PREDICTION IMDB SCORES

project title: predicted for IMDb scores

phase 3: Development

part 1:

Data Preprocessing:

Data preprocessing is a crucial step within the statistics analysis and gadget gaining knowledge of pipeline.
It includes a sequence of strategies and operations finished on uncooked statistics to clean, organize, and transform it right into a layout that is suitable for analysis or device mastering version schooling.
Data preprocessing goals to enhance the first-class of the records, making it greater reliable and conducive to generating accurate consequences.

Here are some common tasks and techniques involved in data preprocessing:

Data Cleaning:

Handling missing values: Deciding how to deal with missing data, whether by imputing values or removing incomplete records.
Outlier detection and treatment: Identifying and handling data points that significantly deviate from the norm.

Noise reduction:

Smoothing noisy data through techniques like filtering.

Data Transformation:

Data normalization: Scaling numerical features to a standard range (e.g., between 0 and 1) to ensure that they have similar influence in the analysis.
Encoding categorical variables: Converting categorical data into numerical format, such as one-hot encoding or label encoding.
Feature engineering: Creating new features or modifying existing ones to capture more meaningful information from the data.
Dimensionality reduction: Reducing the number of features while retaining essential information, using methods like Principal Component Analysis (PCA).

Data Integration:

Merging or joining datasets: Combining data from multiple sources into a single dataset for analysis.

Aggregation: Summarizing data at a higher level of granularity, such as aggregating daily sales into monthly totals.

Data Reduction:

Sampling: Reducing the size of a large dataset by randomly selecting a representative subset.
Binning: Grouping continuous data into discrete bins to simplify analysis.
Filtering: Selecting a subset of data based on specific criteria.

Data Standardization:

Ensuring that data follows a consistent format and structure.
Date and time format conversion: Converting date and time data into a uniform format.
Currency conversion: Converting monetary values into a common currency.

Data Scaling:

Scaling numerical data to a common range to prevent some features from dominating the analysis.

Data preprocessing is an iterative process that may involve several of these steps in various orders, depending on the specific dataset and the analysis goals. Proper data preprocessing is essential for improving the accuracy and effectiveness of machine learning models, as well as for making data more accessible for traditional statistical analysis.

Here is the data preprocessing codes along with the output of the given dataset:

Importing the libraries:

Import three basic libraries which are very common in machine learning and will be used every time you train a model

NumPy: it is a library that allows us to work with arrays and as most machine learning models work on arrays NumPy makes it easier
matplotlib: this library helps in plotting graphs and charts, which are very useful while showing the result of your model
Pandas: pandas allowsus to import our dataset and also creates a matrix of features containing the dependent and independent variable.

Code:

```
#Import libraries

import numPy as np
import pandas as pd
import matplotlib.pyplo
t as plot
import seaborn as sns
from plotnine import *
```

1.1 Background

This dataset contains the information about the movies . For a movie to be commercial success , it depends on various factors like director, actors ,critic reviews and viewers reaction. Imdb score is one of the important factor to measure the movie's success.

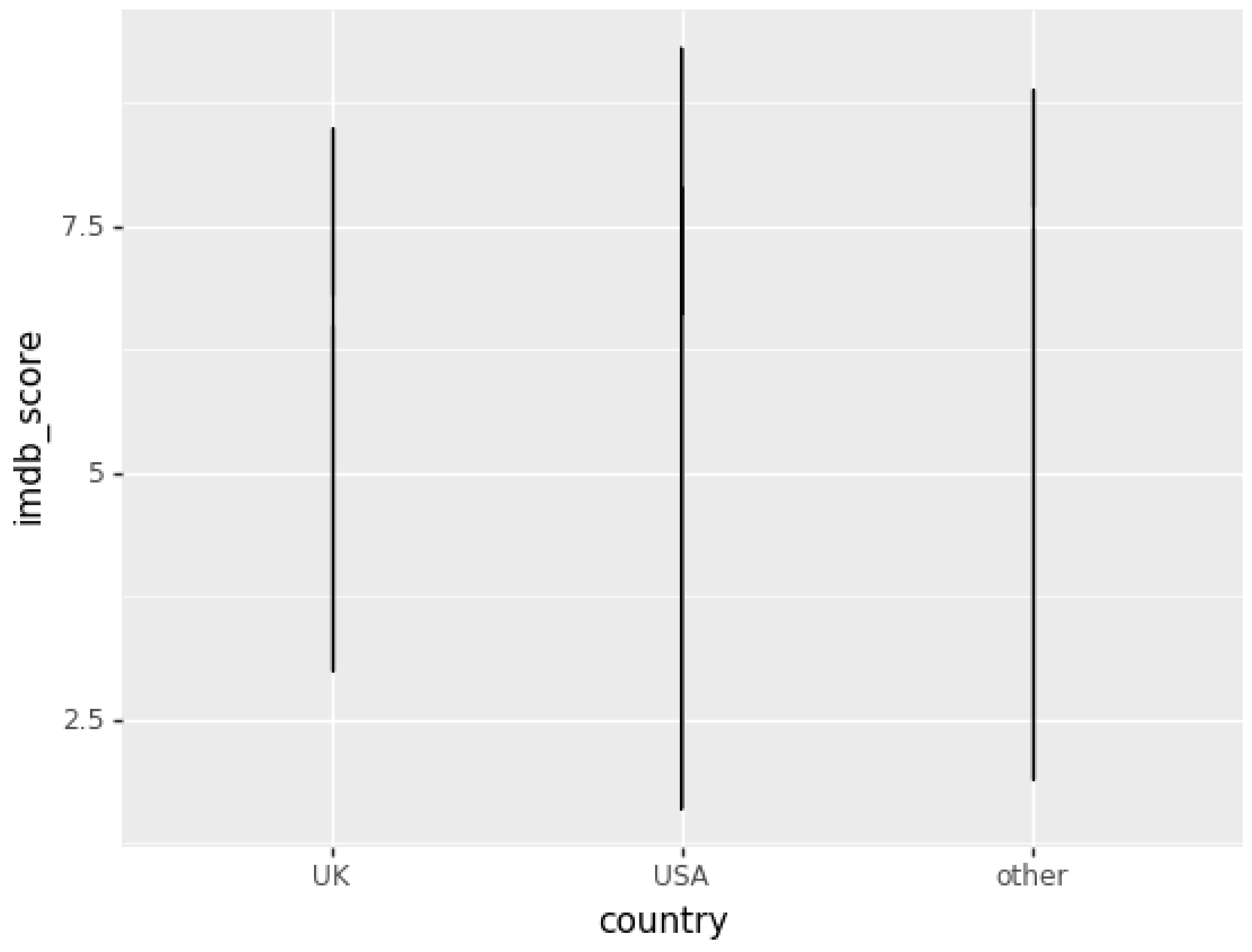
1.2 Description of dataset attributes

Please find the details for the datset attributes:-

1. Color :- Movie is black or coloured
2. Director_name:- Name of the movie director
3. num_critic_for_reviews :- No of critics for the movie
4. duration:- movie duration in minutes
5. director_facebook_likes:-Number of likes for the Director on his Facebook Page
6. actor_3_facebook_likes:- No of likes for the actor 3 on his/her facebook Page
7. actor2_name:- name of the actor 2
8. actor_1_facebook_likes:- No of likes for the actor 1 on his/her facebook Page
9. gross:- Gross earnings of the movie in Dollars
10. genres:- Film categorization like ‘Animation’, ‘Comedy’, ‘Romance’, ‘Horror’, ‘Sci-Fi’, ‘Action’, ‘Family’
11. actor_1_name:- Name of the actor 1
12. movie_title:-Title of the movie
13. num_voted_users:-No of people who voted for the movie
14. cast_total_facebook_likes:- Total facebook like for the movie
15. actor_3_name:- Name of the actor 3
16. facenumber_in_poster:- No of actors who featured in the movie poster
17. plot_keywords:-Keywords describing the movie plots
18. movie_imdb_link:-Link of the movie link
19. num_user_for_reviews:- Number of users who gave a review
20. language:- Language of the movie
21. country:- Country where movie is produced
22. content_rating:- Content rating of the movie
23. budget:- Budget of the movie in Dollars
24. title_year:- The year in which the movie is released
25. actor_2_facebook_likes:- facebook likes for the actor 2
26. imdb_score:- IMDB score of the movie

27. aspect_ratio :- Aspect ratio the movie was made in
28. movie_facebook_likes:- Total no of facebook likes for the movie

29. **1.3 Case Study**
30. The dataset here gives the massive information about the movies and their IMDB scores respectively. We are going to analyze each and every factors which can influence the imdb ratings so that we can predict better results.The movie with the higher imdb score is more successful as compared to the movies with low imdb score
31.



