CSE_351_Final_Project

May 10, 2023

[335]:
```
# Movie folder: https://drive.google.com/drive/folders/
 ↪13JVx5e_zP5ZKrpDk_yFWKa76XebMhTzG?usp=sharing
# Save the movie folder to Google Drive before run the following code

# from google.colab import drive
# drive.mount('/content/drive')
```

[336]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from datetime import datetime
import os
import colorsys
import ast
from sklearn.model_selection import train_test_split, cross_val_score
from sklearn.linear_model import LinearRegression, LogisticRegression
from sklearn.metrics import mean_squared_error,f1_score, confusion_matrix,␣
 ↪accuracy_score
from scipy.stats import percentileofscore
from sklearn.neighbors import KNeighborsClassifier

pd.options.display.max_colwidth = 100
```

[337]:
```
# Load CSV files
# movie_fdr_path = '/content/drive/MyDrive/movie'
# credit_df = pd.read_csv(os.path.join(movie_fdr_path, 'tmdb_5000_credits.csv'))
# movie_df = pd.read_csv(os.path.join(movie_fdr_path, 'tmdb_5000_movies.csv'))
credit_df = pd.read_csv('tmdb_5000_credits.csv')
movie_df = pd.read_csv('tmdb_5000_movies.csv')
```

1 Data Munging

1.1 Data info

[338]:
```
credit_df.head()
```

[338]:
```
   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

                  cast  \
0  [{"cast_id": 242, "character": "Jake Sully", "credit_id":
"5602a8a7c3a3685532001c9a", "gender": …
1  [{"cast_id": 4, "character": "Captain Jack Sparrow", "credit_id":
"52fe4232c3a36847f800b50d", "g…
2  [{"cast_id": 1, "character": "James Bond", "credit_id":
"52fe4d22c3a368484e1d8d6b", "gender": 2,…
3  [{"cast_id": 2, "character": "Bruce Wayne / Batman", "credit_id":
"52fe4781c3a36847f8139869", "g…
4  [{"cast_id": 5, "character": "John Carter", "credit_id":
"52fe479ac3a36847f813ea75", "gender": 2…

                  crew
0  [{"credit_id": "52fe48009251416c750aca23", "department": "Editing", "gender":
0, "id": 1721, "jo…
1  [{"credit_id": "52fe4232c3a36847f800b579", "department": "Camera", "gender":
2, "id": 120, "job"…
2  [{"credit_id": "54805967c3a36829b5002c41", "department": "Sound", "gender":
2, "id": 153, "job":…
3  [{"credit_id": "52fe4781c3a36847f81398c3", "department": "Sound", "gender":
2, "id": 947, "job":…
4  [{"credit_id": "52fe479ac3a36847f813eaa3", "department": "Writing", "gender":
2, "id": 7, "job":…
```

[339]:
```
credit_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4803 entries, 0 to 4802
Data columns (total 4 columns):
 #   Column    Non-Null Count  Dtype
---  ------    --------------  -----
 0   movie_id  4803 non-null   int64
 1   title     4803 non-null   object
 2   cast      4803 non-null   object
 3   crew      4803 non-null   object
```

```
dtypes: int64(1), object(3)
memory usage: 150.2+ KB
```

[340]:
```
movie_df.head()
```

[340]:
```
      budget  \
0  237000000
1  300000000
2  245000000
3  250000000
4  260000000

                genres  \
0  [{"id": 28, "name": "Action"}, {"id": 12, "name": "Adventure"}, {"id": 14,
"name": "Fantasy"}, {…
1       [{"id": 12, "name": "Adventure"}, {"id": 14, "name": "Fantasy"}, {"id":
28, "name": "Action"}]
2         [{"id": 28, "name": "Action"}, {"id": 12, "name": "Adventure"}, {"id":
80, "name": "Crime"}]
3  [{"id": 28, "name": "Action"}, {"id": 80, "name": "Crime"}, {"id": 18,
"name": "Drama"}, {"id": …
4  [{"id": 28, "name": "Action"}, {"id": 12, "name": "Adventure"}, {"id": 878,
"name": "Science Fic…

                                       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

               keywords  \
0  [{"id": 1463, "name": "culture clash"}, {"id": 2964, "name": "future"},
{"id": 3386, "name": "sp…
1  [{"id": 270, "name": "ocean"}, {"id": 726, "name": "drug abuse"}, {"id": 911,
"name": "exotic is…
2  [{"id": 470, "name": "spy"}, {"id": 818, "name": "based on novel"}, {"id":
4289, "name": "secret…
3  [{"id": 849, "name": "dc comics"}, {"id": 853, "name": "crime fighter"},
{"id": 949, "name": "te…
4  [{"id": 818, "name": "based on novel"}, {"id": 839, "name": "mars"}, {"id":
1456, "name": "medal…

  original_language                             original_title  \
0                en                                     Avatar
1                en  Pirates of the Caribbean: At World's End
2                en                                    Spectre
```

```
3                en                      The Dark Knight Rises
4                en                                John Carter

                                                  overview  \
0  In the 22nd century, a paraplegic Marine is dispatched to the moon Pandora on
a unique mission, …
1  Captain Barbossa, long believed to be dead, has come back to life and is
headed to the edge of t…
2  A cryptic message from Bond’s past sends him on a trail to uncover a sinister
organization. Whil…
3  Following the death of District Attorney Harvey Dent, Batman assumes
responsibility for Dent's c…
4  John Carter is a war-weary, former military captain who's inexplicably
transported to the myster…

   popularity  \
0  150.437577
1  139.082615
2  107.376788
3  112.312950
4   43.926995

                                production_companies  \
0  [{"name": "Ingenious Film Partners", "id": 289}, {"name": "Twentieth Century
Fox Film Corporatio…
1  [{"name": "Walt Disney Pictures", "id": 2}, {"name": "Jerry Bruckheimer
Films", "id": 130}, {"na…
2  [{"name": "Columbia Pictures", "id": 5}, {"name": "Danjaq", "id": 10761},
{"name": "B24", "id": …
3  [{"name": "Legendary Pictures", "id": 923}, {"name": "Warner Bros.", "id":
6194}, {"name": "DC E…
4                                                    [{"name": "Walt
Disney Pictures", "id": 2}]

                                production_countries  \
0  [{"iso_3166_1": "US", "name": "United States of America"}, {"iso_3166_1":
"GB", "name": "United …
1                                        [{"iso_3166_1": "US", "name":
"United States of America"}]
2  [{"iso_3166_1": "GB", "name": "United Kingdom"}, {"iso_3166_1": "US", "name":
"United States of …
3                                        [{"iso_3166_1": "US", "name":
"United States of America"}]
4                                        [{"iso_3166_1": "US", "name":
"United States of America"}]

  release_date     revenue  runtime  \
```

```
0   2009-12-10  2787965087    162.0
1   2007-05-19   961000000    169.0
2   2015-10-26   880674609    148.0
3   2012-07-16  1084939099    165.0
4   2012-03-07   284139100    132.0

      spoken_languages  \
0               [{"iso_639_1": "en", "name": "English"}, {"iso_639_1": "es",
"name": "Espa\u00f1ol"}]
1                                                                  [{"iso_639_1":
"en", "name": "English"}]
2  [{"iso_639_1": "fr", "name": "Fran\u00e7ais"}, {"iso_639_1": "en", "name":
"English"}, {"iso_639…
3                                                                  [{"iso_639_1":
"en", "name": "English"}]
4                                                                  [{"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.

                                  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
```

[341]:
```
movie_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4803 entries, 0 to 4802
Data columns (total 20 columns):
 #   Column                Non-Null Count  Dtype
---  ------                --------------  -----
 0   budget                4803 non-null   int64
 1   genres                4803 non-null   object
 2   homepage              1712 non-null   object
 3   id                    4803 non-null   int64
 4   keywords              4803 non-null   object
 5   original_language     4803 non-null   object
 6   original_title        4803 non-null   object
 7   overview              4800 non-null   object
```

```
 8   popularity            4803 non-null   float64
 9   production_companies  4803 non-null   object
 10  production_countries  4803 non-null   object
 11  release_date          4802 non-null   object
 12  revenue               4803 non-null   int64
 13  runtime               4801 non-null   float64
 14  spoken_languages      4803 non-null   object
 15  status                4803 non-null   object
 16  tagline               3959 non-null   object
 17  title                 4803 non-null   object
 18  vote_average          4803 non-null   float64
 19  vote_count            4803 non-null   int64
dtypes: float64(3), int64(4), object(13)
memory usage: 750.6+ KB
```

[342]:
```
credit_df.describe()
```

[342]:

	movie_id
count	4803.000000
mean	57165.484281
std	88694.614033
min	5.000000
25%	9014.500000
50%	14629.000000
75%	58610.500000
max	459488.000000

[343]:
```
movie_df.describe()
```

[343]:

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

1.2 Merge datasets

[344]:
```
merged_df = pd.merge(movie_df, credit_df, left_on='id', right_on="movie_id")
```

[345]:
```
merged_df = merged_df.drop("movie_id", axis=1)
```

[346]:
```
merged_df.head()
```

[346]:
```
      budget  \
0  237000000
1  300000000
2  245000000
3  250000000
4  260000000

                genres  \
0  [{"id": 28, "name": "Action"}, {"id": 12, "name": "Adventure"}, {"id": 14,
"name": "Fantasy"}, {…
1       [{"id": 12, "name": "Adventure"}, {"id": 14, "name": "Fantasy"}, {"id":
28, "name": "Action"}]
2         [{"id": 28, "name": "Action"}, {"id": 12, "name": "Adventure"}, {"id":
80, "name": "Crime"}]
3  [{"id": 28, "name": "Action"}, {"id": 80, "name": "Crime"}, {"id": 18,
"name": "Drama"}, {"id": …
4  [{"id": 28, "name": "Action"}, {"id": 12, "name": "Adventure"}, {"id": 878,
"name": "Science Fic…

                                       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

              keywords  \
0  [{"id": 1463, "name": "culture clash"}, {"id": 2964, "name": "future"},
{"id": 3386, "name": "sp…
1  [{"id": 270, "name": "ocean"}, {"id": 726, "name": "drug abuse"}, {"id": 911,
"name": "exotic is…
2  [{"id": 470, "name": "spy"}, {"id": 818, "name": "based on novel"}, {"id":
4289, "name": "secret…
3  [{"id": 849, "name": "dc comics"}, {"id": 853, "name": "crime fighter"},
{"id": 949, "name": "te…
4  [{"id": 818, "name": "based on novel"}, {"id": 839, "name": "mars"}, {"id":
1456, "name": "medal…
```

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

                                            overview  \
0  In the 22nd century, a paraplegic Marine is dispatched to the moon Pandora on
a unique mission, …
1  Captain Barbossa, long believed to be dead, has come back to life and is
headed to the edge of t…
2  A cryptic message from Bond’s past sends him on a trail to uncover a sinister
organization. Whil…
3  Following the death of District Attorney Harvey Dent, Batman assumes
responsibility for Dent's c…
4  John Carter is a war-weary, former military captain who's inexplicably
transported to the myster…

   popularity  \
0  150.437577
1  139.082615
2  107.376788
3  112.312950
4   43.926995

  production_companies  \
0  [{"name": "Ingenious Film Partners", "id": 289}, {"name": "Twentieth Century
Fox Film Corporatio…
1  [{"name": "Walt Disney Pictures", "id": 2}, {"name": "Jerry Bruckheimer
Films", "id": 130}, {"na…
2  [{"name": "Columbia Pictures", "id": 5}, {"name": "Danjaq", "id": 10761},
{"name": "B24", "id": …
3  [{"name": "Legendary Pictures", "id": 923}, {"name": "Warner Bros.", "id":
6194}, {"name": "DC E…
4                                                  [{"name": "Walt
Disney Pictures", "id": 2}]

   … runtime  \
0  …   162.0
1  …   169.0
2  …   148.0
3  …   165.0
4  …   132.0

      spoken_languages  \
```

```
0                [{"iso_639_1": "en", "name": "English"}, {"iso_639_1": "es",
"name": "Espa\u00f1ol"}]
1                                                                  [{"iso_639_1":
"en", "name": "English"}]
2  [{"iso_639_1": "fr", "name": "Fran\u00e7ais"}, {"iso_639_1": "en", "name":
"English"}, {"iso_639…
3                                                                  [{"iso_639_1":
"en", "name": "English"}]
4                                                                  [{"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.

                                 title_x 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

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

                cast  \
0  [{"cast_id": 242, "character": "Jake Sully", "credit_id":
"5602a8a7c3a3685532001c9a", "gender": …
1  [{"cast_id": 4, "character": "Captain Jack Sparrow", "credit_id":
"52fe4232c3a36847f800b50d", "g…
2  [{"cast_id": 1, "character": "James Bond", "credit_id":
"52fe4d22c3a368484e1d8d6b", "gender": 2,…
3  [{"cast_id": 2, "character": "Bruce Wayne / Batman", "credit_id":
"52fe4781c3a36847f8139869", "g…
4  [{"cast_id": 5, "character": "John Carter", "credit_id":
"52fe479ac3a36847f813ea75", "gender": 2…

                crew
0  [{"credit_id": "52fe48009251416c750aca23", "department": "Editing", "gender":
0, "id": 1721, "jo…
```

```
1  [{"credit_id": "52fe4232c3a36847f800b579", "department": "Camera", "gender":
2, "id": 120, "job"…
2  [{"credit_id": "54805967c3a36829b5002c41", "department": "Sound", "gender":
2, "id": 153, "job":…
3  [{"credit_id": "52fe4781c3a36847f81398c3", "department": "Sound", "gender":
2, "id": 947, "job":…
4  [{"credit_id": "52fe479ac3a36847f813eaa3", "department": "Writing", "gender":
2, "id": 7, "job":…

[5 rows x 23 columns]
```

