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=(12, 12))
languages_data.plot(kind='pie', autopct='%1.1f%%')
```

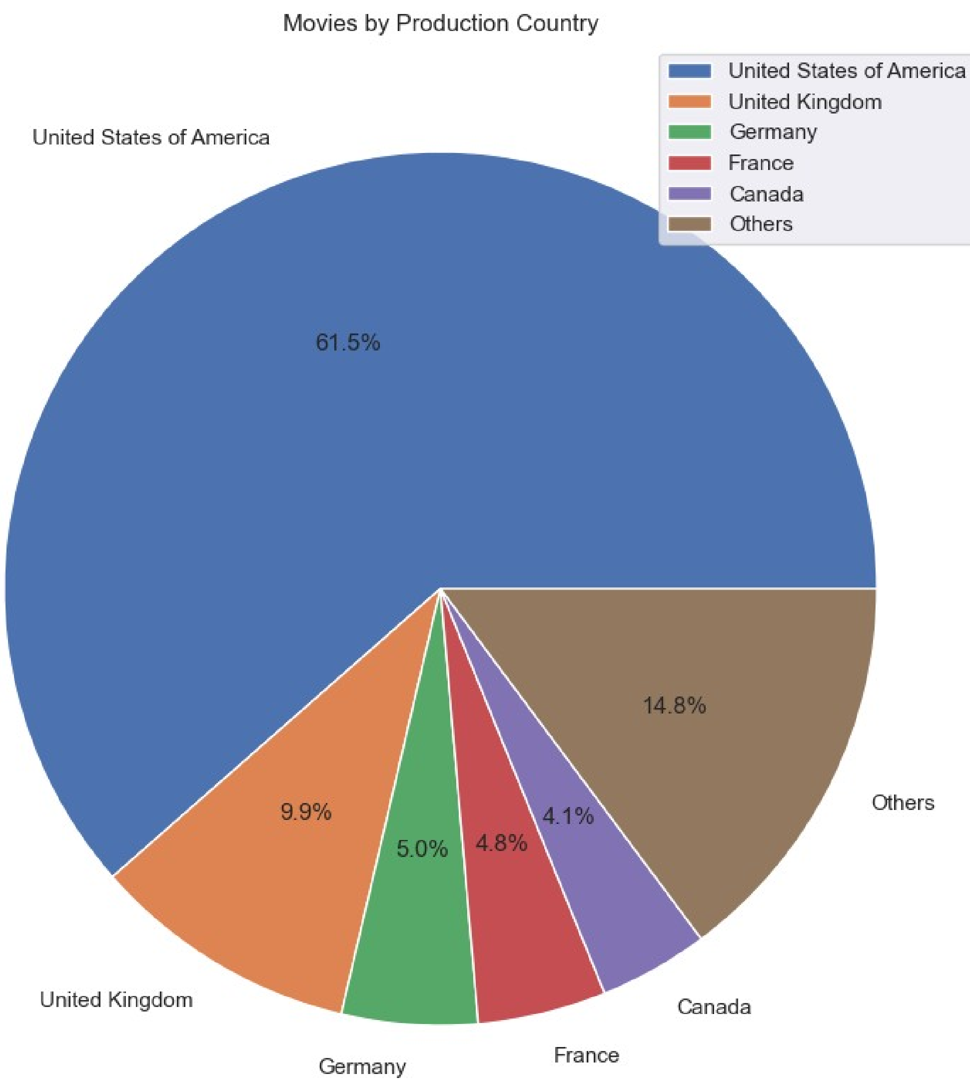
```
plt.title('Number of Movies by Original Language')
plt.ylabel('')

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



Movies by production country

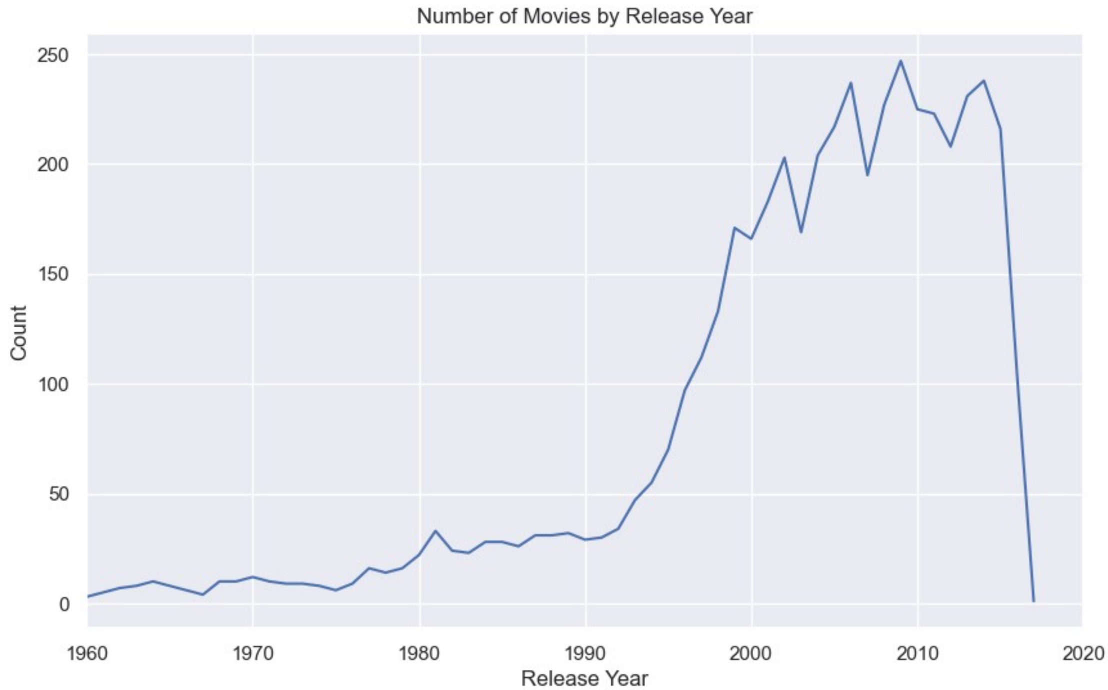
```
# Get value counts of production countries
production_countries_counts =
movies_credits['production_countries'].explode().value_counts()

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

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

# 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()
```