2. Data Preprocessing

```
#Reading the Data

movie_df=pd.read_csv("/kaggle/input/imdb-5000-movie-dataset/movie_metadata.csv")
```

```
#Displaying the first 10 records

movie_df.head(10)
```

#Shape of the dataset (no of rows and no of columns)

```
movie_df.shape
```

Out[4]:

```
(5043, 28)
```

#Displaying the data type of the dataset attributes

```
movie_df.dtypes
```

Out[5]:

```
color                         object
director_name                 object
num_critic_for_reviews       float64
duration                     float64
director_facebook_likes      float64
actor_3_facebook_likes       float64
actor_2_name                  object
actor_1_facebook_likes       float64
gross                        float64
genres                        object
actor_1_name                  object
movie_title                   object
num_voted_users                int64
cast_total_facebook_likes      int64
actor_3_name                  object
facenumber_in_poster         float64
plot_keywords                 object
movie_imdb_link               object
num_user_for_reviews         float64
language                      object
country                       object
content_rating                object
budget                       float64
title_year                   float64
actor_2_facebook_likes       float64
imdb_score                   float64
aspect_ratio                 float64
movie_facebook_likes           int64
dtype: object
```

**We can say we have the datset divided into categorical and numeric columns "

Categorical Columns

Color,Director name, actor name,genres,movie_title,language,country,content_rating.

Numerical Columns

num_critic_for_reviews,duration,director_facebook_likes ,actor_3_facebook_likes,actor_1_facebook_likes ,gross,num_voted_users,cast_total_facebook_likes,facenumber_in_poster,num_user_for_reviews ,budget,title_year, actor_2_facebook_likes ,imdb_score,aspect_ratio,movie_facebook_like

```
Index(['director_name', 'num_critic_for_reviews', 'duration',
       'director_facebook_likes', 'actor_3_facebook_likes', 'actor_2_name',
       'actor_1_facebook_likes', 'gross', 'genres', 'actor_1_name',
       'movie_title', 'num_voted_users', 'cast_total_facebook_likes',
       'actor_3_name', 'facenumber_in_poster', 'plot_keywords',
       'num_user_for_reviews', 'language', 'country', 'content_rating',
       'budget', 'title_year', 'actor_2_facebook_likes', 'imdb_score',
       'aspect_ratio', 'movie_facebook_likes'],
      dtype='object')
```

```
director_name                True
num_critic_for_reviews       True
duration                     True
director_facebook_likes      True
actor_3_facebook_likes       True
actor_2_name                 True
actor_1_facebook_likes       True
gross                        True
genres                       False
actor_1_name                 True
movie_title                  False
num_voted_users              False
cast_total_facebook_likes    False
actor_3_name                 True
facenumber_in_poster         True
plot_keywords                True
num_user_for_reviews         True
language                     True
country                      True
content_rating               True
budget                       True
title_year                   True
actor_2_facebook_likes       True
imdb_score                   False
aspect_ratio                 True
movie_facebook_likes         False
dtype: bool
```

```
movie_df.isna().sum()
```

```
director_name                104
num_critic_for_reviews        50
duration                      15
director_facebook_likes      104
actor_3_facebook_likes        23
actor_2_name                  13
actor_1_facebook_likes         7
gross                        884
genres                         0
actor_1_name                   7
movie_title                    0
num_voted_users                0
cast_total_facebook_likes      0
actor_3_name                  23
```

```
facenumber_in_poster       13
plot_keywords             153
num_user_for_reviews       21
language                   12
country                     5
content_rating            303
budget                    492
title_year                108
actor_2_facebook_likes     13
imdb_score                  0
aspect_ratio              329
movie_facebook_likes        0
dtype: int64
```

```
movie_df.dropna(axis=0,subset=['director_name', 'num_critic_for_reviews','duration','director_facebook_likes','actor_3_facebook_likes','actor_2_name','actor_1_facebook_likes','actor_1_name','actor_3_name','facenumber_in_poster','num_user_for_reviews','language','country','actor_2_facebook_likes','plot_keywords'],inplace=True)
```

```
movie_df.shape
```

```
(4737, 26)
```

We lost only 6% of the data which is acceptable

```
#Replacing the content rating with Value R as it has highest frequency

movie_df["content_rating"].fillna("R", inplace = True)
```

In [15]:

```
#Replacing the aspect_ratio with the median of the value as the graph is right skewed

movie_df["aspect_ratio"].fillna(movie_df["aspect_ratio"].median(),inplace=True)
```

In [16]:

linkcode

```
#We need to replace the value in budget with the median of the value

movie_df["budget"].fillna(movie_df["budget"].median(),inplace=True)
```

```
# We need to replace the value in gross with the median of the value

movie_df['gross'].fillna(movie_df['gross'].median(),inplace=True)
```

In [18]:

```
# Recheck that all the null values are removed

movie_df.isna().sum()
```

Out[18]:

```
director_name             0
num_critic_for_reviews    0


director_facebook_likes   0
actor_3_facebook_likes    0
actor_2_name              0
actor_1_facebook_likes    0
gross                     0
genres                    0
```

```
actor_1_name              0
movie_title               0
num_voted_users           0
cast_total_facebook_likes    0
actor_3_name              0
facenumber_in_poster        0
plot_keywords             0
num_user_for_reviews        0
language                  0
country                   0
content_rating            0
budget                    0
title_year                0
actor_2_facebook_likes      0
imdb_score                0
aspect_ratio              0
movie_facebook_likes        0
dtype: int64
```

```
#Removing the duplicate values in the datset

movie_df.drop_duplicates(inplace=True)
movie_df.shape
```

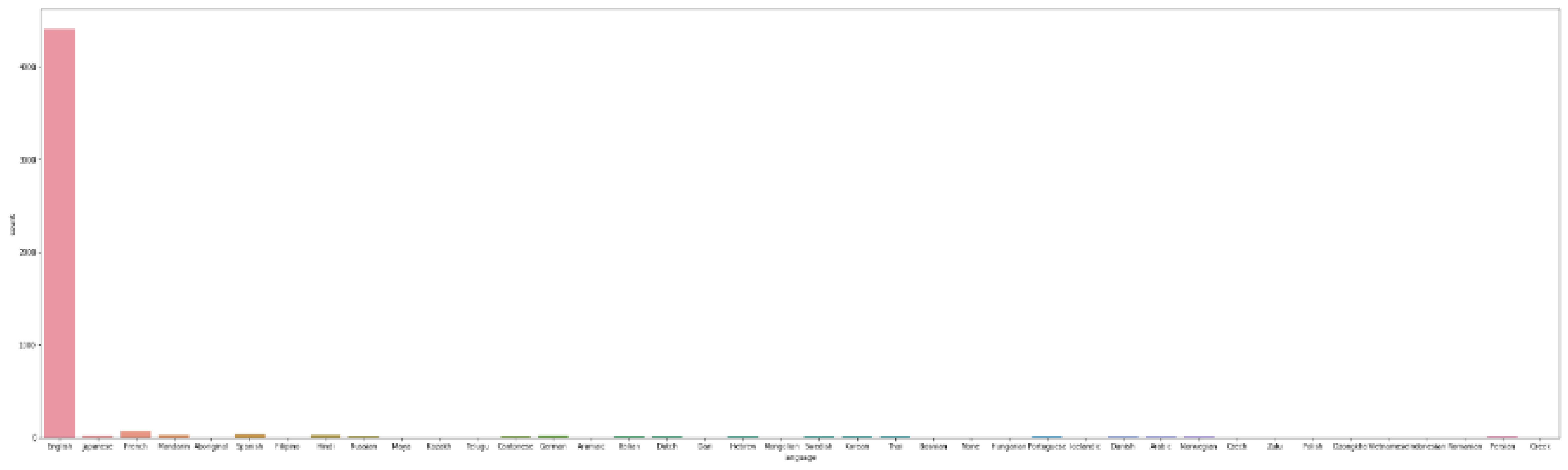
Count of the language values

```
movie_df["language"].value_counts()
```

```
English      4405
French         69
Spanish        35
Hindi          25
Mandarin       24
German         18
Japanese       16
Russian        11
Italian        10
Cantonese      10
Portuguese      8
Korean          8
Danish          5
Norwegian       4
Swedish         4
Hebrew          4
Dutch           4
Persian         4
Arabic          3
Thai            3
Indonesian      2
None            2
Aboriginal      2
Dari            2
Zulu            2
Hungarian       1
Mongolian       1
Greek           1
```

```
Romanian        1
Bosnian         1
Telugu          1
Maya            1
Polish          1
Filipino        1
Czech           1
Dzongkha        1
Kazakh          1
Vietnamese      1
Icelandic       1
Aramaic         1
Name: language, dtype: int64
```

```
# Graphical presentaion
plt.figure(figsize=(40,10))
sns.countplot(movie_df["language"])
plt.show()
```



```
#Most of the values for the languages is english we can drop the english column

movie_df.drop('language',axis=1,inplace=True)
```