[347]:
```
merged_df.columns
```

[347]:
```
Index(['budget', 'genres', 'homepage', 'id', 'keywords', 'original_language',
       'original_title', 'overview', 'popularity', 'production_companies',
       'production_countries', 'release_date', 'revenue', 'runtime',
       'spoken_languages', 'status', 'tagline', 'title_x', 'vote_average',
       'vote_count', 'title_y', 'cast', 'crew'],
      dtype='object')
```

1.3 Clean data

[348]:
```
print(merged_df.isnull().sum())
```

```
budget                     0
genres                     0
homepage                3091
id                         0
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
title_x                    0
vote_average               0
vote_count                 0
title_y                    0
cast                       0
crew                       0
```

```
dtype: int64
```

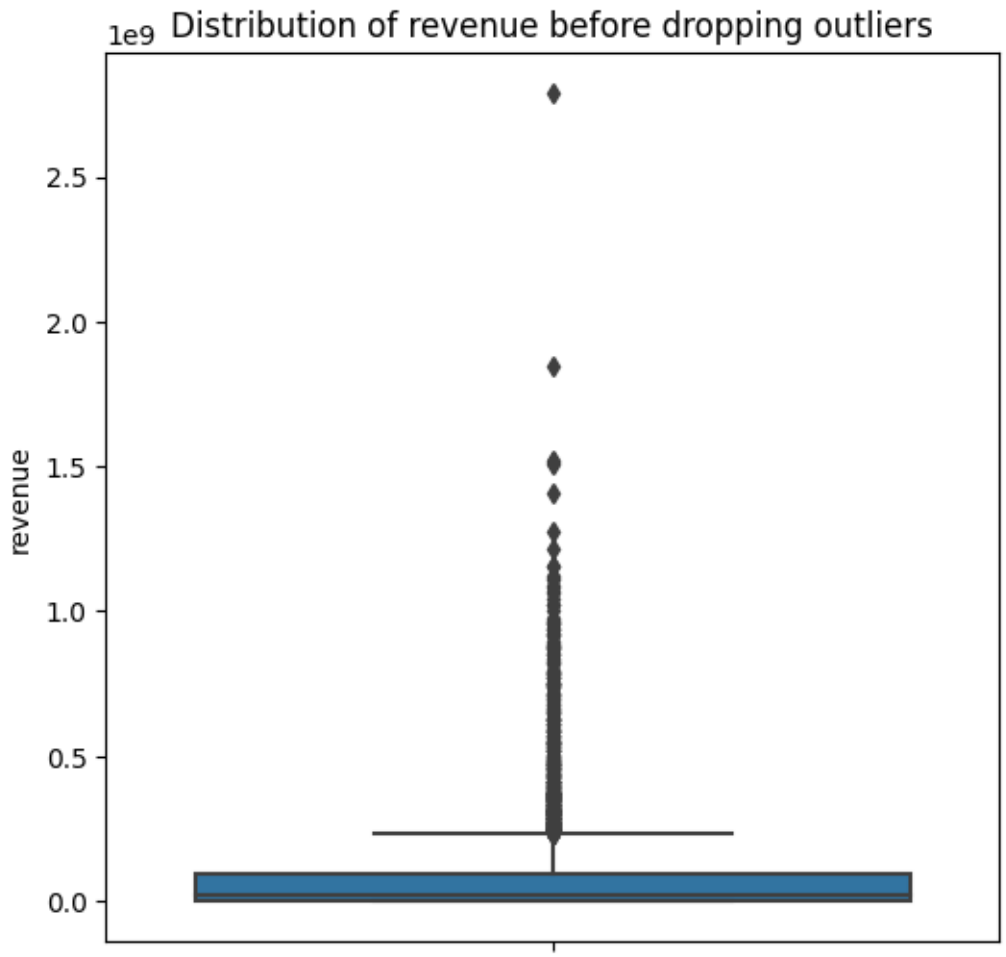
[349]:
```
# the missing data of homepage is 64%, so we can drop this column.
# the missing data of the tagline is 17.5%, so we also want to drop this column.
# and I drop the rows that cotain NA value in runtime, release_date, and overview
merged_df = merged_df.drop(['homepage', 'tagline'], axis=1)
merged_df = merged_df.dropna(subset=['runtime', 'release_date', 'overview'])
print(merged_df.isnull().sum())
```

```
budget                  0
genres                  0
id                      0
keywords                0
original_language       0
original_title          0
overview                0
popularity              0
production_companies    0
production_countries    0
release_date            0
revenue                 0
runtime                 0
spoken_languages        0
status                  0
title_x                 0
vote_average            0
vote_count              0
title_y                 0
cast                    0
crew                    0
dtype: int64
```

[350]:
```
#check duplication
print("movie duplicated: ",merged_df.duplicated().sum())
```

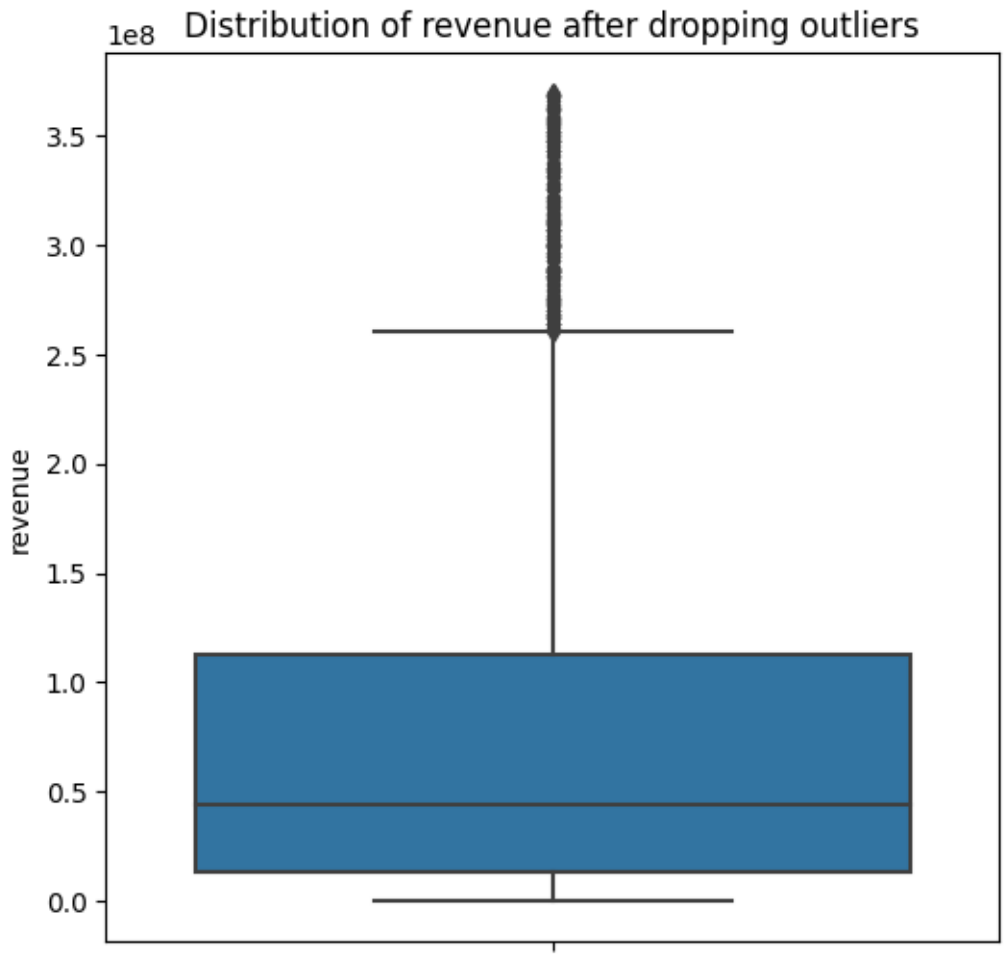
```
movie duplicated:  0
```

[351]:
```
#check outlier
plt.figure(figsize=(6,6))
sns.boxplot(y=movie_df['revenue'])
plt.title("Distribution of revenue before dropping outliers")
plt.show()
```

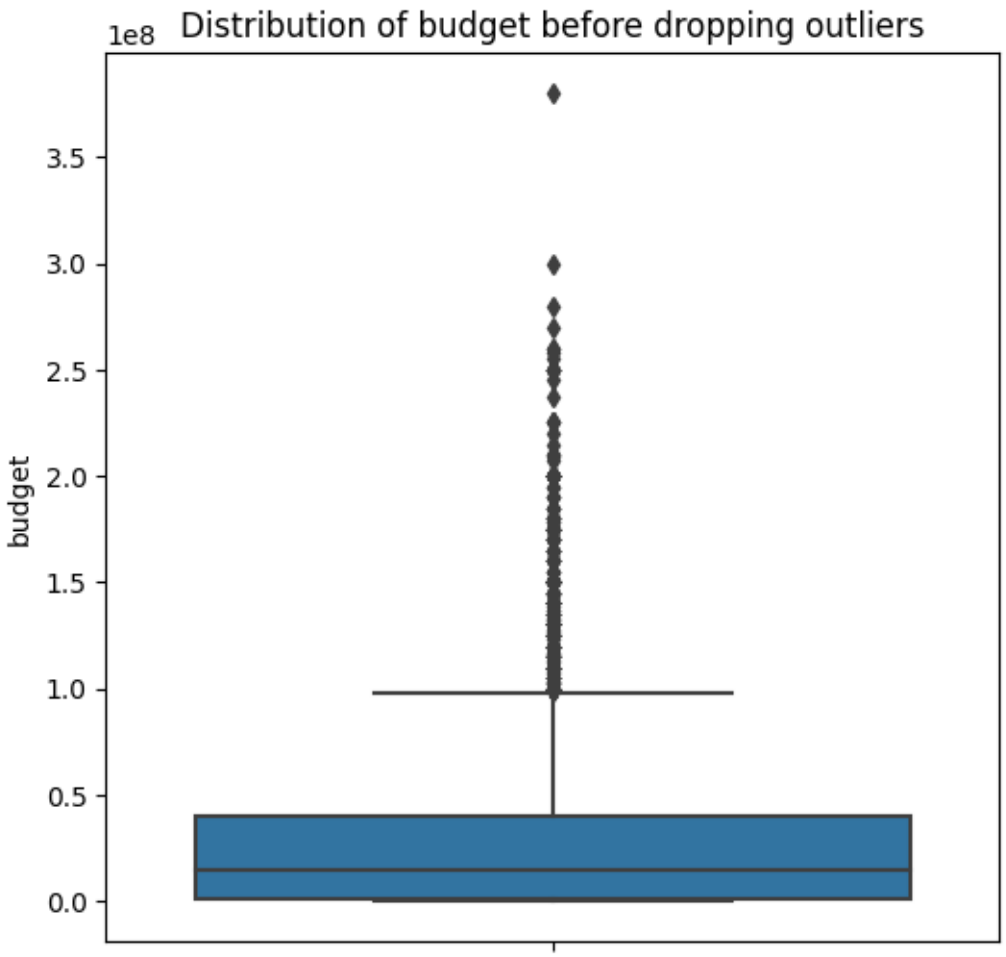


[352]:
```
# the highest thresold
max_thresold = merged_df['revenue'].quantile(0.95)
# the lowest thresold
min_thresold = merged_df['revenue'].quantile(0.05)
# only keep the data with price between the highest thresold and lowest threso
merged_df = merged_df[(merged_df['revenue'] < max_thresold) &␣
 ↪(merged_df['revenue'] > min_thresold)]
```