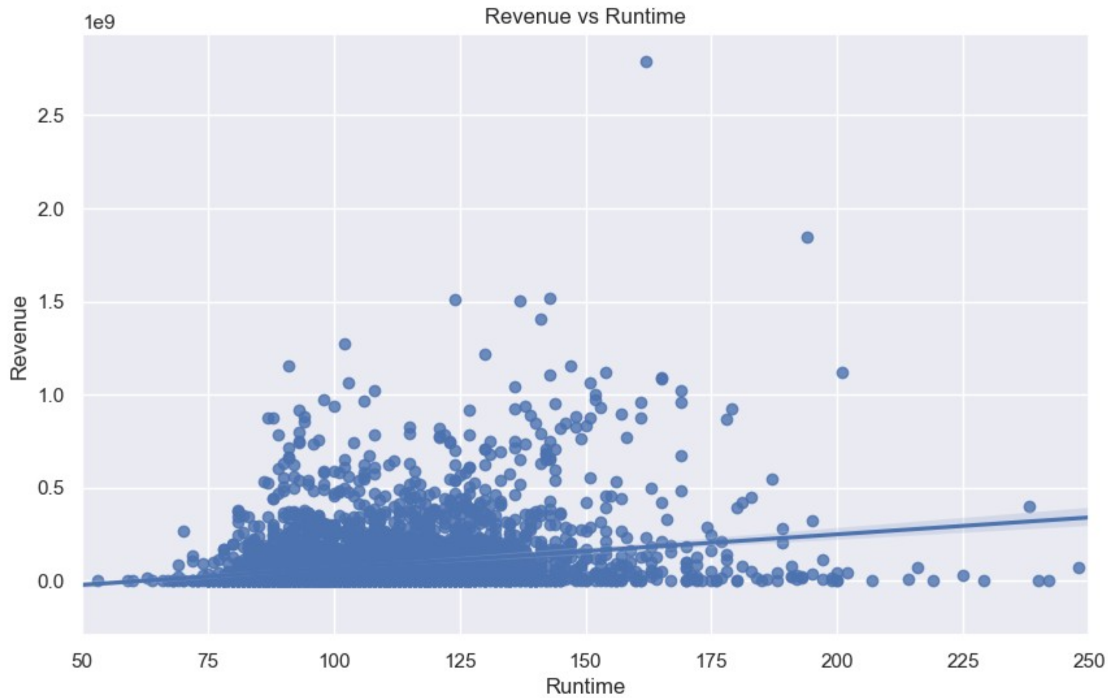
- Movies by release year

```
# 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()
```



- Revenue vs Runtime

```
# 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()
```



Modeling

i) Demographic Recommendation based on Popularity

This model suggests movies to users based on their demographic attributes and the overall popularity of the movies.

Here, we 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
```

```python
# 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)]
```

```python
# Check the shape of the new dataframe
new_dataframe_filtered.shape
```

```
(481, 24)
```

```python
# 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))
```

- we have to use .loc explicitly when trying to splice a pandas dataframe. This allows us to set the values in the 'score column for the rows of the new dataframe

```python
# By using the '.loc and set the new values
new_dataframe_filtered.loc[:, 'score'] =
new_dataframe_filtered.apply(movie_score, axis=1)
```

```python
# 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
```

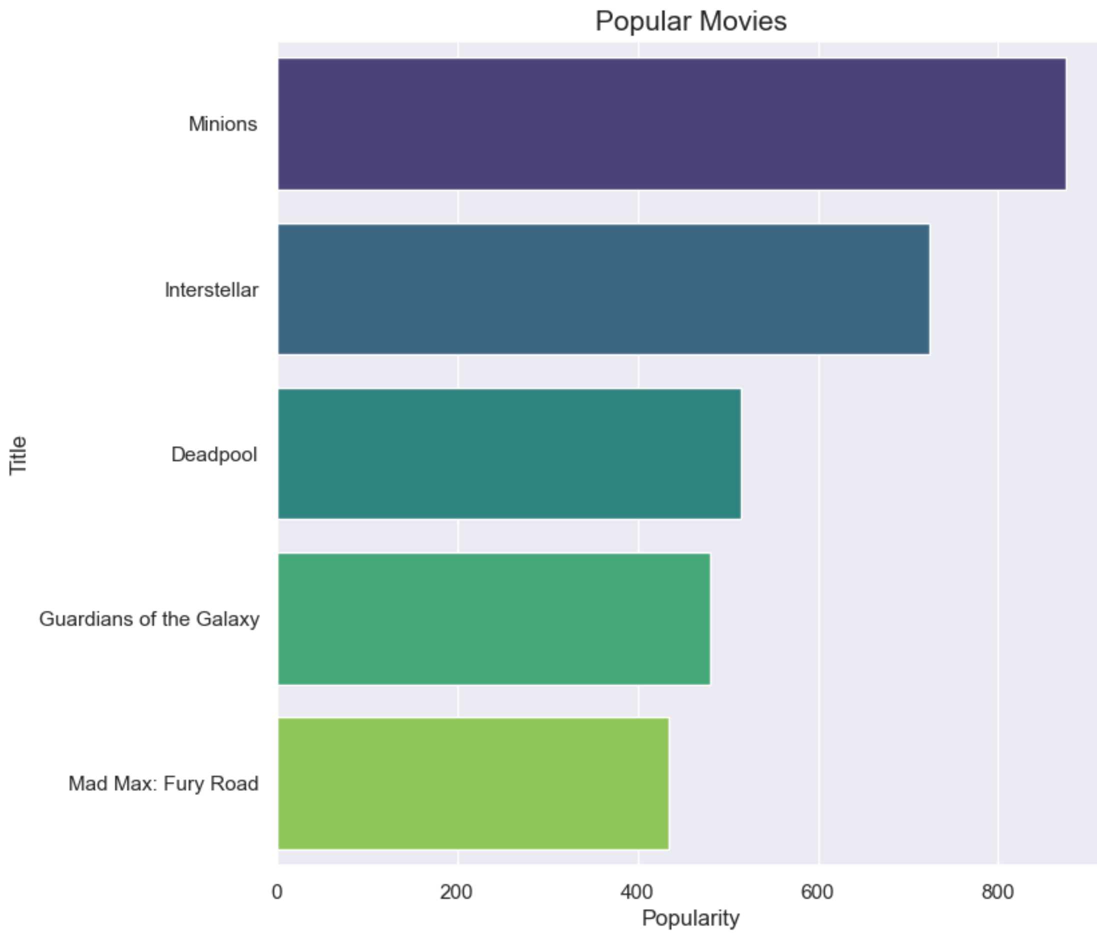
Finding movie popularity

```python
# 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

Below we well now take in a new dataset in order to more predictive modelling. This new dataset contains a ratings column for each user provided rating per movie.