In [23]:

linkcode

```
#Creating a new column to check the net profit made by the company (Gross-Budget)

movie_df["Profit"]=movie_df['budget'].sub(movie_df['gross'], axis = 0)
value_counts=movie_df["country"].value_counts()
print(value_counts)
```

```
USA          3568
UK            420
France        149
Canada        107
Germany        96
Australia      53
Spain          32
India          27
China          24
Japan          21
```

```
Italy             20
Hong Kong          16
New Zealand         14
South Korea         12
Ireland            11
Denmark            11
Russia             11
Mexico             11
South Africa        8
Brazil             8
Norway             7
Netherlands         5
Sweden             5
Thailand           4
Iran              4
Argentina          4
Czech Republic      3
Switzerland         3
Belgium            3
Israel             3
West Germany        3
Poland             2
Taiwan             2
Iceland            2
Romania            2
Hungary            2
Greece             2
Soviet Union        1
Slovakia           1
Finland            1
Official site       1
Turkey             1
Peru              1
Libya             1
Afghanistan         1
Cambodia           1
Indonesia          1
Nigeria            1
Kyrgyzstan          1
Colombia           1
New Line           1
Philippines         1
Bahamas            1
Bulgaria           1
Georgia            1
Aruba             1
Chile             1
Name: country, dtype: int64
```

We can see most of the movies are from USA ,UK and the rest of the countries

In [26]:

##get top 2 values of index

```
##get top 2 values of index
vals = value_counts[:2].index
print (vals)
movie_df['country'] = movie_df.country.where(movie_df.country.isin(vals), 'other')
```

```
Index(['USA', 'UK'], dtype='object')
```

In [27]:

```
#Successfully divided the country into three catogories
movie_df["country"].value_counts()
```

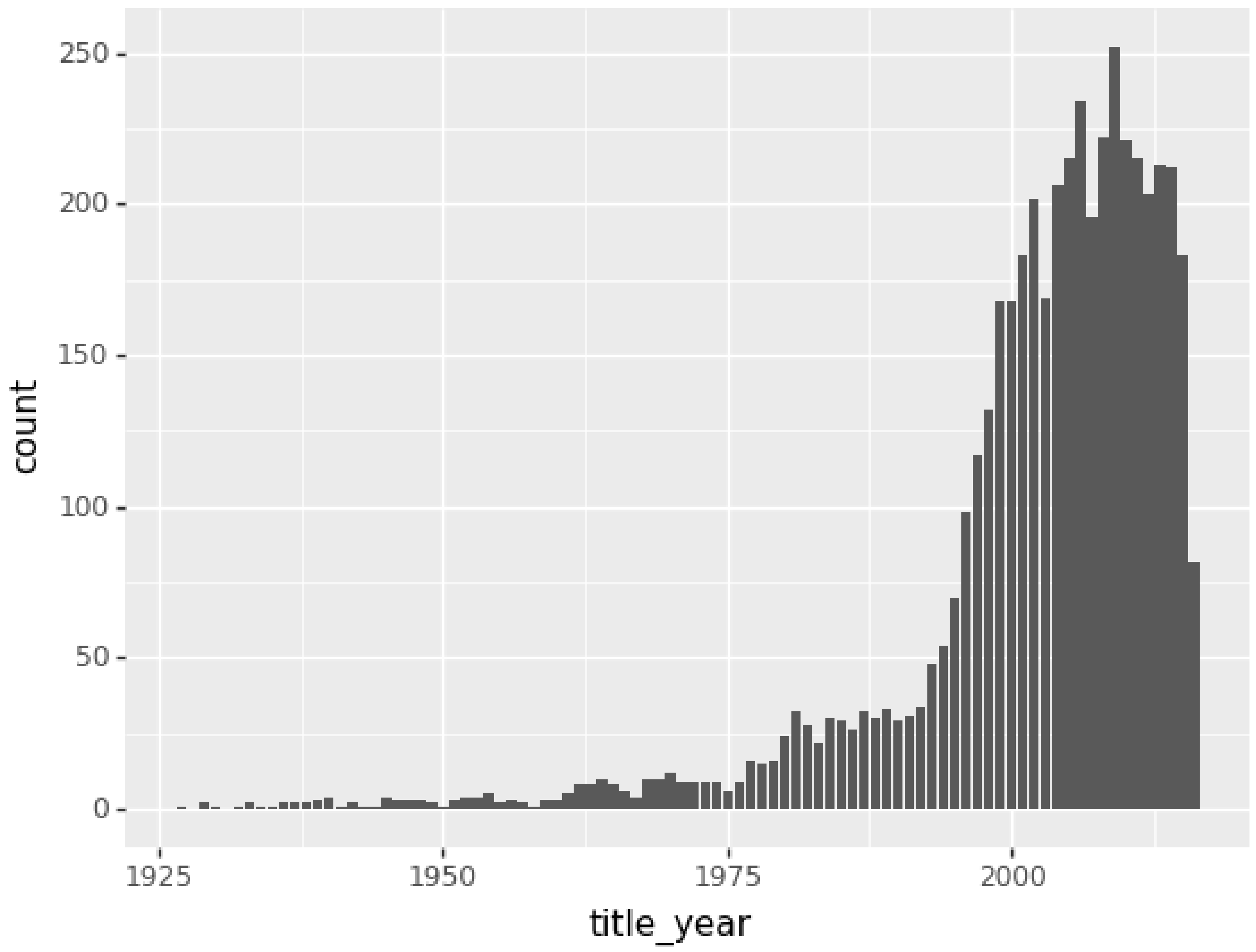
Out[27]:

```
USA      3568
other     707
UK        420
Name: country, dtype: int64
```

In [28]:

```
linkcode
movie_df.head(10)
```

```
/opt/conda/lib/python3.6/site-packages/plotnine/coords/coord_cartesian.py:31: MatplotlibDeprecationWarning: The Bunch class was deprecated in Matplotlib 3.0 and will be removed in 3.2. Use types.SimpleNamespace instead.
  self.limits = Bunch(xlim=xlim, ylim=ylim)
/opt/conda/lib/python3.6/copy.py:274: MatplotlibDeprecationWarning: The Bunch class was deprecated in Matplotlib 3.0 and will be removed in 3.2. Use types.SimpleNamespace instead.
  y = func(*args)
/opt/conda/lib/python3.6/site-packages/plotnine/facets/facet.py:151: MatplotlibDeprecationWarning: The Bunch class was deprecated in Matplotlib 3.0 and will be removed in 3.2. Use types.SimpleNamespace instead.
  scales = Bunch()
/opt/conda/lib/python3.6/site-packages/plotnine/facets/layout.py:147: MatplotlibDeprecationWarning: The Bunch class was deprecated in Matplotlib 3.0 and will be removed in 3.2. Use types.SimpleNamespace instead.
  return Bunch(x=xsc, y=ysc)
```



#Relationship between the imdb score and the profit made by the movie

```
ggplot(aes(x='imdb_score', y='Profit'), data=movie_df) +\
    geom_line() +\
    stat_smooth(colour='blue', span=1)
```

```
/opt/conda/lib/python3.6/site-packages/plotnine/coords/coord_cartesian.py:31: MatplotlibDepre
cationWarning: The Bunch class was deprecated in Matplotlib 3.0 and will be removed in 3.2. Use t
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  scales = Bunch()
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ning: The Bunch class was deprecated in Matplotlib 3.0 and will be removed in 3.2. Use types.Simp
leNamespace instead.
  return Bunch(x=xsc, y=ysc)
/opt/conda/lib/python3.6/site-packages/numpy/core/fromnumeric.py:2389: FutureWarning: Meth
od .ptp is deprecated and will be removed in a future version. Use numpy.ptp instead.


return ptp(axis=axis, out=out, **kwargs)
```