[353]:
```
# figure of the distribution of price with data after dropping outliers
plt.figure(figsize=(6,6))
sns.boxplot(y=merged_df['revenue'])
plt.title("Distribution of revenue after dropping outliers")
plt.show()
```

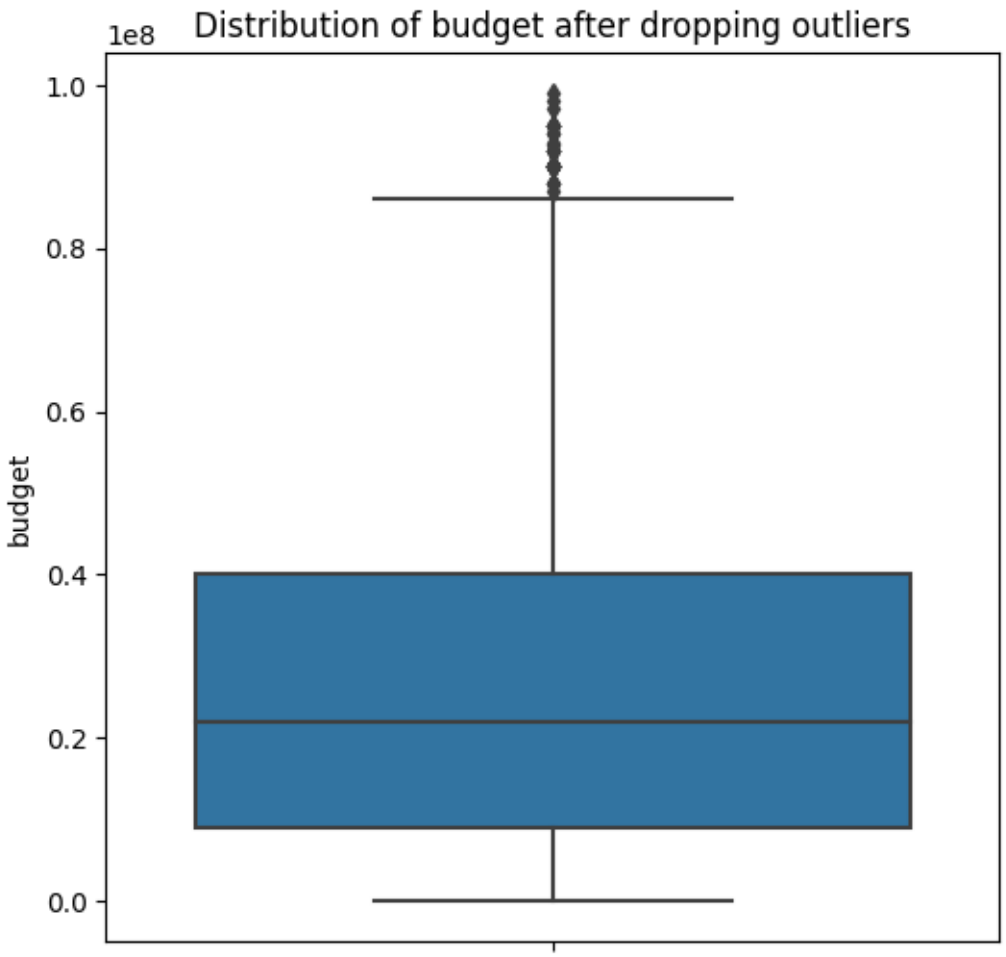


[354]:
```
#check outlier
plt.figure(figsize=(6,6))
sns.boxplot(y=movie_df['budget'])
plt.title("Distribution of budget before dropping outliers")
plt.show()
```

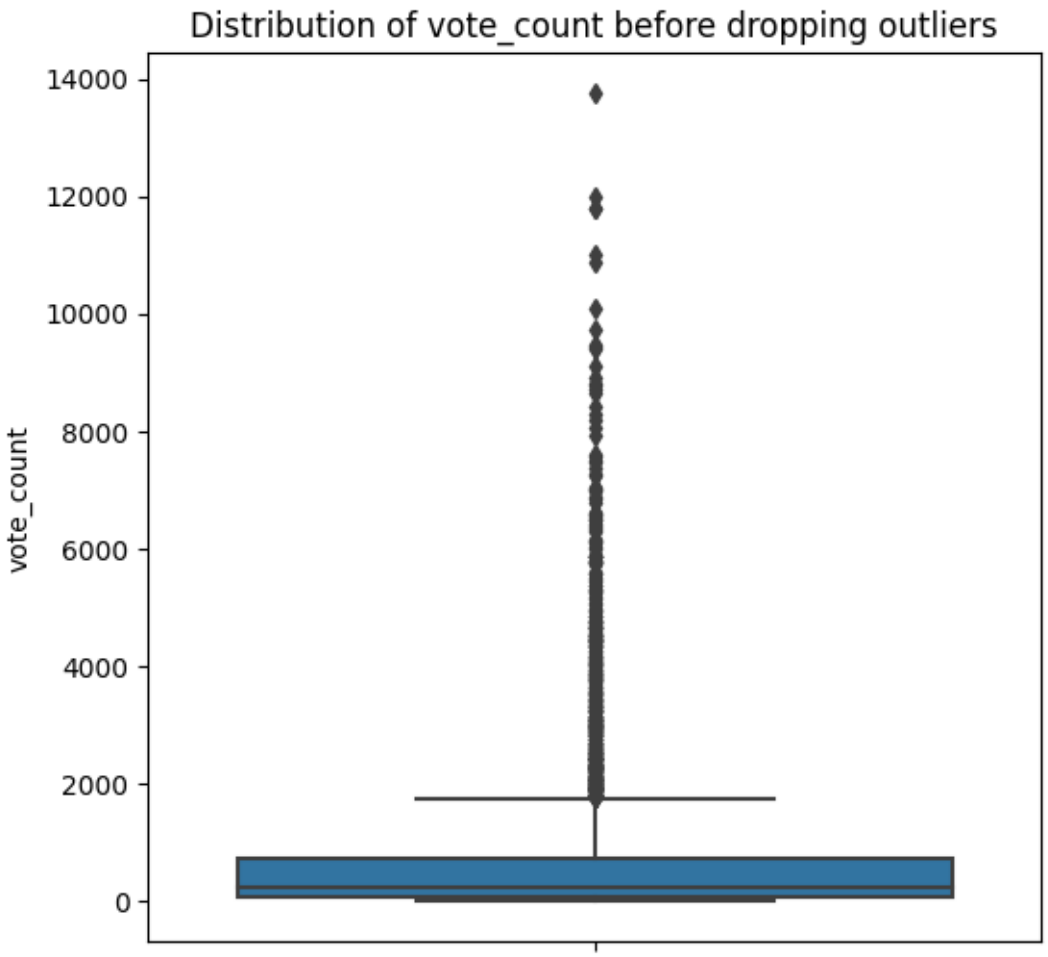


[355]:
```
# the highest thresold
max_thresold = merged_df['budget'].quantile(0.95)
# the lowest thresold
min_thresold = merged_df['budget'].quantile(0.05)
# only keep the data with price between the highest thresold and lowest threso
merged_df = merged_df[(merged_df['budget'] < max_thresold) &␣
 ↪(merged_df['budget'] > min_thresold)]
```

[356]:
```
# figure of the distribution of price with data after dropping outliers
plt.figure(figsize=(6,6))
sns.boxplot(y=merged_df['budget'])
plt.title("Distribution of budget after dropping outliers")
plt.show()
```

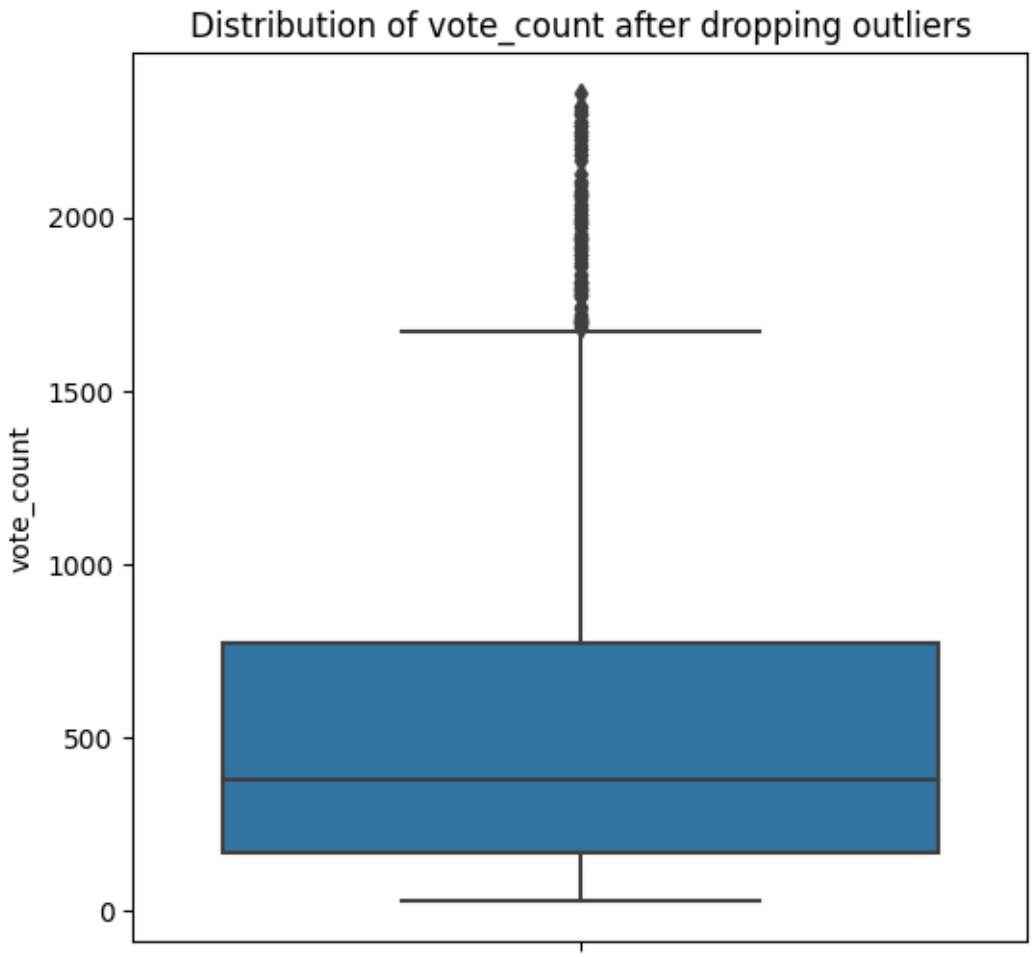


[357]:
```
#check outlier
plt.figure(figsize=(6,6))
sns.boxplot(y=movie_df['vote_count'])
plt.title("Distribution of vote_count before dropping outliers")
plt.show()
```



[358]:
```
# the highest thresold
max_thresold = merged_df['vote_count'].quantile(0.95)
# the lowest thresold
min_thresold = merged_df['vote_count'].quantile(0.05)
# only keep the data with price between the highest thresold and lowest threso
merged_df = merged_df[(merged_df['vote_count'] < max_thresold) &␣
 ↪(merged_df['vote_count'] > min_thresold)]
```

[359]:
```
# figure of the distribution of price with data after dropping outliers
plt.figure(figsize=(6,6))
sns.boxplot(y=merged_df['vote_count'])
plt.title("Distribution of vote_count after dropping outliers")
plt.show()
```