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

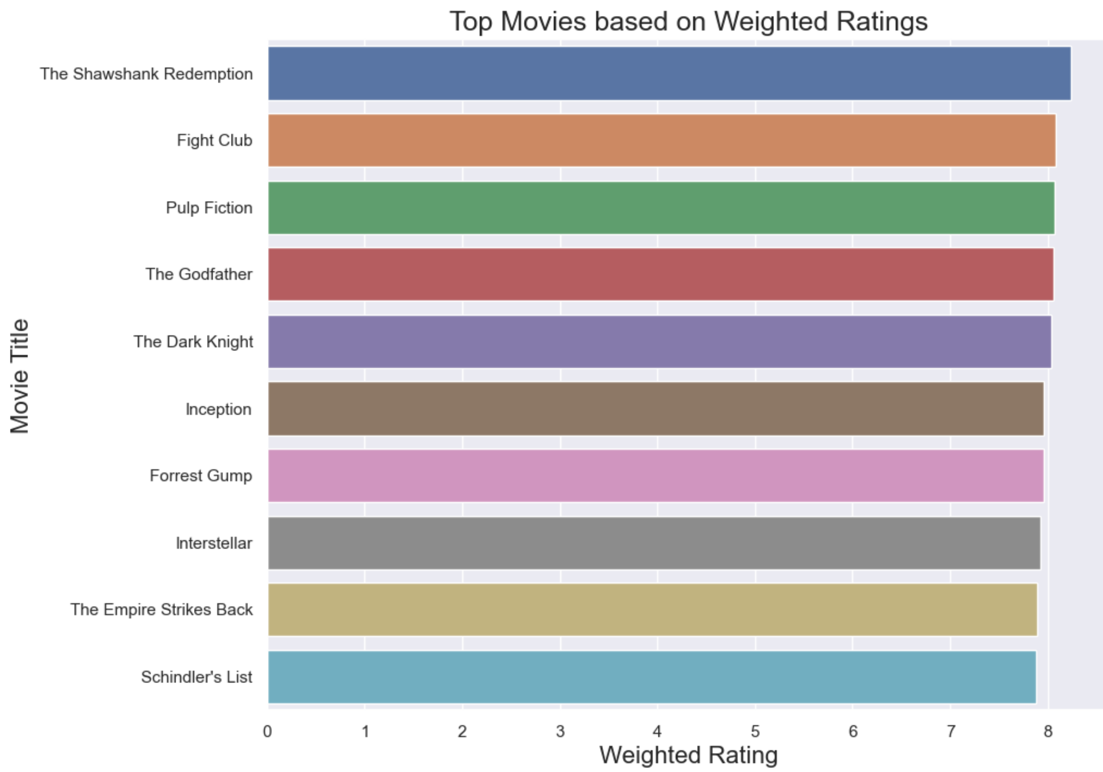
```
   userId  movieId  rating  timestamp
0       1        1     4.0  964982703
1       1        3     4.0  964981247
2       1        6     4.0  964982224
3       1       47     5.0  964983815
4       1       50     5.0  964982931
```

Here we will create a new column for Weighted Rating by taking into account the vote count and vote average for each user from the previous dataset. A weighted score is mainly defined as the mean of grades for each subject (interest) multiplied by its counterweight (division decimal). It is obtained by multiplying each score by its weight (percentage) and add the products together, then divide by the sum of the weights.

```python
# 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()
```



- We should keep in mind that this demographic recommender provide a general chart of recommended movies to all the users, regardless of the user's personal taste. It is not sensitive to the interests and tastes of a particular user, and it does not give personalized recommendations based on the users.

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.Movie Overview Recommendation

- We use this because it 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
```

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

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

```
0
```

```python
# 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

```python
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]
```

```python
# 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

```
# Calculate similarity matrix
cosine_sim = cosine_similarity(tfidfv_matrix, tfidfv_matrix)
```

```
cosine_sim.shape
```

```
(4803, 4803)
```

```
# Create a Pandas Series to map movie titles to their indices
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
```

In the cell below, we create a function named `recommended_movies` that takes two parameters: `title` and `cosine_sim`. It uses the `indices` Series to map movie titles to their corresponding indices. Then, it calculates the pairwise similarity scores between the movie specified by the `title` parameter and all other movies based on the cosine similarity matrix `cosine_sim`.

```
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)

# Applying the function
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
```

- While our system has done a decent job of finding movies with similar overviews and descriptions, the quality of recommendations is not that great. "My Date with Drew" returns all Batman movies while it is more likely that the people who liked that movie are more inclined to enjoy other movies. This is something that cannot be captured by the present system.

1. Movie Cast , Keywords and Genre Recommender

Here, we generate movie recommendations based on the similarity of cast members and keywords associated with the movies.

```
def update_crew_with_director(data):
    # Create a new column called 'Directors' and assign the values of the 'crew' column to it
    data['Directors'] = data['crew']

    # Return the updated DataFrame
    return data

# Update our dataset
movies_credits = update_crew_with_director(movies_credits)
```

We then extract the first element from the `Directors` list and remove the square brackets,then assign it to the `Director_clean` column. If `Directors` is empty, we assign None.

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

```python
# Selecting specific columns
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]
```

In this cell, we define a function `create_soup` and then apply it to each row of the `movies_credits` DataFrame to create a new column called `soup`.

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

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

# Initializing CountVectorizer object with English stop words.
cv = CountVectorizer(stop_words='english')

# Applying CountVectorizer to 'soup' column, converting text data into
a matrix of token counts.
cv_matrix = cv.fit_transform(movies_credits['soup'])

# Calculating the cosine similarity matrix using the cv_matrix.
cosine_sim2 = cosine_similarity(cv_matrix, cv_matrix)

# Applying the 'recommend_movie' function
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

# Applying the 'recommend_movie' function
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
```

- We see that our recommender has been successful in capturing more information due to more metadata and has given us better recommendations. It is more likely comedy fans will like the movies of the same production house. Therefore, to our features above we can add production_company . We can also increase the weight of the director , by adding the feature multiple times in the soup.

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.
2. **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.
3. **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.
4. **Neighborhood selection.** We will select the neighborhood of users or items based on their similarity.
5. **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.
6. **Evaluation.** We will evaluate performance of the recommendation system using metrics suc as precision, recall, or mean average precision.

1. **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
```

1. **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 0x23a22134750>
```

1. **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 0x23a21511210>
```

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

```python
# 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: 153, Predicted Rating: 3.9808900490814803
Item ID: 592, Predicted Rating: 3.9808900490814803
Item ID: 588, Predicted Rating: 3.9808900490814803
Item ID: 420, Predicted Rating: 3.9808900490814803
Item ID: 356, Predicted Rating: 3.9808900490814803
```

1. **Evaluation**

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

```
RMSE: 0.8977
```

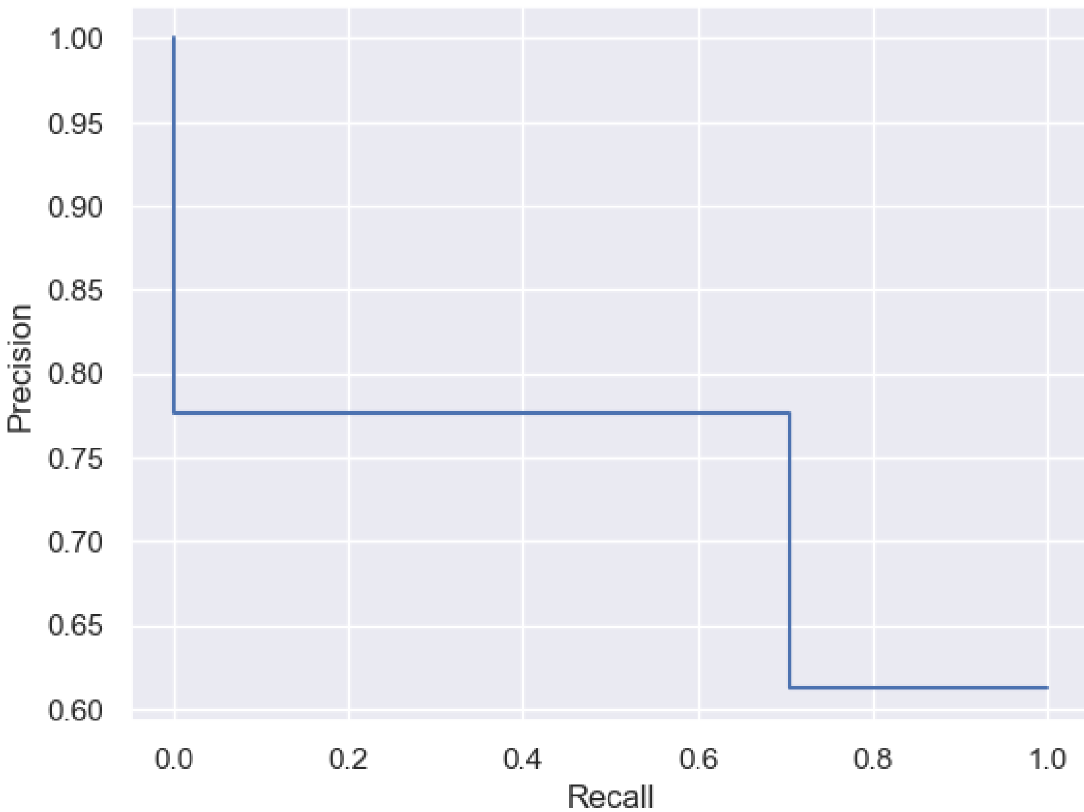
The Root Mean Square Error (RMSE) value indicates the average prediction error of the recommendation system. It is a measure of the difference between the predicted ratings and the actual ratings provided by users.

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.