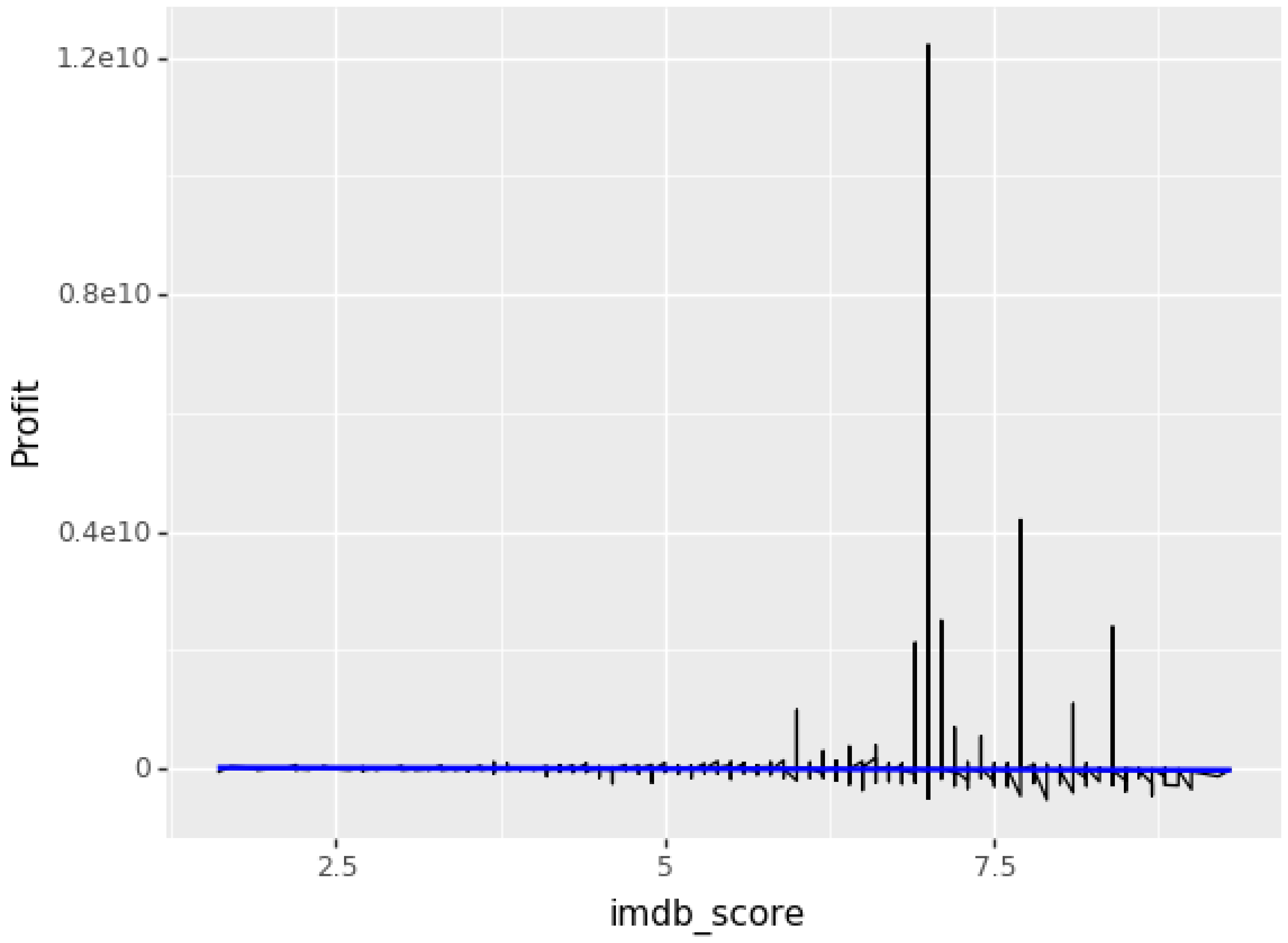

#Finding the corelation between imdb_rating with respect to no of facebook likes

```
(ggplot(movie_df)
 + aes(x='imdb_score', y='movie_facebook_likes')
 + geom_line()
 + labs(title='IMDB_Score vs. Facebook like for Movies', x='IMDB scores', y='Facebook Likes for movies')
)
```

```
/opt/conda/lib/python3.6/site-packages/plotnine/coords/coord_cartesian.py:31: MatplotlibDepre
cationWarning: The Bunch class was deprecated in Matplotlib 3.0 and will be removed in 3.2. Use t
ypes.SimpleNamespace instead.
  self.limits = Bunch(xlim=xlim, ylim=ylim)
/opt/conda/lib/python3.6/copy.py:274: MatplotlibDeprecationWarning: The Bunch class was depr
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  y = func(*args)
/opt/conda/lib/python3.6/site-packages/plotnine/facets/facet.py:151: MatplotlibDeprecationWar
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ning: The Bunch class was deprecated in Matplotlib 3.0 and will be removed in 3.2. Use types.Simp
leNamespace instead.
  return Bunch(x=xsc, y=ysc)
```
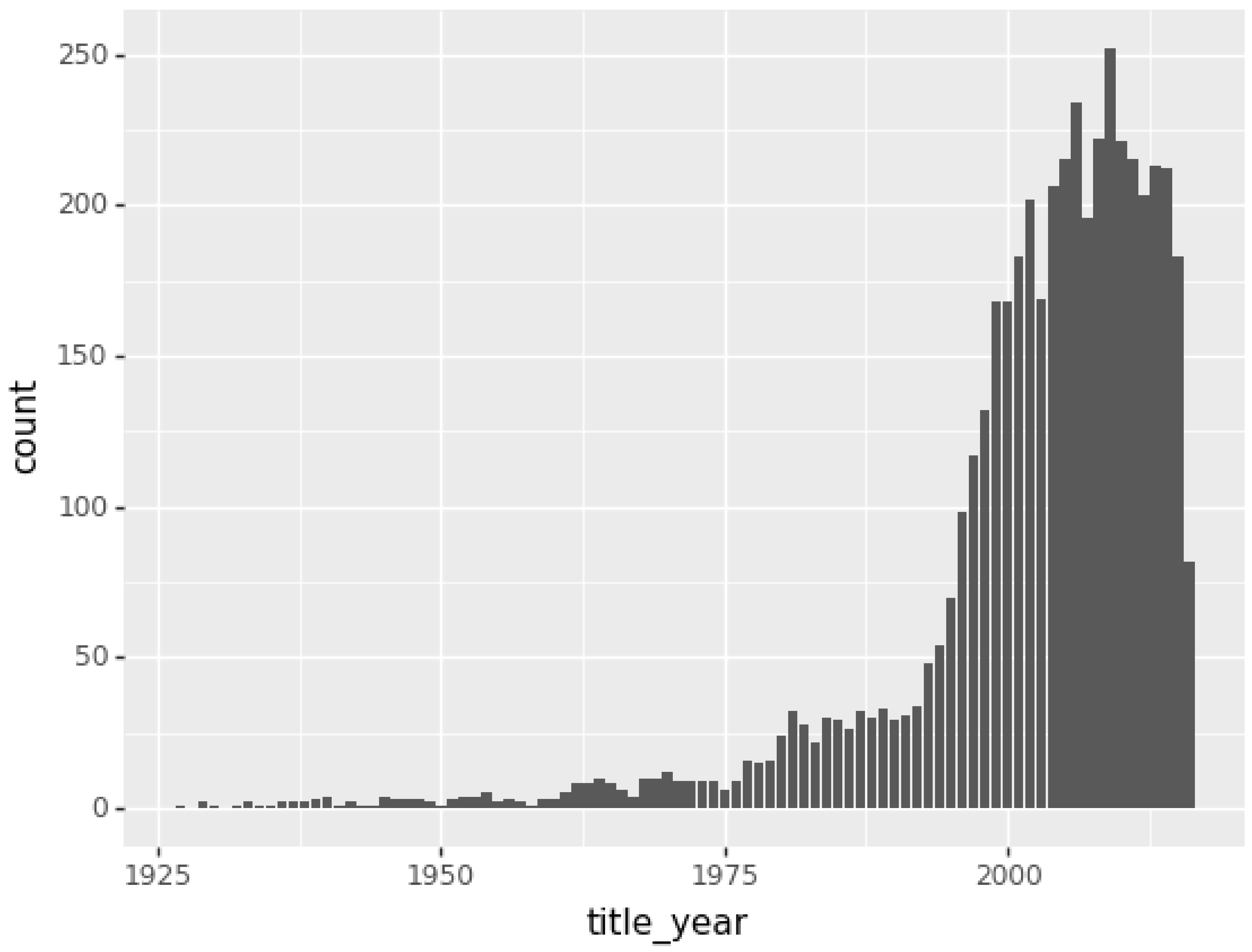
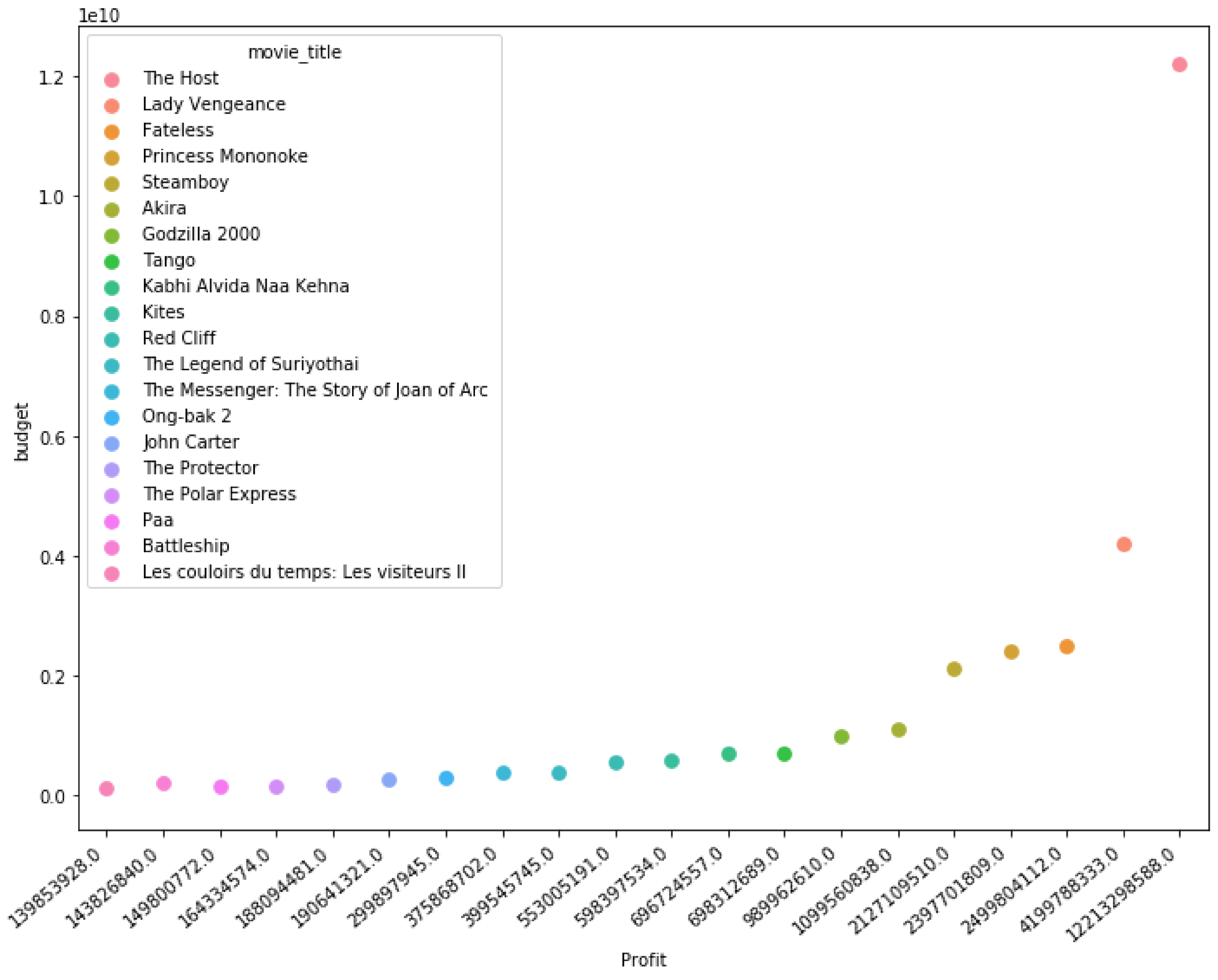