[360]:
```
merged_df
```

[360]:
```
         budget  \
97     15000000
151    70000000
207    65000000
235    97250400
273    90000000
…           …
4773      27000
4788      12000
4792      20000
4796       7000
4798     220000

                    genres  \
97    [{"id": 28, "name": "Action"}, {"id": 12, "name": "Adventure"}, {"id": 18,
```

```
"name": "Drama"}, {"i…
151      [{"id": 12, "name": "Adventure"}, {"id": 28, "name": "Action"}, {"id":
16, "name": "Animation"}]
207   [{"id": 28, "name": "Action"}, {"id": 12, "name": "Adventure"}, {"id":
878, "name": "Science Fic…
235   [{"id": 14, "name": "Fantasy"}, {"id": 12, "name": "Adventure"}, {"id":
35, "name": "Comedy"}, {…
273           [{"id": 28, "name": "Action"}, {"id": 80, "name": "Crime"}, {"id":
53, "name": "Thriller"}]
…
…
4773
[{"id": 35, "name": "Comedy"}]
4788            [{"id": 27, "name": "Horror"}, {"id": 35, "name": "Comedy"},
{"id": 80, "name": "Crime"}]
4792  [{"id": 80, "name": "Crime"}, {"id": 27, "name": "Horror"}, {"id": 9648,
"name": "Mystery"}, {"i…
4796  [{"id": 878, "name": "Science Fiction"}, {"id": 18, "name": "Drama"},
{"id": 53, "name": "Thrill…
4798          [{"id": 28, "name": "Action"}, {"id": 80, "name": "Crime"}, {"id":
53, "name": "Thriller"}]

          id  \
97    315011
151     2310
207      861
235     2395
273     9679
…       …
4773    2292
4788     692
4792   36095
4796   14337
4798    9367

                keywords  \
97    [{"id": 1299, "name": "monster"}, {"id": 7671, "name": "godzilla"}, {"id":
11100, "name": "giant…
151   [{"id": 509, "name": "denmark"}, {"id": 2037, "name": "nordic mythology"},
{"id": 2251, "name": …
207   [{"id": 560, "name": "oxygen"}, {"id": 769, "name": "falsely accused"},
{"id": 836, "name": "res…
235   [{"id": 271, "name": "competition"}, {"id": 1200, "name": "greece"},
{"id": 1396, "name": "colos…
273   [{"id": 380, "name": "brother brother relationship"}, {"id": 703, "name":
"detective"}, {"id": 8…
…
```

…
4773 [{"id": 1361, "name": "salesclerk"}, {"id": 3090, "name": "loser"}, {"id":
179430, "name": "afte…
4788 [{"id": 237, "name": "gay"}, {"id": 900, "name": "trailer park"}, {"id":
1740, "name": "pop cult…
4792 [{"id": 233, "name": "japan"}, {"id": 549, "name": "prostitute"}, {"id":
612, "name": "hotel"}, …
4796 [{"id": 1448, "name": "distrust"}, {"id": 2101, "name": "garage"}, {"id":
3394, "name": "identit…
4798 [{"id": 5616, "name": "united states\u2013mexico barrier"}, {"id": 33649,
"name": "legs"}, {"id"…

     original_language   original_title \
97   ja
151   en   Beowulf
207   en   Total Recall
235   fr Astérix aux Jeux Olympiques
273   en   Gone in Sixty Seconds
…   …   …
4773   en   Clerks
4788   en   Pink Flamingos
4792   ja
4796   en   Primer
4798   es   El Mariachi

                 overview \
97   From the mind behind Evangelion comes a hit larger than life. When a
massive, gilled monster em…
151   6th-century Scandinavian warrior, Beowulf embarks on a mission to slay the
manlike ogre Grendel,…
207   Construction worker Douglas Quaid discovers a memory chip in his brain
during a virtual-reality …
235   Astérix and Obélix have to win the Olympic Games in order to help their
friend Alafolix marry Pr…
273   Upon learning that he has to come out of retirement to steal 50 cars in
one night to save his br…
…
…
4773 Convenience and video store clerks Dante and Randal are sharp-witted,
potty-mouthed and bored ou…
4788 Notorious Baltimore criminal and underground figure Divine goes up against
Connie & Raymond …
4792 A wave of gruesome murders is sweeping Tokyo. The only connection is a
bloody X carved into the …
4796 Friends/fledgling entrepreneurs invent a device in their garage that
reduces the apparent mass o…
4798 El Mariachi just wants to play his guitar and carry on the family

```
tradition. Unfortunately, the …

      popularity  \
97      9.476999
151    35.601665
207    43.129703
235    20.344364
273    52.995628
…          …
4773   19.748658
4788    4.553644
4792    0.212443
4796   23.307949
4798   14.269792

     production_companies  \
97                           [{"name": "Cine Bazar", "id": 5896}, {"name": "Toho
Pictures", "id": 49301}]
151   [{"name": "Paramount Pictures", "id": 4}, {"name": "Shangri-La
Entertainment", "id": 2265}, {"na…
207   [{"name": "TriStar Pictures", "id": 559}, {"name": "Carolco Pictures",
"id": 14723}, {"name": "C…
235   [{"name": "Constantin Film", "id": 47}, {"name": "TF1 Films Productions",
"id": 356}, {"name": "…
273         [{"name": "Jerry Bruckheimer Films", "id": 130}, {"name":
"Touchstone Pictures", "id": 9195}]
…
…
4773               [{"name": "Miramax Films", "id": 14}, {"name": "View Askew
Productions", "id": 16934}]
4788                                                    [{"name": "Dreamland
Productions", "id": 407}]
4792                                                       [{"name":
"Daiei Studios", "id": 881}]
4796                                                           [{"name":
"Thinkfilm", "id": 446}]
4798                                                    [{"name":
"Columbia Pictures", "id": 5}]

     production_countries  \
97
[{"iso_3166_1": "JP", "name": "Japan"}]
151                                          [{"iso_3166_1": "US", "name":
"United States of America"}]
207                                          [{"iso_3166_1": "US", "name":
"United States of America"}]
235   [{"iso_3166_1": "BE", "name": "Belgium"}, {"iso_3166_1": "FR", "name":
```

```
"France"}, {"iso_3166_1":…
273                                          [{"iso_3166_1": "US", "name":
"United States of America"}]
…
…
4773                                         [{"iso_3166_1": "US", "name":
"United States of America"}]
4788                                         [{"iso_3166_1": "US", "name":
"United States of America"}]
4792
[{"iso_3166_1": "JP", "name": "Japan"}]
4796                                         [{"iso_3166_1": "US", "name":
"United States of America"}]
4798   [{"iso_3166_1": "MX", "name": "Mexico"}, {"iso_3166_1": "US", "name":
"United States of America"}]

      …    revenue  runtime  \
97    …   77000000    120.0
151   …  195735876    115.0
207   …  261317921    113.0
235   …  132900000    116.0
273   …  237202299    118.0
…   …        …      …
4773  …    3151130     92.0
4788  …    6000000     93.0
4792  …      99000    111.0
4796  …     424760     77.0
4798  …    2040920     81.0

         spoken_languages  \
97    [{"iso_639_1": "it", "name": "Italiano"}, {"iso_639_1": "de", "name":
"Deutsch"}, {"iso_639_1": …
151                                                        [{"iso_639_1":
"en", "name": "English"}]
207                                                        [{"iso_639_1":
"en", "name": "English"}]
235         [{"iso_639_1": "fr", "name": "Fran\u00e7ais"}, {"iso_639_1": "pt",
"name": "Portugu\u00eas"}]
273                                                        [{"iso_639_1":
"en", "name": "English"}]
…
…
4773                                                       [{"iso_639_1":
"en", "name": "English"}]
4788                                                       [{"iso_639_1":
"en", "name": "English"}]
4792                                                [{"iso_639_1": "ja",
```

```
"name": "\u65e5\u672c\u8a9e"}]
4796                                                                [{"iso_639_1":
"en", "name": "English"}]
4798                                                             [{"iso_639_1": "es",
"name": "Espa\u00f1ol"}]

       status                       title_x vote_average  vote_count  \
97    Released                 Shin Godzilla          6.5         143
151   Released                       Beowulf          5.5         841
207   Released                  Total Recall          7.1        1710
235   Released  Asterix at the Olympic Games          5.0         471
273   Released         Gone in Sixty Seconds          6.1        1485
…        …                               …          …          …
4773  Released                        Clerks          7.4         755
4788  Released                Pink Flamingos          6.2         110
4792  Released                          Cure          7.4          63
4796  Released                        Primer          6.9         658
4798  Released                   El Mariachi          6.6         238

                          title_y  \
97                   Shin Godzilla
151                        Beowulf
207                   Total Recall
235   Asterix at the Olympic Games
273          Gone in Sixty Seconds
…                              …
4773                        Clerks
4788                Pink Flamingos
4792                          Cure
4796                        Primer
4798                   El Mariachi

                     cast  \
97    [{"cast_id": 4, "character": "Rando Yaguchi : Deputy Chief Cabinet
Secretary", "credit_id": "560…
151   [{"cast_id": 24, "character": "Beowulf / Golden Man / Dragon",
"credit_id": "52fe434cc3a36847f80…
207   [{"cast_id": 23, "character": "Douglas Quaid/Hauser", "credit_id":
"52fe4283c3a36847f8024e9b", "…
235   [{"cast_id": 15, "character": "Asterix", "credit_id":
"52fe4354c3a36847f804c0c1", "gender": 2, "…
273   [{"cast_id": 1, "character": "Randall 'Memphis' Raines", "credit_id":
"52fe451ac3a36847f80bc977"…
…
…
4773  [{"cast_id": 7, "character": "Dante Hicks", "credit_id":
"52fe434bc3a36847f8049275", "gender": 2…
```

```
4788  [{"cast_id": 8, "character": "Divine / Babs Johnson", "credit_id":
"52fe426bc3a36847f801d22b", "…
4792  [{"cast_id": 3, "character": "Kenichi Takabe", "credit_id":
"52fe45cc9251416c9103eb85", "gender"…
4796  [{"cast_id": 1, "character": "Aaron", "credit_id":
"52fe45e79251416c75066787", "gender": 2, "id"…
4798  [{"cast_id": 1, "character": "El Mariachi", "credit_id":
"52fe44eec3a36847f80b27f9", "gender": 2…

                    crew
97    [{"credit_id": "5921d321c3a368799b05933f", "department": "Sound",
"gender": 0, "id": 17132, "job…
151   [{"credit_id": "52fe434cc3a36847f8049c1b", "department": "Sound",
"gender": 2, "id": 37, "job": …
207   [{"credit_id": "52fe4283c3a36847f8024ec5", "department": "Writing",
"gender": 2, "id": 584, "job…
235   [{"credit_id": "52fe4354c3a36847f804c0b1", "department": "Camera",
"gender": 2, "id": 997, "job"…
273   [{"credit_id": "52fe451ac3a36847f80bc99f", "department": "Production",
"gender": 2, "id": 770, "…
…
…
4773  [{"credit_id": "52fe434ac3a36847f8049253", "department": "Directing",
"gender": 2, "id": 19303, …
4788  [{"credit_id": "52fe426bc3a36847f801d203", "department": "Directing",
"gender": 2, "id": 10367, …
4792  [{"credit_id": "52fe45cc9251416c9103eb7b", "department": "Directing",
"gender": 2, "id": 26882, …
4796  [{"credit_id": "52fe45e79251416c75066791", "department": "Directing",
"gender": 2, "id": 76624, …
4798  [{"credit_id": "52fe44eec3a36847f80b280b", "department": "Directing",
"gender": 0, "id": 2294, "…

[2534 rows x 21 columns]
```

1.4 Parse Json

[361]:
```
merged_df['genres'].head(1)
```

[361]:
```
97    [{"id": 28, "name": "Action"}, {"id": 12, "name": "Adventure"}, {"id": 18,
"name": "Drama"}, {"i…
Name: genres, dtype: object
```

[362]:
```
def extract_name(data, attr = ['name']):
    result = []
    for i in ast.literal_eval(data):
        for a in attr:
```

```
            result.append(i[a])
    return result
```

[363]:
```
merged_df['genres'] = merged_df['genres'].apply(extract_name)
merged_df['keywords'] = merged_df['keywords'].apply(extract_name)
merged_df['production_companies'] = merged_df['production_companies'].
 ↪apply(extract_name)
merged_df['production_countries'] = merged_df['production_countries'].
 ↪apply(extract_name)
merged_df['spoken_languages'] = merged_df['spoken_languages'].
 ↪apply(extract_name)
merged_df['cast'] = merged_df["cast"].apply(extract_name)
```

[364]:
```
merged_df[['genres', 'keywords', 'production_companies',␣
 ↪'production_countries', 'spoken_languages', 'cast']]
```