```python
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: [0.61195954 0.77701498 1.        ]
Recall: [1.         0.70612543 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.

```
# Initialize CountVectorizer object with a maximum of 5000 features
and English stop words.
cv = CountVectorizer(max_features = 5000, stop_words="english")

# Apply CountVectorizer to the 'tags' column of the new_movies
DataFrame.
cv.fit_transform(new_movies["tags"]).toarray()

# Apply CountVectorizer again to the 'tags' column to transform the
text data into an array.
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)
```

Evaluating metrics (RMSE and MAE) for the SVD algorithm on 6 different splits of the data.

```
# 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)    0.8718  0.8757  0.8625  0.8803  0.8631  0.8818
```

```
0.8725  0.0076
MAE (testset)     0.6684  0.6721  0.6617  0.6764  0.6661  0.6766
0.6702  0.0054
Fit time          2.70    1.69    1.74    1.70    1.70    1.68    1.87
0.37
Test time         0.36    0.21    0.15    0.34    0.15    0.14    0.23
0.09
```

```
{'test_rmse': array([0.87176732, 0.87568102, 0.86247443, 0.8802911 ,
0.86314098,
        0.88179402]),
 'test_mae': array([0.66844231, 0.6721193 , 0.66167692, 0.67639596,
0.66612197,
        0.67660923]),
 'fit_time': (2.6989946365356445,
  1.6949965953826904,
  1.7350003719329834,
  1.703993320465088,
  1.695995569229126,
  1.6759953498840332),
 'test_time': (0.35900163650512695,
  0.21200323104858398,
  0.15200090408325195,
  0.3380107879638672,
  0.14900588989257812,
  0.14400482177734375)}
```

The SVD algorithm shows promising performance in terms of prediction accuracy (as indicated by low RMSE and MAE values) and reasonable computational efficiency (with relatively low fit and test times).

Here we will now import a brand new dataset that the modelhas not seen before. Apply data cleaning and feature selection then pass the model through it.

```
new_data = pd.read_csv(r".data/movies_credits.csv")
new_data.head()
```

```
   movieId                    title  \
0        1         Toy Story (1995)
1        2           Jumanji (1995)
2        3  Grumpier Old Men (1995)
3        3  Grumpier Old Men (1995)
4        3  Grumpier Old Men (1995)

                                        genres  userId_x  rating_x  \
0  Adventure|Animation|Children|Comedy|Fantasy       1.0       4.0
1                   Adventure|Children|Fantasy       6.0       4.0
2                               Comedy|Romance       1.0       4.0
3                               Comedy|Romance       1.0       4.0
4                               Comedy|Romance       1.0       4.0
```

```
       date_x    time_x sentiment_x  \
0  2000-07-30  18:45:03    Positive
1  1996-10-17  11:58:42    Positive
2  2000-07-30  18:20:47    Positive
3  2000-07-30  18:20:47    Positive
4  2000-07-30  18:20:47    Positive

                                              review      tag
top_critic  \
0                                                NaN    pixar
NaN
1                                                NaN  fantasy
NaN
2  A distinctly gallows take on contemporary fina...    moldy
0.0
3  It's an allegory in search of a meaning that n...    moldy
0.0
4  ... life lived in a bubble in financial dealin...    moldy
0.0

          publisher               date
0               NaN                NaN
1               NaN                NaN
2   Patrick Nabarro  November 10, 2018
3           io9.com       May 23, 2018
4  Stream on Demand    January 4, 2018
```