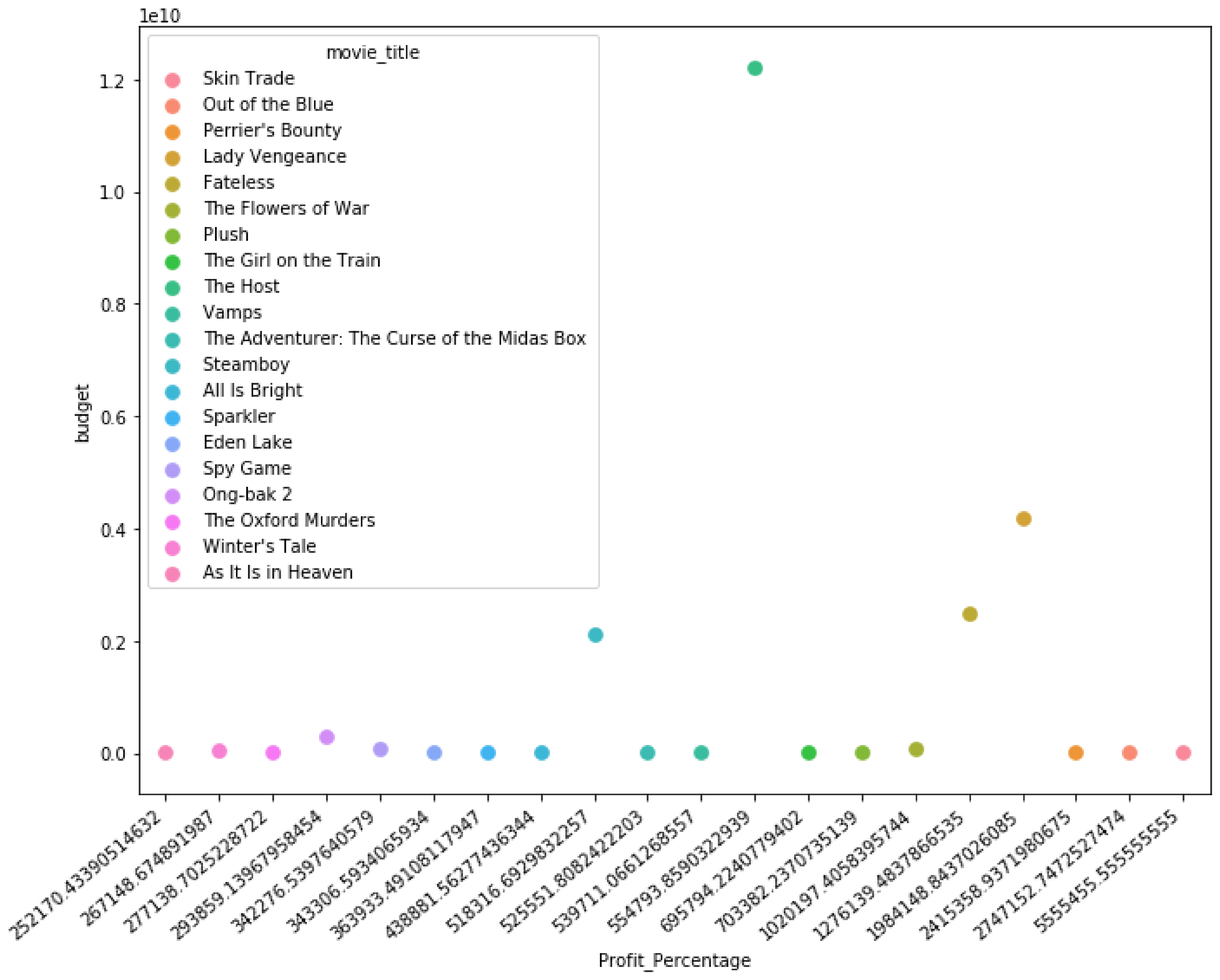
```
#Top 20 movies based on the profit they made

plt.figure(figsize=(10,8))
movie_df= movie_df.sort_values(by ='Profit' , ascending=False)
movie_df_new=movie_df.head(20)
ax=sns.pointplot(movie_df_new['Profit'], movie_df_new['budget'], hue=movie_df_new['movie_title'])
ax.set_xticklabels(ax.get_xticklabels(), rotation=40, ha="right")
plt.tight_layout()
plt.show()
```

```
#Top 20 movies based on the profit they made

plt.figure(figsize=(10,8))
movie_df= movie_df.sort_values(by ='Profit' , ascending=False)
movie_df_new=movie_df.head(20)
ax=sns.pointplot(movie_df_new['Profit'], movie_df_new['budget'], hue=movie_df_new['movie_title'])
```