[364]:
```
                                                genres  \
97    [Action, Adventure, Drama, Horror, Science Fiction]
151                         [Adventure, Action, Animation]
207                  [Action, Adventure, Science Fiction]
235                  [Fantasy, Adventure, Comedy, Family]
273                            [Action, Crime, Thriller]
…                                                     …
4773                                           [Comedy]
4788                             [Horror, Comedy, Crime]
4792                   [Crime, Horror, Mystery, Thriller]
4796                   [Science Fiction, Drama, Thriller]
4798                            [Action, Crime, Thriller]

                 keywords  \
97                                          [monster, godzilla, giant monster,
destruction, kaiju, toyko]
151   [denmark, nordic mythology, lie, pride and vanity, folk hero, human
weakness, viking, alienation…
207   [oxygen, falsely accused, resistance, mars, double life, telepathy,
mutant, hologram, space colo…
235   [competition, greece, colosseum, olympic games, emperor, magic, horse,
roman, wild boar, governa…
273   [brother brother relationship, detective, car race, car thief, blackmail,
brother, remake, heist…
…
…
4773                                                              [salesclerk,
loser, aftercreditsstinger]
4788  [gay, trailer park, pop culture, drug dealer, heroin, fetishism, spanner,
excrements , disgust, …
4792  [japan, prostitute, hotel, based on novel, hallucination, interview,
```

```
investigation, murder, junk…
4796  [distrust, garage, identity crisis, time travel, time machine,
mathematics, independent film, pa…
4798                                  [united states-mexico barrier, legs, arms,
paper knife, guitar case]

     production_companies  \
97
[Cine Bazar, Toho Pictures]
151                       [Paramount Pictures, Shangri-La Entertainment,
ImageMovers, Paramount Animation]
207                                        [TriStar Pictures, Carolco Pictures,
Carolco International N.V.]
235   [Constantin Film, TF1 Films Productions, Pathé Renn Productions, La Petite
Reine, Tri Pictures, …
273                                                          [Jerry Bruckheimer
Films, Touchstone Pictures]
…
…
4773                                                                 [Miramax
Films, View Askew Productions]
4788
[Dreamland Productions]
4792
[Daiei Studios]
4796
[Thinkfilm]
4798
[Columbia Pictures]

                         production_countries  \
97                                     [Japan]
151                 [United States of America]
207                 [United States of America]
235   [Belgium, France, Germany, Italy, Spain]
273                 [United States of America]
…                                         …
4773                [United States of America]
4788                [United States of America]
4792                                   [Japan]
4796                [United States of America]
4798        [Mexico, United States of America]

                       spoken_languages  \
97    [Italiano, Deutsch, English,   ]
151                            [English]
207                            [English]
```

```
235               [Français, Português]
273                           [English]
…                                   …
4773                          [English]
4788                          [English]
4792                              [ ]
4796                          [English]
4798                          [Español]

                      cast
97    [Hiroki Hasegawa, Yutaka Takenouchi, Satomi Ishihara, Kengo Kora, Matsuo
Satoru, Mikako Ichikawa…
151   [Ray Winstone, Angelina Jolie, Anthony Hopkins, Robin Wright, John
Malkovich, Brendan Gleeson, C…
207   [Arnold Schwarzenegger, Sharon Stone, Rachel Ticotin, Ronny Cox, Michael
Ironside, Marshall Bell…
235   [Clovis Cornillac, Gérard Depardieu, Franck Dubosc, José Garcia, Stéphane
Rousseau, Jean-Pierre …
273   [Nicolas Cage, Angelina Jolie, Giovanni Ribisi, Delroy Lindo, Will Patton,
Christopher Eccleston…
…
…
4773  [Brian O'Halloran, Jeff Anderson, Jason Mewes, Kevin Smith, Lisa
Spoonhauer, Marilyn Ghigliotti,…
4788  [Divine, David Lochary, Mary Vivian Pearce, Mink Stole, Danny Mills, Edith
Massey, Channing Wilr…
4792  [Koji Yakusho, Masato Hagiwara, Tsuyoshi Ujiki, Anna Nakagawa, Yukijiro
Hotaru, Denden, Ren Osug…
4796  [Shane Carruth, David Sullivan, Casey Gooden, Anand Upadhyaya, Carrie
Crawford, Jay Butler, John…
4798  [Carlos Gallardo, Jaime de Hoyos, Peter Marquardt, Reinol Martinez, Ramiro
Gomez, Consuelo Gómez…

[2534 rows x 6 columns]
```

[365]:
```python
def get_director(data):
    for i in ast.literal_eval(data):
        if i['department'] == 'Directing':
            return i['name']

def get_producer(data):
    for i in ast.literal_eval(data):
        if i['job'] == 'Producer':
            return i['name']
```

[366]:
```python
merged_df['Director'] = merged_df['crew'].apply(get_director)
merged_df['Producer'] = merged_df['crew'].apply(get_producer)
```

[367]:
```
merged_df = merged_df.drop(["crew"], axis=1)
```

[368]:
```
merged_df[['Director', 'Producer']]
```

[368]:
```
              Director            Producer
97         Hideaki Anno  Kazutoshi Wadakura
151     Robert Zemeckis     Robert Zemeckis
207      Paul Verhoeven      Ronald Shusett
235     Thomas Langmann     Thomas Langmann
273        Dominic Sena   Jerry Bruckheimer
…                   …                   …
4773       Kevin Smith         Kevin Smith
4788       John Waters         John Waters
4792  Kiyoshi Kurosawa                None
4796     Shane Carruth       Shane Carruth
4798  Robert Rodriguez    Robert Rodriguez

[2534 rows x 2 columns]
```

2 Data Visualization

2.1 Release Date Analysis

[369]:
```
merged_df["release_date"]
```

[369]:
```
97      2016-07-29
151     2007-11-05
207     1990-06-01
235     2008-01-13
273     2000-06-09
           …
4773    1994-09-13
4788    1972-03-12
4792    1997-11-06
4796    2004-10-08
4798    1992-09-04
Name: release_date, Length: 2534, dtype: object
```

[370]:
```
merged_df["release_date_obj"] = pd.to_datetime(merged_df['release_date'],␣
↪format='%Y-%m-%d')
```

[371]:
```
# Extract information about release year, month, and day of week
merged_df["release_month"] = merged_df['release_date_obj'].dt.month
merged_df["release_year"] = merged_df['release_date_obj'].dt.year
merged_df['release_day_of_week'] = merged_df['release_date_obj'].dt.day_name()
```

[372]:
```
# display the results
merged_df[["release_month", "release_year","release_day_of_week"]]
```

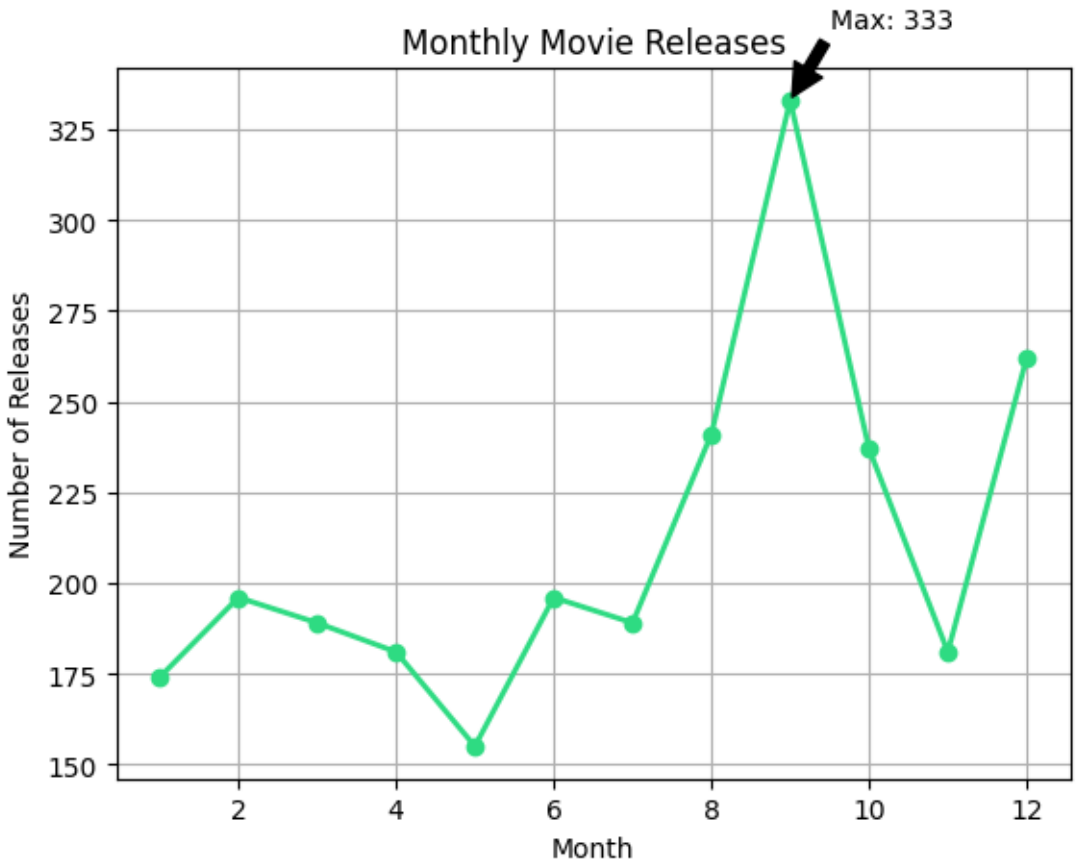
[372]:

	release_month	release_year	release_day_of_week
97	7	2016	Friday
151	11	2007	Monday
207	6	1990	Friday
235	1	2008	Sunday
273	6	2000	Friday
…	…	…	…
4773	9	1994	Tuesday
4788	3	1972	Sunday
4792	11	1997	Thursday
4796	10	2004	Friday
4798	9	1992	Friday

[2534 rows x 3 columns]

[373]:
```
month_count = []
for i in range(1,13):
    month_count.append(len(merged_df[merged_df["release_month"] == i]))
```

[374]:
```
# Plot the data
plt.plot(range(1,13), month_count, '-o', linewidth=2, color='#2edb82')

# Add labels and gridlines
plt.title('Monthly Movie Releases')
plt.xlabel('Month')
plt.ylabel('Number of Releases')
plt.grid(True)

# Add annotations (optional)
max_month = max(month_count)
max_index = month_count.index(max_month)
plt.annotate(f'Max: {max_month}', xy=(max_index+1, max_month),␣
 ↪xytext=(max_index+1.5, max_month+20),
             arrowprops=dict(facecolor='black', shrink=0.05))

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

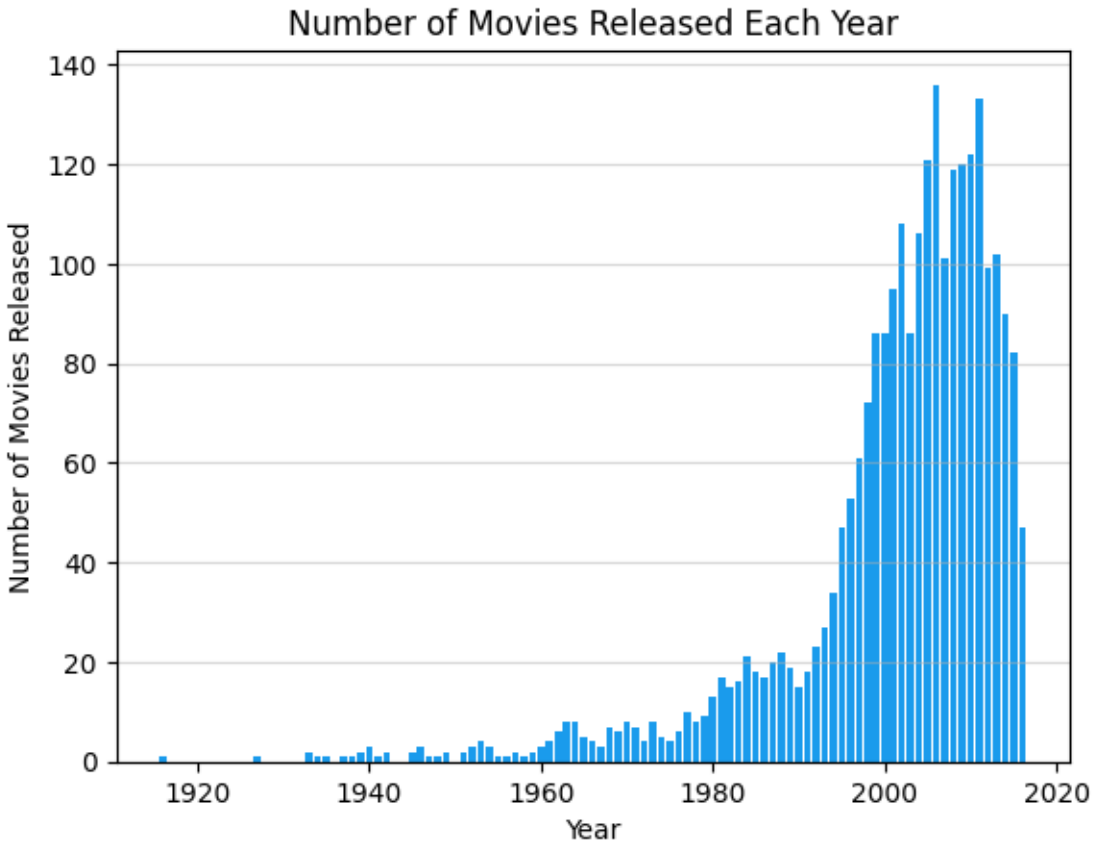


To better understand how the data evolves over time and identify peak points, we organized the release data into lists for each month and plotted it using line charts. After analyzing the data in this way, we discovered that the month of September had the highest number of movie releases, with a total of 333 movies. This approach allowed us to easily identify the highest data points for each month and visualize the changes in the data over time.

[375]:
```
year_dic = {}
for year in merged_df["release_year"]:
    if year in year_dic:
        year_dic[year] += 1
    else:
        year_dic[year] = 1


year_dic = dict(sorted(year_dic.items()))
```

[376]:
```
# Create a bar chart of the number of movies released each year
plt.bar(year_dic.keys(), year_dic.values(), color="#1a9bec")