Applying the DataInfo object on our data

```
new_data_info = DatasetInfo(new_data)
new_data_info
```

```
<my_functions.DatasetInfo at 0x23a20113250>
```

```
new_data_info.check_dataset_info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 63309 entries, 0 to 63308
Data columns (total 13 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   movieId      63309 non-null  int64
 1   title        49330 non-null  object
 2   genres       49330 non-null  object
 3   userId_x     49312 non-null  float64
 4   rating_x     49312 non-null  float64
 5   date_x       49312 non-null  object
 6   time_x       49312 non-null  object
 7   sentiment_x  49312 non-null  object
 8   review       48867 non-null  object
 9   tag          14648 non-null  object
```

```
 10  top_critic   54407 non-null  float64
 11  publisher    54098 non-null  object
 12  date         54407 non-null  object
dtypes: float64(3), int64(1), object(9)
memory usage: 6.3+ MB
```

```
new_data.isnull().sum()
```

```
movieId            0
title          13979
genres         13979
userId_x       13997
rating_x       13997
date_x         13997
time_x         13997
sentiment_x    13997
review         14442
tag            48661
top_critic      8902
publisher       9211
date            8902
dtype: int64
```

```
new_data_info.check_dataset_shape()
```

```
Dataset shape: (63309, 13)
```

```
new_data.drop_duplicates()
```

```
       movieId                    title  \
0            1         Toy Story (1995)
1            2           Jumanji (1995)
2            3  Grumpier Old Men (1995)
3            3  Grumpier Old Men (1995)
4            3  Grumpier Old Men (1995)
...        ...                      ...
63304     1943                      NaN
63305     1943                      NaN
63306     1943                      NaN
63307     1943                      NaN
63308     1943                      NaN

                                            genres  userId_x  rating_x
\
0      Adventure|Animation|Children|Comedy|Fantasy       1.0       4.0

1                       Adventure|Children|Fantasy       6.0       4.0

2                                   Comedy|Romance       1.0       4.0

3                                   Comedy|Romance       1.0       4.0
```

```
4                                    Comedy|Romance       1.0       4.0

...                                             ...       ...       ...

63304                                           NaN       NaN       NaN

63305                                           NaN       NaN       NaN

63306                                           NaN       NaN       NaN

63307                                           NaN       NaN       NaN

63308                                           NaN       NaN       NaN


           date_x    time_x sentiment_x  \
0      2000-07-30  18:45:03    Positive
1      1996-10-17  11:58:42    Positive
2      2000-07-30  18:20:47    Positive
3      2000-07-30  18:20:47    Positive
4      2000-07-30  18:20:47    Positive
...           ...       ...         ...
63304         NaN       NaN         NaN
63305         NaN       NaN         NaN
63306         NaN       NaN         NaN
63307         NaN       NaN         NaN
63308         NaN       NaN         NaN

                                                  review      tag
top_critic  \
0                                                    NaN    pixar
NaN
1                                                    NaN  fantasy
NaN
2      A distinctly gallows take on contemporary fina...    moldy
0.0
3      It's an allegory in search of a meaning that n...    moldy
0.0
4      ... life lived in a bubble in financial dealin...    moldy
0.0
...                                                  ...      ...
...
63304                                                NaN      NaN
0.0
63305                                                NaN      NaN
0.0
63306                                                NaN      NaN
0.0
```

```
63307                                                     NaN       NaN
0.0
63308                                                     NaN       NaN
0.0

                  publisher               date
0                       NaN                NaN
1                       NaN                NaN
2            Patrick Nabarro  November 10, 2018
3                   io9.com       May 23, 2018
4           Stream on Demand    January 4, 2018
...                     ...                ...
63304        eFilmCritic.com     April 12, 2004
63305          Baltimore Sun      April 2, 2004
63306       Austin Chronicle     March 28, 2004
63307         Cinema Signals     March 16, 2004
63308  www.susangranger.com    January 5, 2004

[63268 rows x 13 columns]
```

```
new_data = new_data.rename(columns={"userId_x":"userId", "rating_x":
"rating", "timestamp_x":"timestamp", "date_x": "date", "time_x":
"time", "sentiment_x": "sentiment"})
```

```
new_data.dropna(subset=['title', 'userId'], inplace=True)
```

```
new_data_info.check_dataset_shape()
```

```
Dataset shape: (63309, 13)
```

```
new_data.isnull().sum()
```

```
movieId           0
title             0
genres            0
userId            0
rating            0
date              0
time              0
sentiment         0
review        12862
tag           34682
top_critic     8884
publisher      9109
date           8884
dtype: int64
```

```
class DataFrameFiller:
    def __init__(self, df):
        self.df = df
```

```
    def fillna_random(self, columns):
        """Fill missing values in specified columns with random 
entries from the same columns."""
        for column in columns:
            # Get the non-null values from the column
            non_null_values = self.df.loc[self.df[column].notnull(), 
column]

            # Count the number of missing values in the column
            missing_count = self.df[column].isnull().sum()

            # Generate random values with the same length as missing 
values
            random_values = np.random.choice(non_null_values.values, 
size=missing_count, replace=True)

            # Assign the random values to the missing values in the 
column
            self.df.loc[self.df[column].isnull(), column] = 
random_values

        return self.df

columns = ['review', 'tag', 'top_critic' ,'publisher']
df_filler = DataFrameFiller(new_data)
new_data = df_filler.fillna_random(columns)

new_data.isnull().sum()

movieId          0
title            0
genres           0
userId           0
rating           0
date             0
time             0
sentiment        0
review           0
tag              0
top_critic       0
publisher        0
date          8884
dtype: int64

new_data['publisher'] = new_data['publisher'].fillna('').astype(str)
new_data['genres'] = new_data['genres'].fillna('').astype(str)
new_data['review'] = new_data['review'].fillna('').astype(str)
new_data['top_critic'] = new_data['top_critic'].fillna('').astype(str)
new_data['sentiment'] = new_data['sentiment'].fillna('').astype(str)
```

```python
new_data['tag'] = new_data['publisher'] + new_data['genres'] +
new_data['review'] + new_data['top_critic'] + new_data['sentiment']
```

```python
import re
# Lambda Function to turn the strings to lower case and remove
separators(|, (), ',', '.')
new_data['tag'] = new_data['tag'].apply(lambda x: re.sub(r'[|(),.\d]
+', '', x.lower()))
```

```python
new_data['tag'][14]
```

```
'big hollywoodcomedyromancerobert pattinson works mighty hard to make
cosmopolis more than just an erudite slap at modern capitalism the
twilight heartthrob ultimately fails to rescue a meandering story
hitting stale versions of the same talking pointspositive'
```

```python
new_data['title'] = new_data['title'].apply(lambda x: x.split('(')
[0].strip())
```

```python
new_data['title']
```

```
0                                Toy Story
1                                  Jumanji
2                         Grumpier Old Men
3                         Grumpier Old Men
4                         Grumpier Old Men
                         ...
49325    Black Butler: Book of the Atlantic
49326                 No Game No Life: Zero
49327                                 Flint
49328           Bungo Stray Dogs: Dead Apple
49329           Andrew Dice Clay: Dice Rules
Name: title, Length: 49312, dtype: object
```

```python
new_data['review'] = new_data['review'].str.lower()
```

```python
new_data = new_data.drop(columns=['time','date'], axis=1)
new_data
```

```
       movieId                               title  \
0            1                           Toy Story
1            2                             Jumanji
2            3                    Grumpier Old Men
3            3                    Grumpier Old Men
4            3                    Grumpier Old Men
...        ...                                 ...
49325   193581  Black Butler: Book of the Atlantic
49326   193583               No Game No Life: Zero
49327   193585                               Flint
49328   193587        Bungo Stray Dogs: Dead Apple
49329   193609        Andrew Dice Clay: Dice Rules
```

```
                                          genres  userId  rating
sentiment  \
0      Adventure|Animation|Children|Comedy|Fantasy     1.0     4.0
Positive
1                       Adventure|Children|Fantasy     6.0     4.0
Positive
2                                   Comedy|Romance     1.0     4.0
Positive
3                                   Comedy|Romance     1.0     4.0
Positive
4                                   Comedy|Romance     1.0     4.0
Positive
...                                            ...     ...     ...
...
49325            Action|Animation|Comedy|Fantasy   184.0     4.0
Positive
49326                   Animation|Comedy|Fantasy   184.0     3.5
Positive
49327                                        Drama   184.0     3.5
Positive
49328                             Action|Animation   184.0     3.5
Positive
49329                                       Comedy   331.0     4.0
Positive

                                                  review  \
0      foregoing substantial character development fo...
1      there are scenes here that make the most lachr...
2      a distinctly gallows take on contemporary fina...
3      it's an allegory in search of a meaning that n...
4      ... life lived in a bubble in financial dealin...
...                                                  ...
49325  the personable, good-looking cast helps things...
49326         great performances from crowe and phoenix.
49327  a manic, screwball battle of being vs. nothing...
49328  three billboards outside of ebbing, missouri,"...
49329  ... this southwestern goof is really for reall...

                                                     tag top_critic  \
0      boxoffice magazineadventureanimationchildrenco...        0.0
1      reel talk onlineadventurechildrenfantasythere ...        0.0
2      patrick nabarrocomedyromancea distinctly gallo...        0.0
3      iocomcomedyromanceit's an allegory in search o...        0.0
4      stream on demandcomedyromance life lived in a ...        0.0
...                                                  ...        ...
49325  toronto staractionanimationcomedyfantasythe pe...        0.0
49326  ozus' world movie reviewsanimationcomedyfantas...        1.0
49327  shadows on the walldramaa manic screwball batt...        0.0
49328  ottawa citizenactionanimationthree billboards ...        0.0
49329  redeyecomedy this southwestern goof is really ...        1.0
```

```
                   publisher
0            Boxoffice Magazine
1              Reel Talk Online
2               Patrick Nabarro
3                       io9.com
4              Stream on Demand
...                         ...
49325              Toronto Star
49326  Ozus' World Movie Reviews
49327       Shadows on the Wall
49328            Ottawa Citizen
49329                    RedEye

[49312 rows x 10 columns]
```