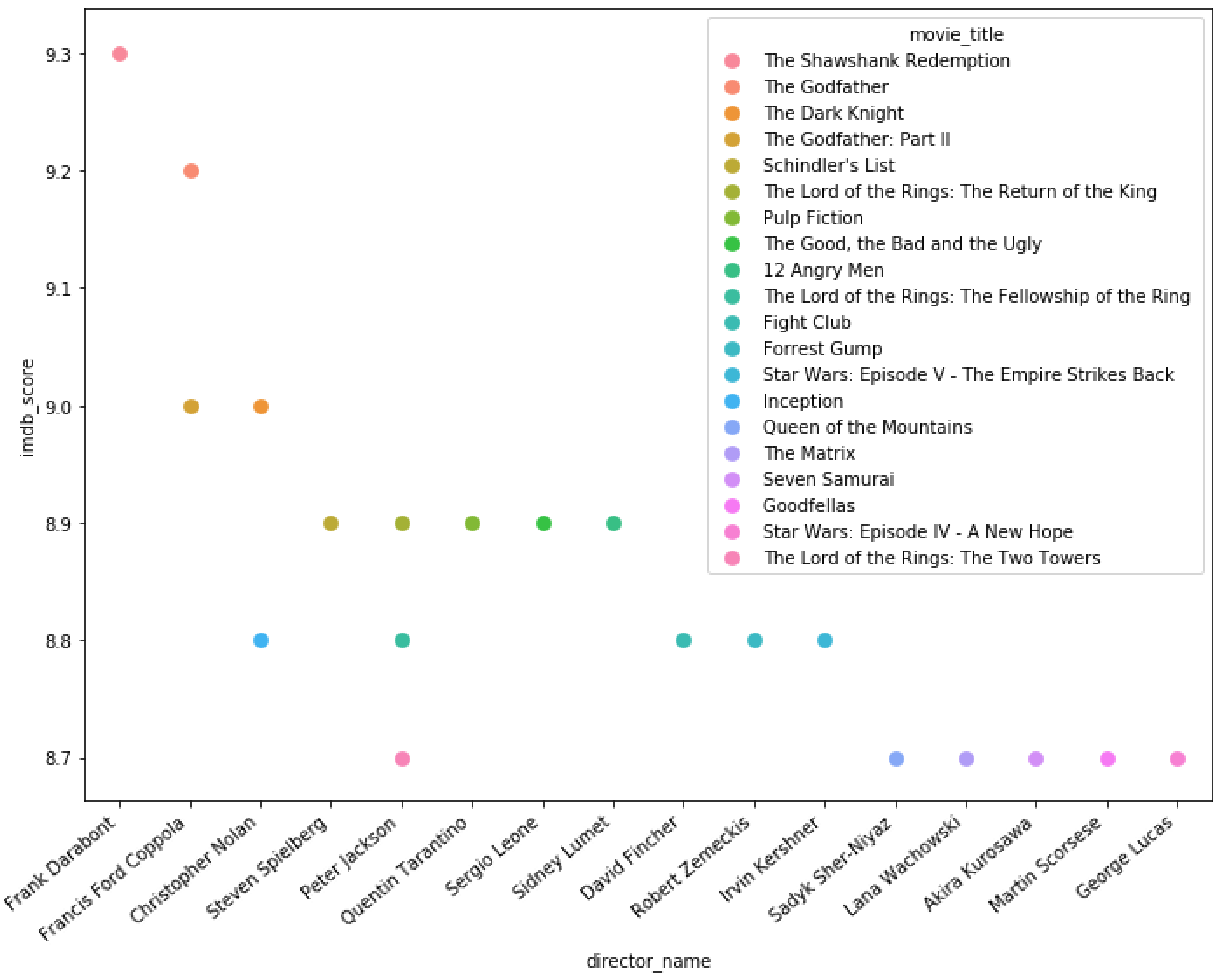
```
ax.set_xticklabels(ax.get_xticklabels(), rotation=40, ha="right")
plt.tight_layout()
```



```
# Top 20 movies based on the profit percentage
plt.figure(figsize=(10,8))
movie_df= movie_df.sort_values(by ='Profit_Percentage' , ascending=False)
movie_df_new=movie_df.head(20)
ax=sns.pointplot(movie_df_new['Profit_Percentage'], movie_df_new['budget'], hue=movie_df_new['
movie_title'])
ax.set_xticklabels(ax.get_xticklabels(), rotation=40, ha="right")
plt.tight_layout()
plt.show()
```



```
#Top 20 directors based on the IMDB ratings
plt.figure(figsize=(10,8))

movie_df= movie_df.sort_values(by ='imdb_score' , ascending=False)
movie_df_new=movie_df.head(20)
ax=sns.pointplot(movie_df_new['director_name'], movie_df_new['imdb_score'], hue=movie_df_new['
movie_title'])
ax.set_xticklabels(ax.get_xticklabels(), rotation=40, ha="right")
plt.tight_layout()
plt.show()
```



```
#Commercial success vs critial acclaim
movie_df= movie_df.sort_values(by ='Profit_Percentage' , ascending=False)
movie_df_new=movie_df.head(20)
(ggplot(movie_df_new)
 + aes(x='imdb_score', y='gross',color = "content_rating")
 + geom_point()
 +  geom_hline(aes(yintercept = 600)) +
  geom_vline(aes(xintercept = 10)) +
  xlab("Imdb score") +
  ylab("Gross money earned in million dollars") +
  ggtitle("Commercial success Vs Critical acclaim") +
  annotate("text", x = 8.5, y = 700, label = "High ratings \n & High gross"))
/opt/conda/lib/python3.6/site-packages/plotnine/coords/coord_cartesian.py:31: Mat
/opt/conda/lib/python3.6/site-packages/plotnine/coords/coord_cartesian.py:31: MatplotlibDepre
cationWarning: The Bunch class was deprecated in Matplotlib 3.0 and will be removed in 3.2. Use t
ypes.SimpleNamespace instead.
  self.limits = Bunch(xlim=xlim, ylim=ylim)
/opt/conda/lib/python3.6/copy.py:274: MatplotlibDeprecationWarning: The Bunch class was depr
ecated in Matplotlib 3.0 and will be removed in 3.2. Use types.SimpleNamespace instead.
  y = func(*args)
/opt/conda/lib/python3.6/site-packages/plotnine/layer.py:520: MatplotlibDeprecationWarning: isi
nstance(..., numbers.Number)
  return not cbook.iterable(value) and (cbook.is_numlike(value) or
/opt/conda/lib/python3.6/site-packages/plotnine/facets/facet.py:151: MatplotlibDeprecationWar
ning: The Bunch class was deprecated in Matplotlib 3.0 and will be removed in 3.2. Use types.Simp
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  scales = Bunch()
/opt/conda/lib/python3.6/site-packages/plotnine/facets/layout.py:147: MatplotlibDeprecationWar
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  return Bunch(x=xsc, y=ysc)
/opt/conda/lib/python3.6/site-packages/plotnine/coords/coord.py:144: MatplotlibDeprecationWa
rning: The Bunch class was deprecated in Matplotlib 3.0 and will be removed in 3.2. Use types.Sim
pleNamespace instead.
  y=panel_params['y_range'])
/opt/conda/lib/python3.6/site-packages/plotnine/guides/guide_legend.py:179: MatplotlibDepreca
tionWarning: The Bunch class was deprecated in Matplotlib 3.0 and will be removed in 3.2. Use typ
es.SimpleNamespace instead.
  self.glayers.append(Bunch(geom=geom, data=data, layer=l))
```
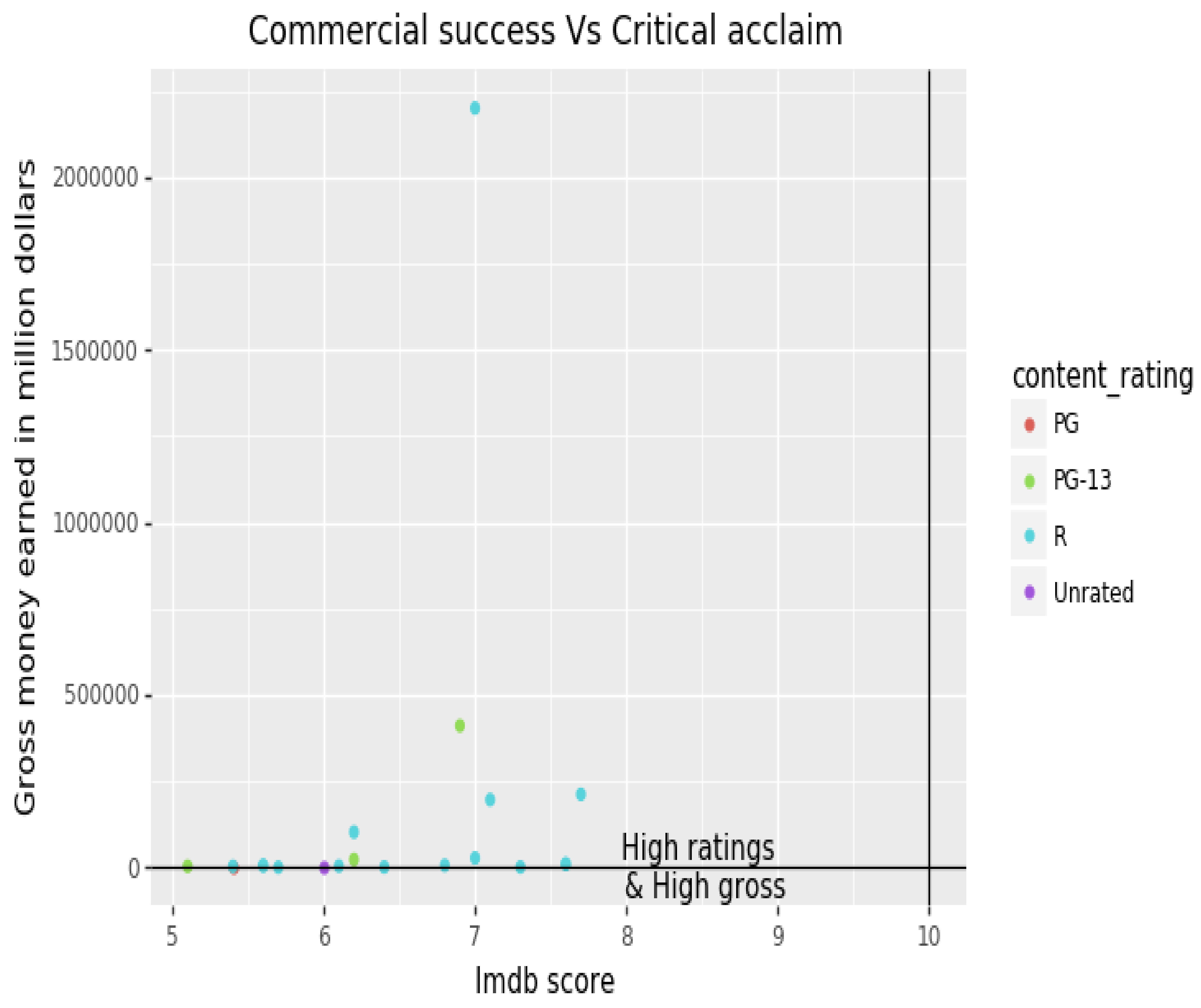
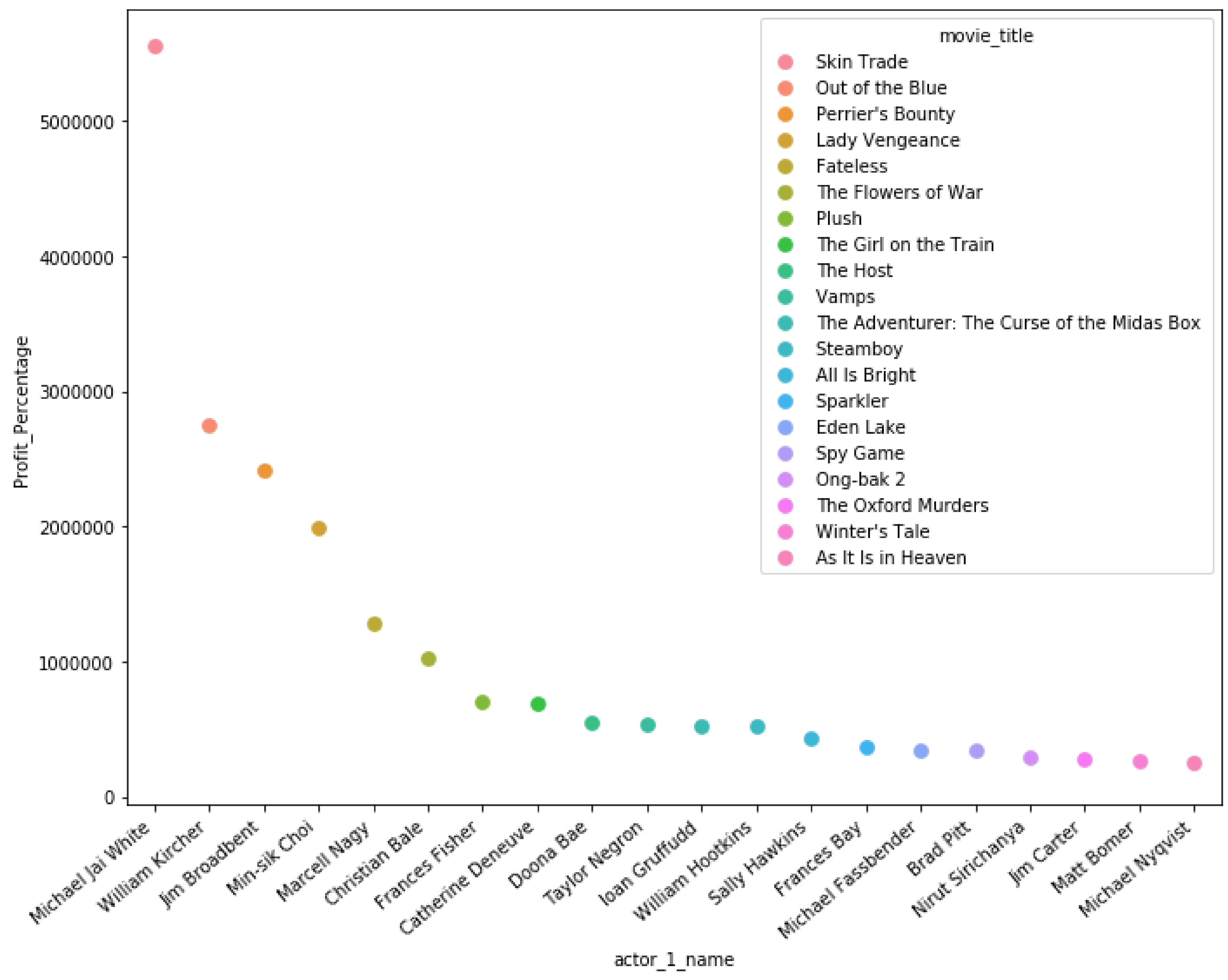
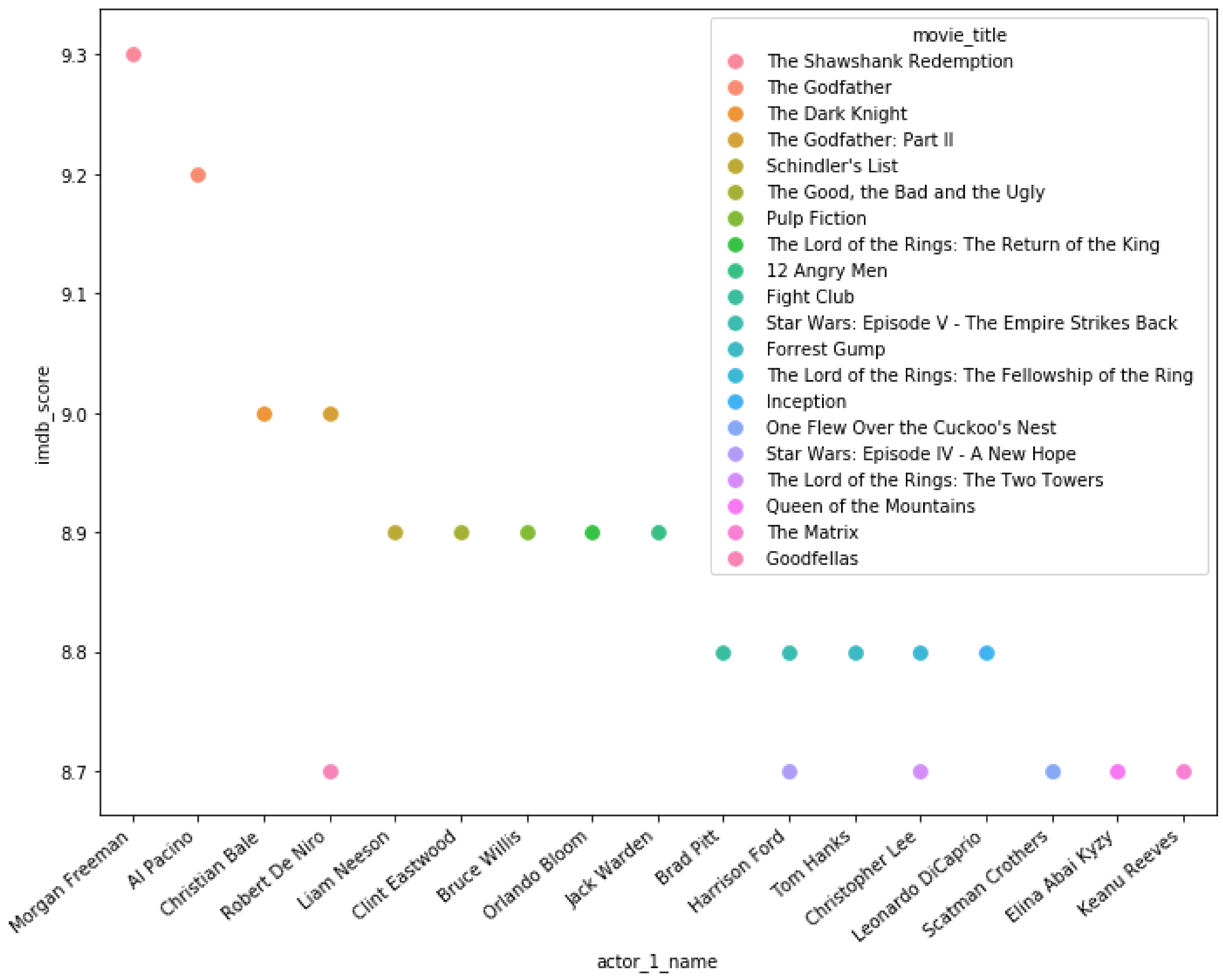