# Add axis labels and a title to the plot
```

```
plt.xlabel("Year")
plt.ylabel("Number of Movies Released")
plt.title("Number of Movies Released Each Year")

# Increase the font size of the axis labels and title
plt.xticks(fontsize=10)
plt.yticks(fontsize=10)
plt.title("Number of Movies Released Each Year", fontsize=12)

# Add a grid to the plot
plt.grid(axis='y', alpha=0.5)

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

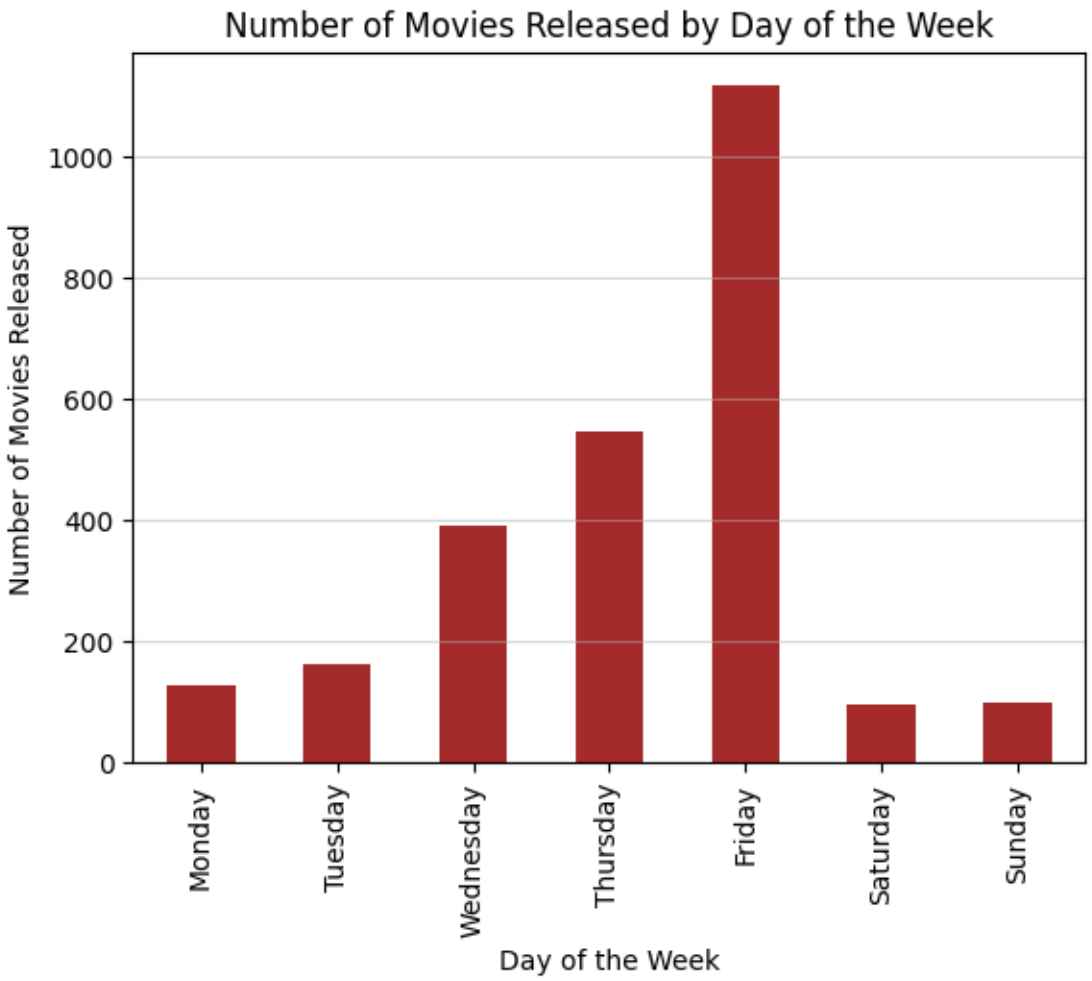


The bar chart shows that the number of movies released each year has increased steadily from the early 2000s, with a peak of 136 movies released in 2006. After this peak, there appears to be a plateau in the number of movies released, followed by a slight decrease in more recent years.

[377]:
```
peak_movies = max(year_dic.values())
peak_year = [(k,v) for k,v in year_dic.items() if v == peak_movies][0][0]
print(peak_year, peak_movies)
```

```
2006 136
```

[378]:
```
# Group the DataFrame by day of week and count the number of movies released on␣
 ↪each day
day_of_week_counts = merged_df.groupby("release_day_of_week").count()["id"]

# Sort the days of the week in ascending order
day_of_week_counts = day_of_week_counts.reindex(["Monday", "Tuesday",␣
 ↪"Wednesday", "Thursday", "Friday", "Saturday", "Sunday"])

# Create a bar chart of the number of movies released on each day of the week
day_of_week_counts.plot.bar(color = "brown")

# Add axis labels and a title to the plot
plt.xlabel("Day of the Week")
plt.ylabel("Number of Movies Released")
plt.title("Number of Movies Released by Day of the Week")

# Increase the font size of the axis labels and title
plt.xticks(fontsize=10)
plt.yticks(fontsize=10)
plt.title("Number of Movies Released by Day of the Week", fontsize=12)

# Add a grid to the plot
plt.grid(axis='y', alpha=0.5)

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



The resulting plot shows that the number of movies released varies by day of the week, with a peak on Fridays and a gradual decrease in the number of releases on weekends. The lowest number of releases occurs on Mondays.

2.2 Movie Genre Analysis

[379]:
```
merged_df["genres"]
```

[379]:
```
97      [Action, Adventure, Drama, Horror, Science Fiction]
151                          [Adventure, Action, Animation]
207                  [Action, Adventure, Science Fiction]
235                  [Fantasy, Adventure, Comedy, Family]
273                            [Action, Crime, Thriller]
                              ...
4773                                              [Comedy]
4788                           [Horror, Comedy, Crime]
```

```
4792                    [Crime, Horror, Mystery, Thriller]
4796                    [Science Fiction, Drama, Thriller]
4798                              [Action, Crime, Thriller]
Name: genres, Length: 2534, dtype: object
```

[380]:
```
merged_df["release_year"]
```

[380]:
```
97      2016
151     2007
207     1990
235     2008
273     2000
        …
4773    1994
4788    1972
4792    1997
4796    2004
4798    1992
Name: release_year, Length: 2534, dtype: int64
```

[381]:
```
# create a 2D dictionary s.t the key of outer dictionary is the year and the␣
 ↪key of inner
# dictionary is the genre. The inner dictionary stores the frequency of each␣
 ↪genre occur in the dataset
genre_dic = {}
for index, row in merged_df.iterrows():
    if row['release_year'] not in genre_dic:
        genre_dic[row['release_year']] = {}

    for genre in row['genres']:
        if genre in genre_dic[row['release_year']]:
            genre_dic[row['release_year']][genre] += 1
        else:
            genre_dic[row['release_year']][genre] = 1
```

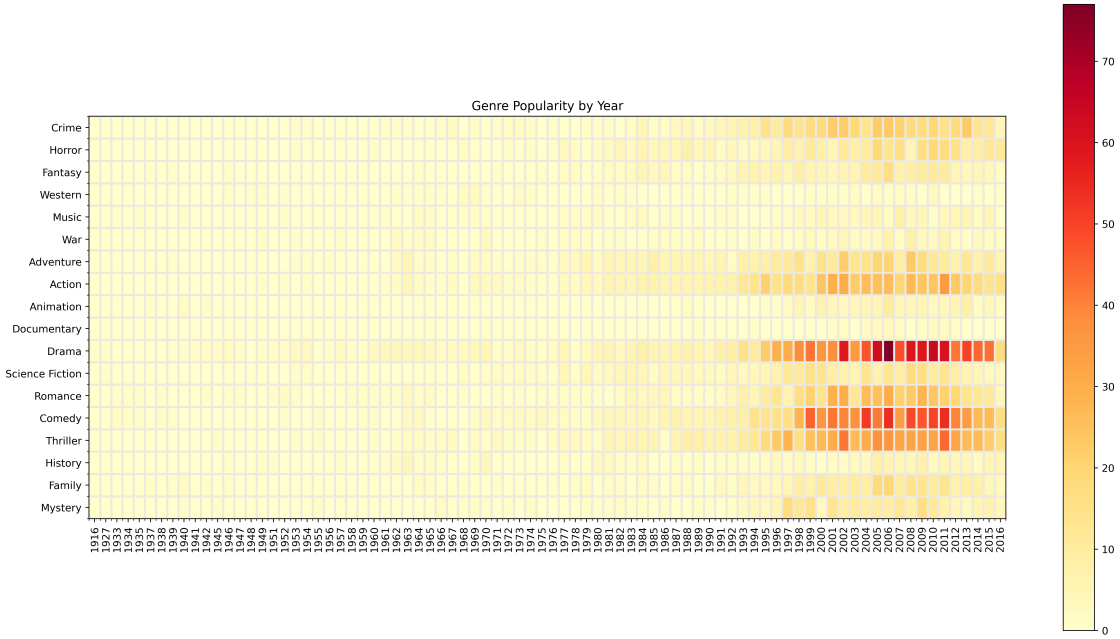
[382]:
```
all_genres = set()
for year in genre_dic:
    for genre in genre_dic[year]:
        if genre not in all_genres:
            all_genres.add(genre)

# fill zeros
for year in genre_dic:
    for genre in all_genres:
        if genre not in genre_dic[year]:
            genre_dic[year][genre] = 0
```

[383]:
```
genre_dic[2016]
```

[383]:
```
{'Action': 15,
 'Adventure': 6,
 'Drama': 17,
 'Horror': 11,
 'Science Fiction': 3,
 'Family': 3,
 'Animation': 2,
 'History': 5,
 'Thriller': 16,
 'Crime': 4,
 'Comedy': 16,
 'War': 2,
 'Romance': 4,
 'Fantasy': 2,
 'Western': 1,
 'Mystery': 4,
 'Music': 0,
 'Documentary': 0}
```

[384]:
```
# # create a list of genres and years
plt.figure(figsize = (20,11), dpi=400)
# plt.figure(figsize=(10, 6), dpi=200)

data = np.zeros((len(all_genres),len(genre_dic)))
years = sorted([key for key in genre_dic])

for y_index, y in enumerate(years):
    for g_index, g in enumerate(all_genres):
        data[g_index, y_index] = genre_dic[y][g]

# create the heatmap with aspect ratio of 2:1 and light-to-dark color scheme
plt.imshow(data, cmap='YlOrRd', aspect=2, vmin=0, vmax=data.max(),␣
 ↪interpolation='nearest', extent=[-0.5, len(years) - 0.5, -0.5,␣
 ↪len(all_genres) - 0.5])

# add borders to each pixel
plt.gca().set_xticks(np.arange(-0.5, len(years)), minor=True)
plt.gca().set_yticks(np.arange(-0.5, len(all_genres)), minor=True)
plt.grid(which='minor', color='#ede9df', linestyle='-', linewidth=2)