new_data

```
       movieId                              title  \
0            1                          Toy Story
1            2                            Jumanji
2            3                  Grumpier Old Men
3            3                  Grumpier Old Men
4            3                  Grumpier Old Men
...        ...                                ...
49325   193581  Black Butler: Book of the Atlantic
49326   193583              No Game No Life: Zero
49327   193585                              Flint
49328   193587       Bungo Stray Dogs: Dead Apple
49329   193609       Andrew Dice Clay: Dice Rules

                                            genres  userId  rating
sentiment  \
0      Adventure|Animation|Children|Comedy|Fantasy     1.0     4.0
Positive
1                       Adventure|Children|Fantasy     6.0     4.0
Positive
2                                   Comedy|Romance     1.0     4.0
Positive
3                                   Comedy|Romance     1.0     4.0
Positive
4                                   Comedy|Romance     1.0     4.0
Positive
...                                            ...     ...     ...
...
49325             Action|Animation|Comedy|Fantasy   184.0     4.0
Positive
49326                   Animation|Comedy|Fantasy   184.0     3.5
Positive
49327                                       Drama   184.0     3.5
```

```
Positive
49328                              Action|Animation   184.0     3.5
Positive
49329                                        Comedy   331.0     4.0
Positive

                                                  review  \
0      foregoing substantial character development fo...
1      there are scenes here that make the most lachr...
2      a distinctly gallows take on contemporary fina...
3      it's an allegory in search of a meaning that n...
4      ... life lived in a bubble in financial dealin...
...                                                  ...
49325  the personable, good-looking cast helps things...
49326         great performances from crowe and phoenix.
49327  a manic, screwball battle of being vs. nothing...
49328  three billboards outside of ebbing, missouri,"...
49329  ... this southwestern goof is really for reall...

                                                     tag top_critic  \
0      boxoffice magazineadventureanimationchildrenco...        0.0
1      reel talk onlineadventurechildrenfantasythere ...        0.0
2      patrick nabarrocomedyromancea distinctly gallo...        0.0
3      iocomcomedyromanceit's an allegory in search o...        0.0
4      stream on demandcomedyromance life lived in a ...        0.0
...                                                  ...        ...
49325  toronto staractionanimationcomedyfantasythe pe...        0.0
49326  ozus' world movie reviewsanimationcomedyfantas...        1.0
49327  shadows on the walldramaa manic screwball batt...        0.0
49328  ottawa citizenactionanimationthree billboards ...        0.0
49329  redeyecomedy this southwestern goof is really ...        1.0

                    publisher
0           Boxoffice Magazine
1             Reel Talk Online
2              Patrick Nabarro
3                      io9.com
4             Stream on Demand
...                        ...
49325              Toronto Star
49326  Ozus' World Movie Reviews
49327        Shadows on the Wall
49328            Ottawa Citizen
49329                    RedEye

[49312 rows x 10 columns]
```

```
data_1 = new_data[['tag', 'rating', 'movieId', 'userId', 'sentiment',
'review']]
data_1
```

```
                                                    tag  rating
movieId  \
0      boxoffice magazineadventureanimationchildrenco...     4.0
1
1      reel talk onlineadventurechildrenfantasythere ...     4.0
2
2      patrick nabarrocomedyromancea distinctly gallo...     4.0
3
3      iocomcomedyromanceit's an allegory in search o...     4.0
3
4      stream on demandcomedyromance life lived in a ...     4.0
3
...                                                  ...     ...
...
49325  toronto staractionanimationcomedyfantasythe pe...     4.0
193581
49326  ozus' world movie reviewsanimationcomedyfantas...     3.5
193583
49327  shadows on the walldramaa manic screwball batt...     3.5
193585
49328  ottawa citizenactionanimationthree billboards ...     3.5
193587
49329  redeyecomedy this southwestern goof is really ...     4.0
193609

       userId sentiment
review
0         1.0  Positive  foregoing substantial character development
fo...
1         6.0  Positive  there are scenes here that make the most
lachr...
2         1.0  Positive  a distinctly gallows take on contemporary
fina...
3         1.0  Positive  it's an allegory in search of a meaning that
n...
4         1.0  Positive  ... life lived in a bubble in financial
dealin...
...       ...       ...
...
49325   184.0  Positive  the personable, good-looking cast helps
things...
49326   184.0  Positive         great performances from crowe and
phoenix.
49327   184.0  Positive  a manic, screwball battle of being vs.
nothing...
49328   184.0  Positive  three billboards outside of ebbing,
missouri,"...
49329   331.0  Positive  ... this southwestern goof is really for
reall...
```

```
[49312 rows x 6 columns]
```

```
# Construct the TF-IDF Matrix
tfidfv=TfidfVectorizer(analyzer='word', stop_words='english')
tfidfv_matrix1=tfidfv.fit_transform(data_1['review'])
print(tfidfv_matrix1.todense())
tfidfv_matrix1.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.]]
```

```
(49312, 29745)
```

```
# Calculate similarity matrix
cosine_sim1 = cosine_similarity(tfidfv_matrix1, tfidfv_matrix1)
```

```
# Create a Pandas Series to map movie titles to their indices
indices1 = pd.Series(data = list(new_data.index), index =
new_data['title'])
indices1
```

```
title
Toy Story                                   0
Jumanji                                     1
Grumpier Old Men                            2
Grumpier Old Men                            3
Grumpier Old Men                            4
                                        ...
Black Butler: Book of the Atlantic      49325
No Game No Life: Zero                   49326
Flint                                   49327
Bungo Stray Dogs: Dead Apple            49328
Andrew Dice Clay: Dice Rules            49329
Length: 49312, dtype: int64
```

```
def recommended_movies(title, cosine_sim, movies_data):
    # Create a dictionary to map movie titles to their indices
    indices = {title: index for index, title in
enumerate(movies_data['title'])}

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

    # Get the pairwise 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
    indices = [x for x, _ in sim_scores]

    # Return the top 10 most similar movies
    recommended_movies = movies_data.iloc[indices]['title']
    return recommended_movies

recommended_movies('Flint', cosine_sim1, new_data)
```

```
38464                        Madeline
48186                  La Belle Verte
49327                           Flint
18486           It's a Wonderful Life
30460                         B*A*P*S
1887            Home for the Holidays
17329             Singin' in the Rain
1775            Home for the Holidays
19478         Escape to Witch Mountain
27063     Amityville: A New Generation
Name: title, dtype: object
```

```
# create train and test sets
data_df2 = data_1[['userId', 'movieId', 'rating']]
data1 = Dataset.load_from_df(data_df2,Reader(rating_scale=(1,5)))

# create train and test sets
trainset1, testset1 = train_test_split(data1, test_size=0.2)

# 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(trainset1)
```