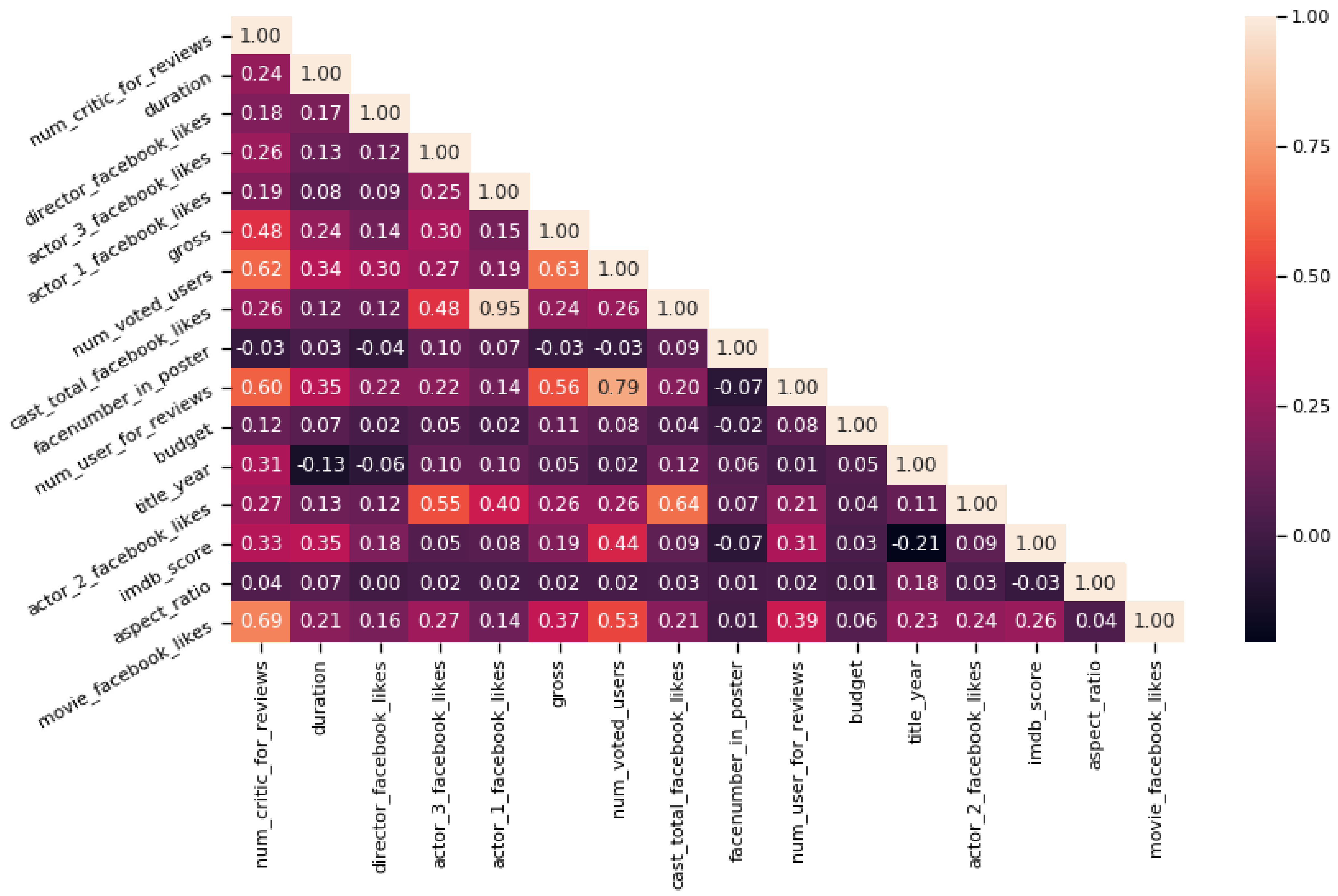
Top 20 actors of movies based on the commerical success

```
plt.figure(figsize=(10,8))

movie_df= movie_df.sort_values(by ='Profit_Percentage' , ascending=False)
movie_df_new=movie_df.head(20)
ax=sns.pointplot(movie_df_new['actor_1_name'], movie_df_new['Profit_Percentage'], hue=movie_df
_new['movie_title'])
ax.set_xticklabels(ax.get_xticklabels(), rotation=40, ha="right")
plt.tight_layout()
plt.show()
```