# invert the colormap
# plt.set_cmap(plt.cm.reversed('viridis'))
```

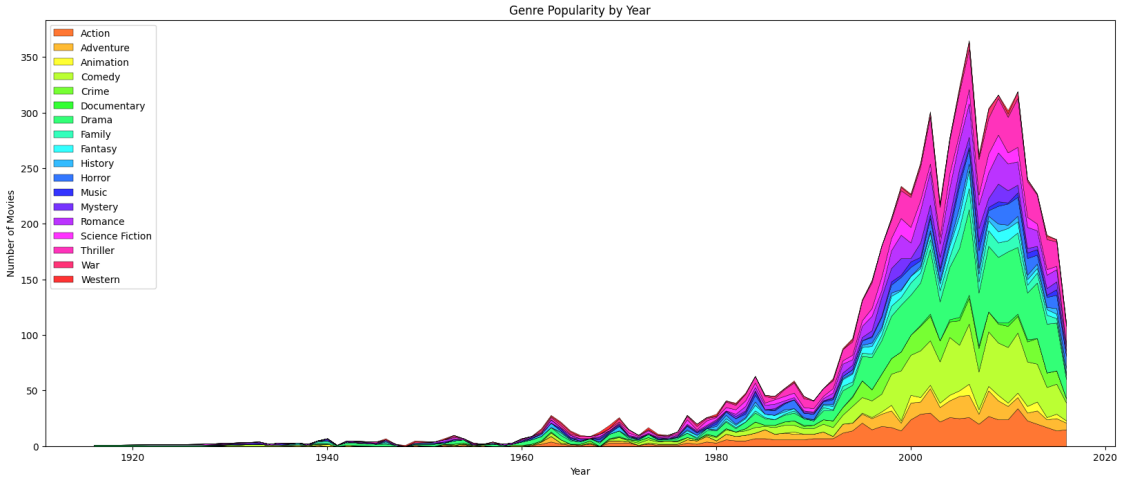
```
# add colorbar legend
plt.colorbar()

# set x-axis and y-axis labels and ticks
plt.xticks(np.arange(len(years)), years, rotation=90)
plt.yticks(np.arange(len(all_genres)), list(all_genres)[::-1])

# set title and display the plot
plt.title('Genre Popularity by Year')
plt.show()
```



From the heatmap, we can see that the popularity of some genres has remained consistent over time, such as drama, comedy, and thriller. Other genres, such as fantasy and science fiction, have become more popular over the years. We can also see some fluctuations in popularity for certain genres, such as horror and romance.

[385]:
```
# create a list of genres and years
plt.figure(figsize=(20,8))
genres = sorted(list(set([genre for year in genre_dic for genre in␣
 ↪genre_dic[year]])))
years = sorted(list(set([year for year in genre_dic])))

# create a data matrix for the stacked area plot
data = []
for genre in genres:
```

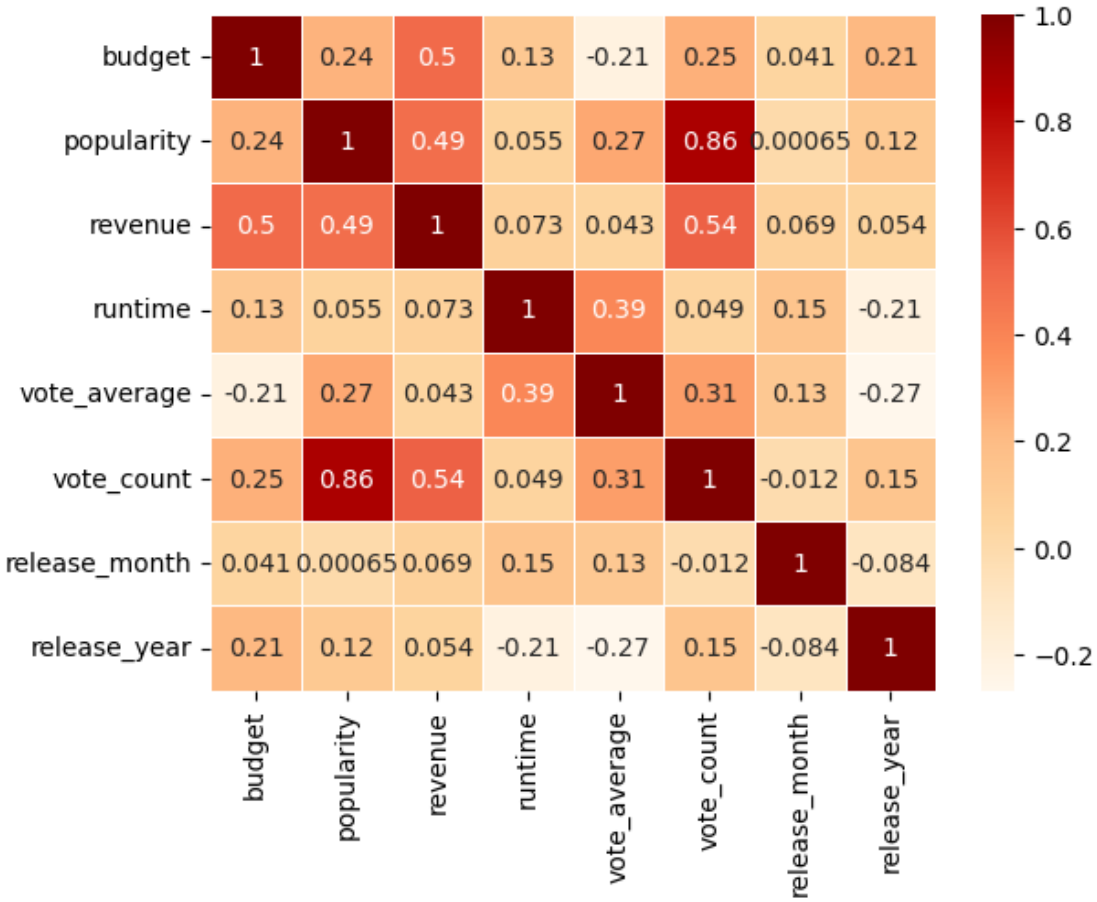
```
    genre_data = [genre_dic[year][genre] if genre in genre_dic[year] else 0 for␣
 ↪year in years]
    data.append(genre_data)


# define the colors for the stacked area plot
# colors = ["blue","green", "yellow", "red", "black", "lightblue", "lightred",␣
 ↪"lightgreen", "lightyellow"]
colors = []
for i in range(1, len(genres) + 1):
    color = colorsys.hsv_to_rgb(i/len(genres), 0.8, 1)
    colors.append((color[0], color[1], color[2], 1))

# create the stacked area plot
plt.stackplot(years, data, labels=genres, colors=colors, edgecolor='black',␣
 ↪linewidth=0.3)

# add x-axis and y-axis labels
plt.xlabel('Year')
plt.ylabel('Number of Movies')

# set title and legend
plt.title('Genre Popularity by Year')
plt.legend(loc='upper left')



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



[386]:
```
# Based on the heapmap, vote_average is the weakest feature correlated with␣
 ↪revenue, whereas vote_count is the strongest feature correlated with revenue


cols = list(merged_df.columns)
cols.remove("id")
pearsoncorr = merged_df.loc[:,cols].corr(method='pearson')
sns.heatmap(pearsoncorr,
xticklabels=pearsoncorr.columns,
yticklabels=pearsoncorr.columns,
cmap='OrRd',
annot=True,
linewidth=0.5)
```

```
/var/folders/qb/vmdtz4r91t3891jx6ftsd6v80000gn/T/ipykernel_92594/2195940439.py:6
: FutureWarning: The default value of numeric_only in DataFrame.corr is
deprecated. In a future version, it will default to False. Select only valid
columns or specify the value of numeric_only to silence this warning.
  pearsoncorr = merged_df.loc[:,cols].corr(method='pearson')
```

[386]: <Axes: >



#Modelling

2.3 Linear Regression

[387]:
```
x = pd.DataFrame()
x["log_bud"] = merged_df["budget"].map(lambda x:np.log(x+1))
x["log_pop"] = merged_df["popularity"].map(lambda x:np.log(x+1))
x["log_vc"] = merged_df["vote_count"].map(lambda x:np.log(x+1))

y = merged_df["revenue"].map(lambda x:np.log(x+1))
```

[388]:
```
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.2)
```

[389]:
```
linear_regression_model = LinearRegression()
linear_regression_model.fit(x_train, y_train)
prediction = linear_regression_model.predict(x_test)
```

[390]:
```
rmse = mean_squared_error(y_test, prediction, squared=False)
print("root mean squared error: ", rmse)

# Calculate the mean squared error of the model on the testing set
mse_test = mean_squared_error(y_test, prediction)

# Calculate the residual standard error of the model on the testing set
rse_test = np.sqrt(mse_test * (len(y_test) - 1) / (len(y_test) - x_test.
 ↪shape[1] - 1))

print("Residual Standard Error (RSE) on testing set:", rse_test)
```

```
root mean squared error:  1.4665562195967348
Residual Standard Error (RSE) on testing set: 1.4709231460451266
```

The result indicates that the model has relatively low errors and can be used to predict the revenue of movies in the dataset with a reasonable degree of accuracy.

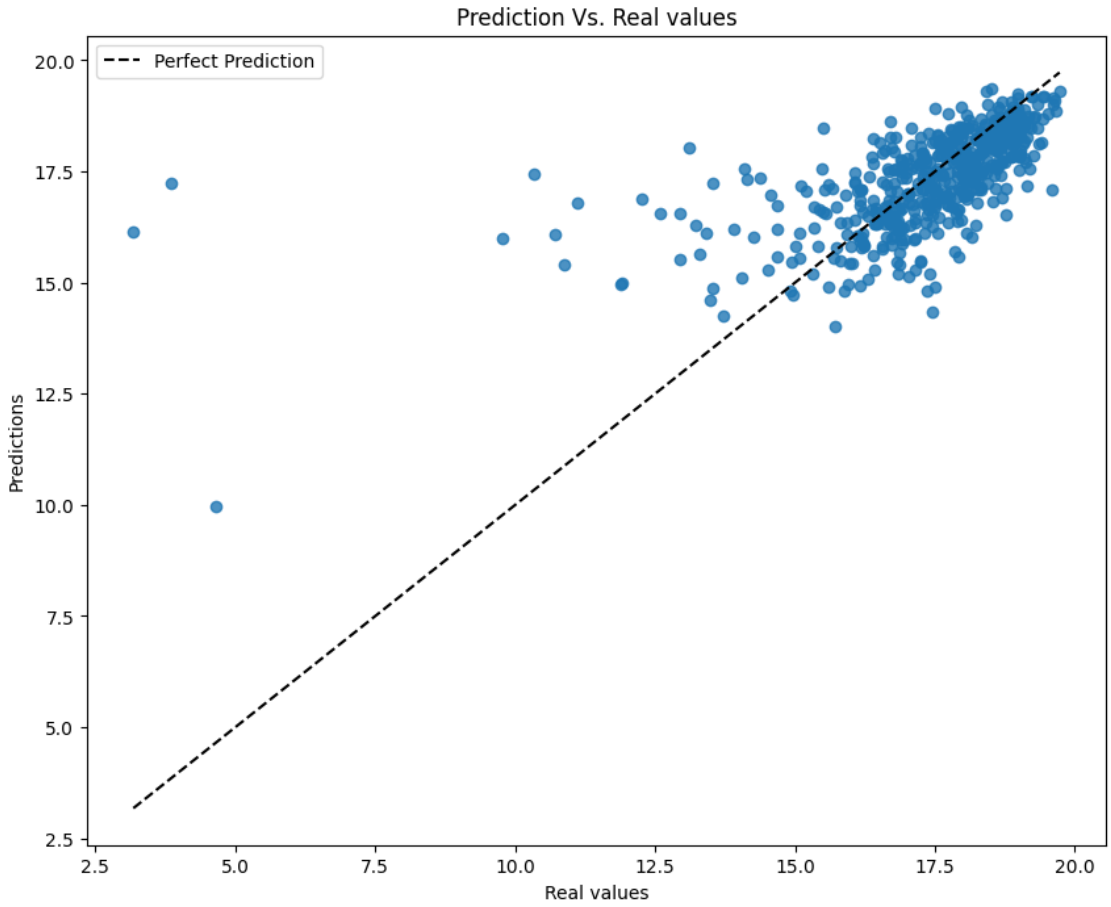
[391]:
```
linear_regression_model.coef_
```

[391]:
```
array([0.48527198, 0.03677784, 0.70729002])
```

[392]:
```
# Define data
y1 = list(y_test)
y2 = list(prediction)

# Compute line of perfect prediction
perfect_prediction = np.linspace(min(y1 + y2), max(y1 + y2), 100)
```

```
# Create plot
fig, ax = plt.subplots(figsize=(10, 8))
sc = ax.scatter(y1, y2, cmap='cool', alpha=0.8)
ax.plot(perfect_prediction, perfect_prediction, 'k--', label='Perfect␣
 ↪Prediction')

# Add axis labels and title
ax.set_xlabel('Real values')
ax.set_ylabel('Predictions')
ax.set_title('Prediction Vs. Real values')

# Add legend
ax.legend()

# Show plot
plt.show()
```

```
/var/folders/qb/vmdtz4r91t3891jx6ftsd6v80000gn/T/ipykernel_92594/721934583.py:10
: UserWarning: No data for colormapping provided via 'c'. Parameters 'cmap' will
be ignored
  sc = ax.scatter(y1, y2, cmap='cool', alpha=0.8)
```