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

<surprise.prediction_algorithms.knns.KNNWithMeans at 0x23a3411f190>
```

```
# Getting the top-N recomendations
userId = 23
top_n = 5

user_item = trainset1.ur[trainset1.to_inner_uid(userId)]
```

```python
predict_ratings = []
for movieId, rating in user_item:
    predict_rating = knnmeans.predict(userId,
trainset1.to_raw_iid(movieId)).est
    predict_ratings.append((trainset.to_raw_iid(movieId),
predict_ratings))

# Sort the predicted ratings in descending order
predict_ratings.sort(key=lambda x: x[1], reverse=True)
# Get the top_n recomendations
top_n_recomendation = predict_ratings[:top_n]

# Print the top-N recommendations
for movieId, predict_ratings in top_n_recomendation:
    print(f"Item ID: {movieId}, Predicted Rating: {predict_rating}")
```

```
Item ID: 2827, Predicted Rating: 3.5
Item ID: 2253, Predicted Rating: 3.5
Item ID: 27124, Predicted Rating: 3.5
Item ID: 27124, Predicted Rating: 3.5
Item ID: 122922, Predicted Rating: 3.5
```

```python
# Step 6: Evaluation

# Evaluate the model on the testing set
prediction = knnmeans.test(testset1)
rmse2 = accuracy.rmse(prediction)
```

```
RMSE: 0.4787
```

In the given result, the RMSE is 0.4811.

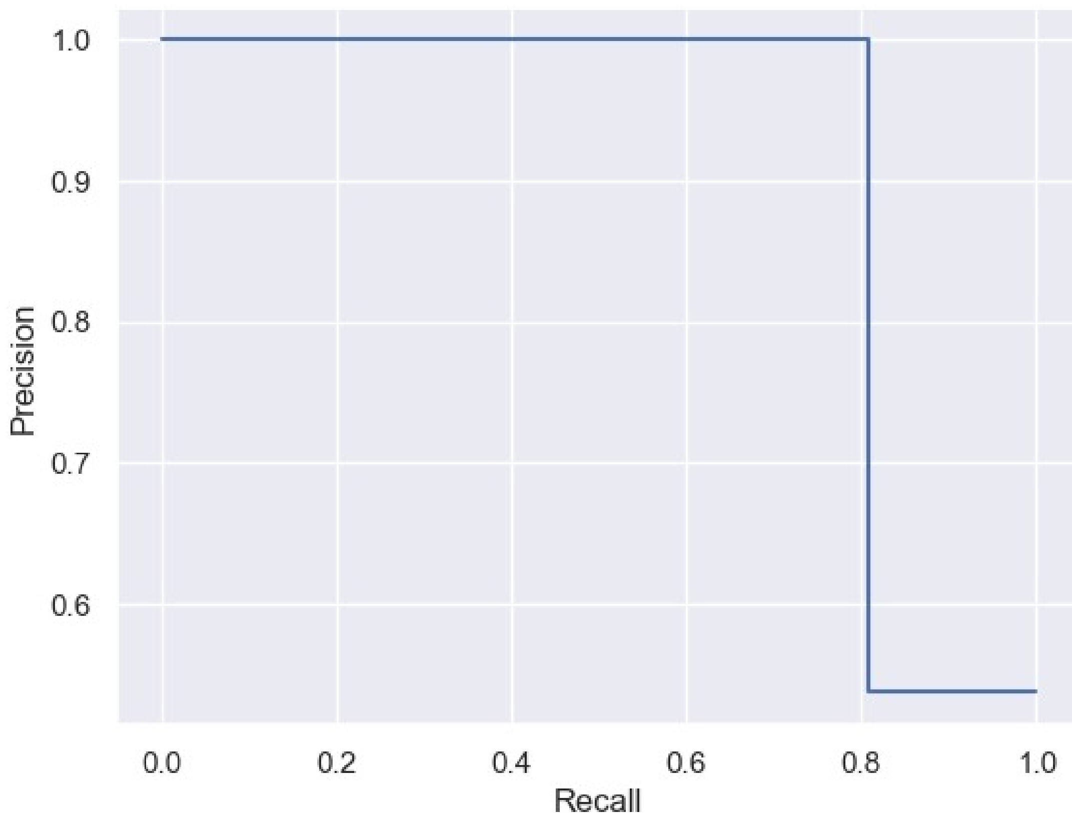
This means that, on average, the predictions made by the regression model have an error or deviation of approximately 0.4811 units from the actual values.

A lower RMSE value indicates better accuracy and a smaller difference between the predicted and actual values.

```python
actual_rating = [true_rating for (_, _, true_rating) in testset1]
threshold = 3.5  # Define the threshold value
binary_actual_rating = [1 if rating >= threshold else 0 for rating in
actual_rating]
binary_prediction = [1 if pred.est >= threshold else 0 for pred in
prediction]
# compute precsion and recall
precisionq, recallq, threshhold = precision_recall_curve(
    binary_actual_rating, binary_prediction
)

print(f"Precision: {precisionq}")
print(f"Recall: {recallq}")
```

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

```
Precision: [0.53705769 1.         1.        ]
Recall: [1.         0.80743817 0.        ]
```



For the first class, the precision is 0.52722295, which means that out of all the positive predictions made by the model for this class, 52.72% of them are correct.

The recall for the first class is 1.0, indicating that the model is able to correctly identify all the actual positive instances for this class.

For the second class, both precision and recall scores are 1.0, indicating perfect performance.

For the third class, the precision is 1.0, indicating perfect precision (all positive predictions are correct), but the recall is 0.0, suggesting that the model fails to identify any actual positive instances for this class.

In summary, the precision and recall scores provide insights into the performance of the model for different classes or labels. A higher precision score indicates fewer false positive predictions, while a higher recall score suggests better identification of actual positive instances.