[393]:
```
scores = -cross_val_score(linear_regression_model, x_train, y_train, cv=5,␣
 ↪scoring='neg_mean_absolute_error')
print(scores)
print(scores.mean())
```

```
[0.79221949 0.81682326 0.89047189 0.8441636  0.74975834]
0.8186873150887228
```

2.4 Logistic Regression

[394]:
```
x = pd.DataFrame()
x["log_bud"] = merged_df["budget"].map(lambda x:np.log(x+1))
x["log_pop"] = merged_df["popularity"].map(lambda x:np.log(x+1))
x["log_vc"] = merged_df["vote_count"].map(lambda x:np.log(x+1))


log_rev = merged_df["revenue"].map(lambda x:np.log(x+1))
x["target"] = [0 if z[0] < z[1] else 1 for z in zip(log_rev, x["log_bud"])]
```

```
# Balancing the class size for model performance
copied_data = x[x["target"] == 0]
x = x.append(copied_data)


y = x["target"]
x = x.drop(["target"], axis=1)
```

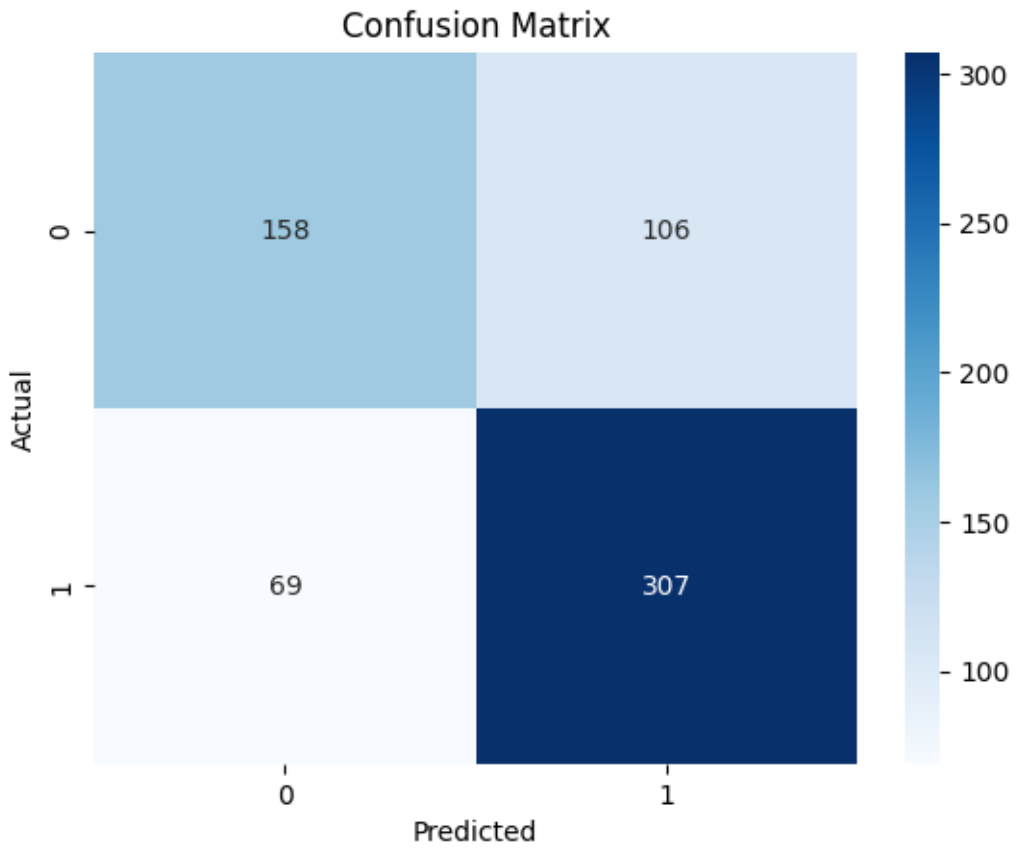
```
/var/folders/qb/vmdtz4r91t3891jx6ftsd6v80000gn/T/ipykernel_92594/3275586662.py:1
2: FutureWarning: The frame.append method is deprecated and will be removed from
pandas in a future version. Use pandas.concat instead.
  x = x.append(copied_data)
```

[395]:
```
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.2,␣
 ↪random_state = 42)

logistic_regression_model = LogisticRegression()
logistic_regression_model.fit(x_train, y_train)

prediction = logistic_regression_model.predict(x_test)
```

[396]:
```
score = f1_score(y_test, prediction)
print("Fl score:", score)
```

```
Fl score: 0.7782002534854247
```

[397]:
```
# Create confusion matrix
cm = confusion_matrix(y_test, prediction)

# Create heatmap with Seaborn
sns.heatmap(cm, annot=True, cmap='Blues', fmt='g')
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.title('Confusion Matrix')
plt.show()
```



[398]:
```
# Calculate the mean squared error of the model on the testing set
mse_test = mean_squared_error(y_test, prediction)

# Calculate the residual standard error of the model on the testing set
rse_test = np.sqrt(mse_test * (len(y_test) - 1) / (len(y_test) - x_test.
 ↪shape[1] - 1))

print("Residual Standard Error (RSE) on testing set:", rse_test)
```

```
Residual Standard Error (RSE) on testing set: 0.5241443498963829
```

[399]:
```
scores = cross_val_score(logistic_regression_model, x_train, y_train, cv=5,␣
 ↪scoring='accuracy')
print(scores)
print(scores.mean())
```

```
[0.734375   0.71484375 0.70507812 0.70898438 0.74951076]
0.7225584026418786
```

The logistic regression model achieved an F1 score of 0.778, indicating that it can accurately predict whether a movie will earn above or below its budget based on the selected features. The RSE value

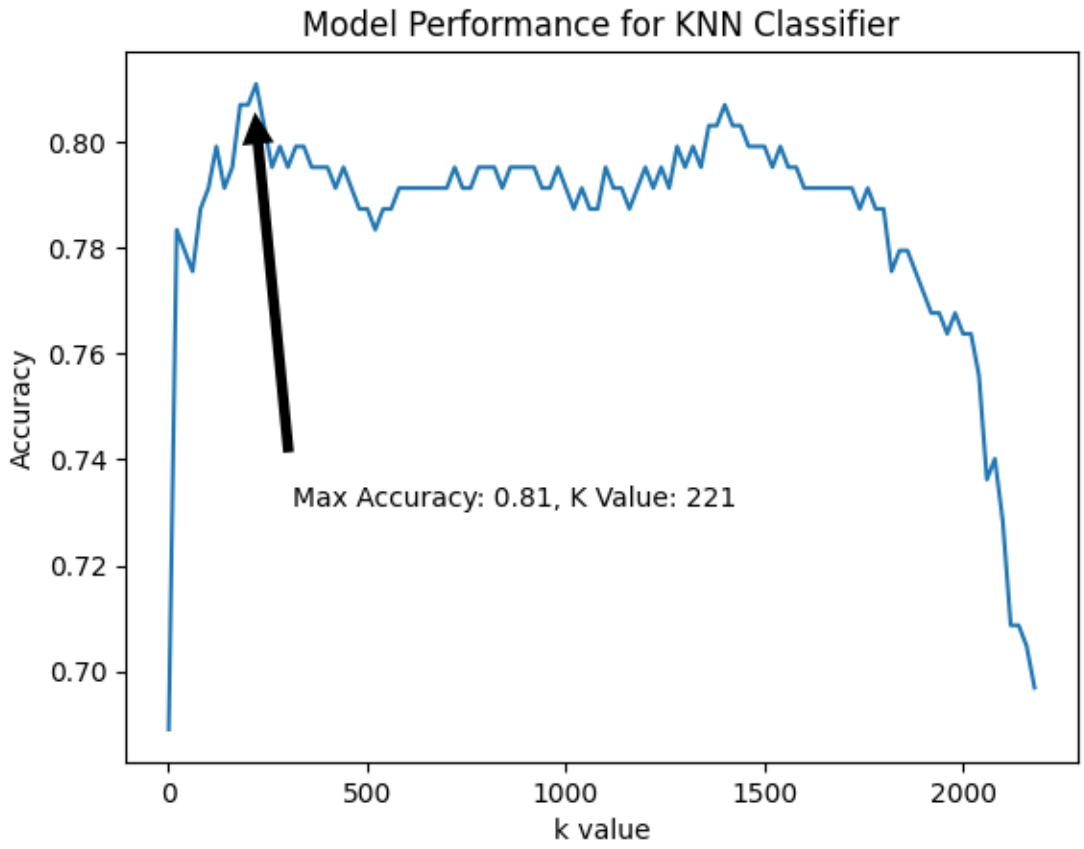
of 0.524 suggests that there is some level of error in the model's predictions. Overall, the model's performance is decent, but there is still room for improvement.

2.5 KNN Classifier

[400]:
```
x = pd.DataFrame()
x["log_bud"] = merged_df["budget"].map(lambda x:np.log(x+1))
x["log_pop"] = merged_df["popularity"].map(lambda x:np.log(x+1))
x["log_vc"] = merged_df["vote_count"].map(lambda x:np.log(x+1))

y = merged_df["revenue"]

# get y label (high-revenue and low revenue)
y_label = [1 if percentileofscore(y, i) > 50 else 0 for i in y]

# split data into training and testing sets
x_train, x_test, y_train, y_test = train_test_split(x, y_label, test_size=0.1,␣
 ↪random_state=42)

# Initialize empty lists for k values and accuracy
k_values = []
accuracies = []

for i in range(1, 2200, 20):
    # instantiate KNN model with k=5
    knn = KNeighborsClassifier(n_neighbors=i)

    # fit the model on training data
    knn.fit(x_train, y_train)

    # make predictions on test data
    prediction = knn.predict(x_test)

    # evaluate the model's accuracy
    accuracy = accuracy_score(y_test, prediction)
    k_values.append(i)
    accuracies.append(accuracy)
```

[401]:
```
# Plot the graph
plt.plot(k_values, accuracies)
plt.title('Model Performance for KNN Classifier')
plt.xlabel('k value')
plt.ylabel('Accuracy')

# Add annotations (optional)
max_acc = max(accuracies)
```

```
max_index = accuracies.index(max_acc)
plt.annotate(f'Max Accuracy: {max_acc:.2f}, K Value: {k_values[max_index]}',␣
↪xy=(max_index+200, max_acc), xytext=(max_index+300, max_acc-0.08),
arrowprops=dict(facecolor='black', shrink=0.07, linewidth=0.01))

plt.show()
```



[402]:
```
knn = KNeighborsClassifier(n_neighbors=221)

# fit the model on training data
knn.fit(x_train, y_train)

# make predictions on test data
prediction = knn.predict(x_test)

# evaluate the model's accuracy
accuracy = accuracy_score(y_test, prediction)
```

[403]:
```
score = f1_score(y_test, prediction)
print("Fl score:", score)


# Calculate the mean squared error of the model on the testing set
mse_test = mean_squared_error(y_test, prediction)

# Calculate the residual standard error of the model on the testing set
rse_test = np.sqrt(mse_test * (len(y_test) - 1) / (len(y_test) - x_test.
 ↪shape[1] - 1))

print("Residual Standard Error (RSE) on testing set:", rse_test)
```

```
Fl score: 0.808
Residual Standard Error (RSE) on testing set: 0.4373146401484736
```

[404]:
```
scores = cross_val_score(knn, x_train, y_train, cv=5, scoring='accuracy')
print(scores)
print(scores.mean())
```

```
[0.77631579 0.76535088 0.80263158 0.75877193 0.79824561]
0.7802631578947369
```

The linear regression model has an F1 score of 0.808 and RSE of 0.437, indicating that the model has a relatively good fit to the data.

3 Conclusion

Linear Regression Model - The model is a regression model that utilizes budget, popularity, and vote count as input features to predict movie revenue. It learns the patterns and correlations between these features and revenue from a training dataset, and can then generate revenue predictions for new movies based on these learned relationships.

Logistic Regression Model - The logistic regression model takes budget, popularity, and vote count as input features to classify movies as either profitable or not. It learns the relationship between these features and the binary outcome of profitability from a training dataset, using a logistic function to model the probability of a movie being profitable.

KNN Model - The model takes into consideration the budget, popularity, and vote count of movies to classify them as high-revenue or low-revenue. It does this by comparing the features of a new movie to the K number of nearest neighbors in the training dataset. The label assigned to the new movie is determined by the majority class of its K nearest neighbors.

[ ]:
```

```