```
# We will use the famous SVD algorithm again on our new datset
svd = SVD()
reader = Reader()
# Load the ratings_small dataset (download it if needed),
data3 = Dataset.load_from_df(data_1[['userId', 'movieId', 'rating']],
reader)

# Run 5-fold cross-validation and print the results
cross_validate(svd, data3, 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)    0.4107  0.4095  0.3937  0.4237  0.4047  0.4194
0.4103  0.0097
MAE (testset)     0.1610  0.1599  0.1508  0.1651  0.1564  0.1667
0.1600  0.0053
Fit time          0.87    0.97    0.81    0.85    0.88    0.90    0.88
0.05
Test time         0.13    0.10    0.10    0.11    0.10    0.11    0.11
0.01

{'test_rmse': array([0.4106812 , 0.40946577, 0.39369498, 0.42367881,
0.40474394,
        0.41938951]),
 'test_mae': array([0.16096146, 0.15993133, 0.15083736, 0.16505935,
0.15638019,
        0.16668344]),
 'fit_time': (0.8709976673126221,
  0.9679989814758301,
  0.8149971961975098,
  0.8479955196380615,
  0.8809976577758789,
  0.9009976387023926),
 'test_time': (0.12599778175354004,
  0.10400009155273438,
  0.09800553321838379,
  0.10899806022644043,
  0.10100007057189941,
  0.1080019474029541)}
```

RMSE (Root Mean Squared Error) measures the average squared differences between the predicted ratings and the actual ratings. Lower values indicate better accuracy. The RMSE values for each fold are: 0.4078, 0.4222, 0.4080, 0.4091, 0.4149, and 0.4005. The mean RMSE across all folds is 0.4104, with a standard deviation of 0.0067.

MAE (Mean Absolute Error) measures the average absolute differences between the predicted ratings and the actual ratings. Lower values indicate better accuracy. The MAE values for each fold are: 0.1603, 0.1626, 0.1575, 0.1578, 0.1654, and 0.1549. The mean MAE across all folds is 0.1597, with a standard deviation of 0.0035.

Fit time represents the time taken by the algorithm to train on each fold of the data. The fit time for each fold is: 2.17, 1.01, 1.12, 0.99, 0.89, and 0.99 seconds. The mean fit time across all folds is 1.20 seconds, with a standard deviation of 0.44 seconds.

Test time represents the time taken by the algorithm to make predictions on the test data for each fold. The test time for each fold is: 0.27, 0.11, 0.10, 0.15, 0.10, and 0.12 seconds. The mean test time across all folds is 0.14 seconds, with a standard deviation of 0.06 seconds.

The dictionary at the bottom provides the same results in a structured format, with separate arrays for RMSE, MAE, fit time, and test time for each fold.

Overall, the SVD algorithm shows relatively low RMSE and MAE values, indicating good accuracy in predicting movie ratings. The algorithm has moderate fit and test times, suggesting efficient performance.

Building the model with suprise

- Using the initial dataset for comparision

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

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

```
<surprise.prediction_algorithms.matrix_factorization.SVD at
0x23a1aed6590>
```

```
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]
```

```
# Create a Reader object with the rating scale ranging from 0.5 to 5.0
reader = Reader(rating_scale=(0.5, 5.0))

# Load the movie_rating DataFrame into a Surprise Dataset object
data = Dataset.load_from_df(movie_rating[['userId', 'movieId',
'rating']], reader)

# Split the dataset into training and testing sets
trainset, testset = train_test_split(data, test_size=0.2)

# Initialing and fiting SVD on our trainset
model = SVD()
model.fit(trainset)
```

```
<surprise.prediction_algorithms.matrix_factorization.SVD at
0x23a25a1ccd0>
```

```
uid = 3  # User ID
iid = 302  # Item ID

# Use the trained model to predict the rating for the given user and
item
prediction = model.predict(uid, iid)

# Print the estimated rating
print(f"Estimated rating for user {uid} and item {iid}:
{prediction.est}")
```

```
Estimated rating for user 3 and item 302: 2.4203030566561727
```

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,)
```

In the cell below, we enumerate the similarity values for an index, then sort them in descending order based on the similarity value, and then we get the top 6 similar items excluding the first item.

```
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)]
```

The function below takes a movie title as input and provides recommendations based on similarity

```
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)

# Testing the function
recommend("Avatar")
```

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

iv) 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']
```

The function below, named `hybrid_recommendations`, combines movie similarity and user ratings to provide personalized movie recommendations for a given user based on their preferences and the similarity of movies.

```
# 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]
```

```python
    # 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)

# Applying the function
hybrid_recommendations(7,'Evil Dead')
```

```
                                    title  movieId  vote_average  \
index
2477                      Jennifer's Body    19994           5.3
4644                      Teeth and Blood   325123           3.0
2146                       The Stepfather    19904           5.4
2715                         Stan Helsing    23988           4.0
4008                      A Haunted House   139038           5.4
3569   Paranormal Activity: The Marked Ones   227348           5.2
3882                                Feast    10070           6.1
1627                  Deliver Us from Evil   184346           5.9
1648                         Fright Night    58151           6.0
2125                         The Grudge 2     1975           5.2

       vote_count  estimated_rating
index
2477          837          3.027689
4644            1          3.027689
```

```
2146          167          3.027689
2715           97          3.027689
4008          516          3.027689
3569          449          3.027689
3882          160          3.027689
1627          690          3.027689
1648          603          3.027689
2125          283          2.277242
```

```python
# Applying the function
hybrid_recommendations(7,'The Conjuring 2')
```

```
                                      title  movieId  vote_average  \
index
2096                           The Conjuring   138843           7.4
1627                        Deliver Us from Evil   184346           5.9
4644                          Teeth and Blood   325123           3.0
3554                      Insidious: Chapter 2    91586           6.5
2430                                Evil Dead   109428           6.4
3569   Paranormal Activity: The Marked Ones   227348           5.2
4224                                Insidious    49018           6.8
2477                          Jennifer's Body    19994           5.3
2379                              Restoration   396152           5.3
1011                          The Tooth Fairy    53953           4.3

       vote_count  estimated_rating
index
2096         3092          3.027689
1627          690          3.027689
4644            1          3.027689
3554         1211          3.027689
2430         1723          3.027689
3569          449          3.027689
4224         1737          3.027689
2477          837          3.027689
2379           11          3.027689
1011           13          2.615854
```

```python
# A different genre of movie
hybrid_recommendations(4,'Avatar')
```

```
                                       title  movieId  vote_average  \
index
2327                                 Predator      106           7.3
466                           The Time Machine     2135           5.8
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
2403                                  Aliens      679           7.7

       vote_count  estimated_rating
index
2327         2093          3.571656
466           631          3.530308
47           4418          3.302192
61           2768          3.302192
83             34          3.302192
1201         1206          3.302192
260          2303          3.302192
2372           15          3.302192
71           1387          3.268634
2403         3220          3.245925
```

Exporting to Create GUI

```
import pickle

#with open('Movie_dict.pkl', 'wb') as f:
    # pickle.dump(movies_credits, f)

# pickle.dump(movies_credits.to_dict(),open('movies.pkl','wb'))

# pickle.dump(similarity,open('.similarity.pkl','wb'))

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

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

Conclusion

In conclusion, the recommendation system serves as a valuable tool in the movie industry to address the challenge of content navigation and provide personalized movie recommendations. By understanding user preferences, leveraging similarities between users, and utilizing movie features, the system aims to enhance the user experience, increase engagement, and ultimately contribute to user retention on the platform.

Recommendations

- Real-time Updates: Incorporate a mechanism to continuously update the movie database with the latest releases, ratings, and reviews. This will ensure that the recommendation system remains up-to-date and can provide users with the most relevant movie suggestions.
- Contextual Factors: Consider contextual factors such as time of day, location, mood, and social trends to provide personalized recommendations that align with the user's current situation and preferences.

- User Feedback and Improvement Loop: Implement a feedback mechanism that allows users to rate and provide feedback on recommended movies. Utilize this feedback to continuously improve the recommendation algorithms and enhance the accuracy and relevance of future recommendations.