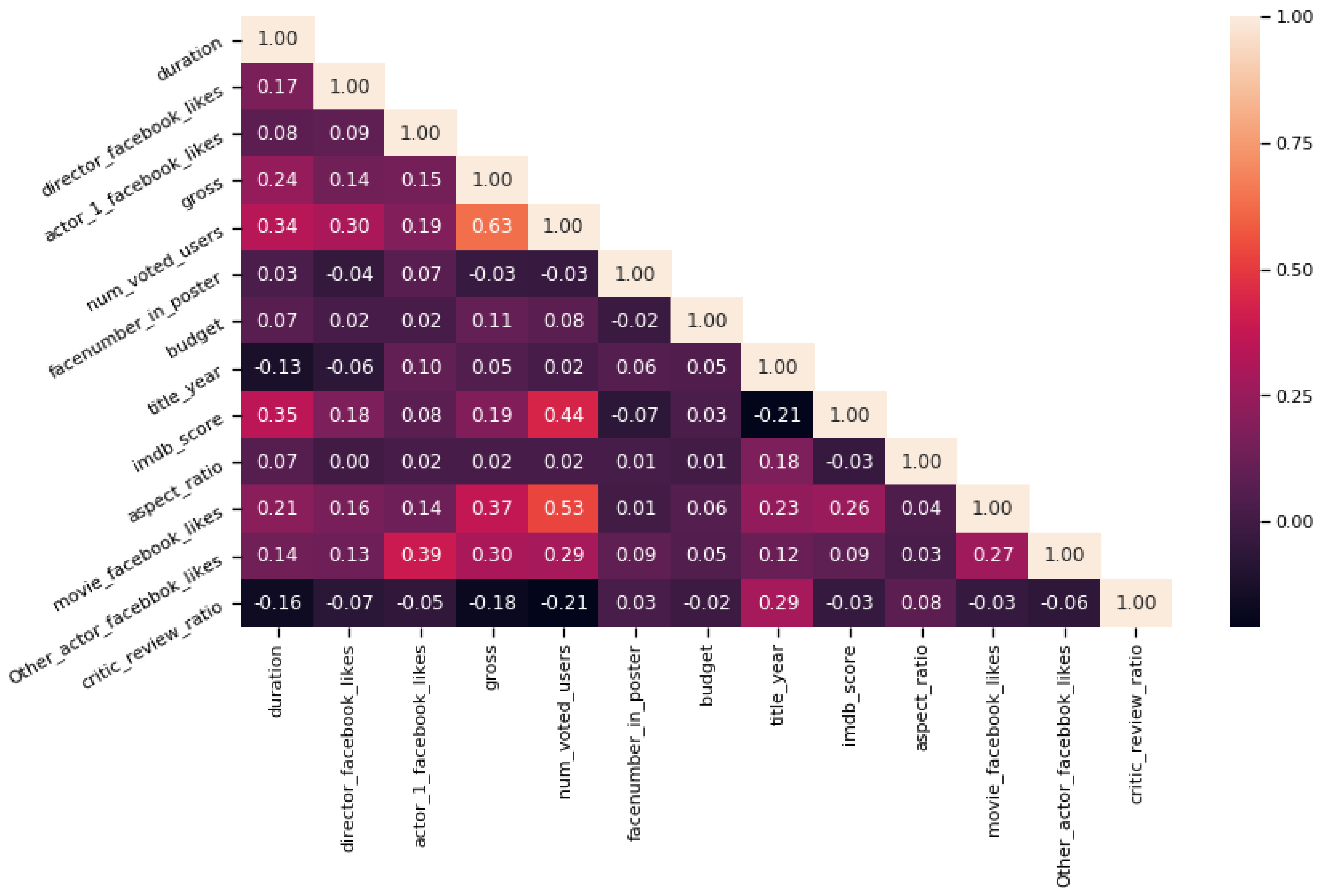
```
# Correlation with heat map
import matplotli.pyplot as plot
import seaborn as sns
corr = movie_df.corr()
sns.set_context("notebook", font_scale=1.0, rc={"lines.linewidth": 2.5})
plt.figure(figsize=(13,7))
# create a mask so we only see the correlation values once
mask = np.zeros_like(corr)
mask[np.triu_indices_from(mask, 1)] = True
a = sns.heatmap(corr,mask=mask, annot=True, fmt='.2f')
rotx = a.set_xticklabels(a.get_xticklabels(), rotation=90)
roty = a.set_yticklabels(a.get_yticklabels(), rotation=30)
```



We can see that the cast_total_facebook_likes and actor_1_facebook_like are highly correlated to each other. Both actor2 and actor3 are also somehow correlated to the total. So we want to modify them into two variables: actor_1_facebook_likes and other_actors_facebook_likes.

There are high correlations among num_voted_users, num_user_for_reviews and num_critic_for_reviews. We want to keep num_voted_users and take the ratio of num_user_for_reviews and num_critic_for_reviews.

```
# New Correlation matrix shown in the figure

import matplotlib.pyplot as plot
import seaborn as sns
corr = movie_df.corr()
sns.set_context("notebook", font_scale=1.0, arc={"lines.linewidth": 2.5})
plt.figure(figsize=(13,7))
# create a mask so we only see the correlation values once
mask = np.zeros_like(corr)
mask[np.triu_indices_from(mask, 1)] = True
a = sns.heatmap(corr,mask=mask, annot=True, fts='.2f')
rotx = a.set_xticklabels(a.get_xticklabels(), rotation=90)
roty = a.set_yticklabels(a.get_yticklabels(), rotation=30)
```



```
from sklearn.metrics import classification_report

print('Logistic  Reports\n',classification_report(y_test, y_pred))
print('KNN Reports\n',classification_report(y_test, knnpred))
print('SVC Reports\n',classification_report(y_test, svcpred))
print('Naive BayesReports\n',classification_report(y_test, gaussiannbpred))
print('Decision Tree Reports\n',classification_report(y_test, dtreepred))
print('Ada Boosting\n',classification_report(y_test, abcl_pred))
print('Random Forests Reports\n',classification_report(y_test, rfcpred))
print('Bagging Clasifier',bgcl.oob_score_)
print('Gradient Boosting',classification_report(y_test, test_pred))
print('XGBoosting\n',classification_report(y_test, xgbprd))
```

```
logistic

 Reports
              precision    recall  f1-score   support

           1      0.00      0.00      0.00        46
           2      0.50      0.25      0.33       378
           3      0.72      0.92      0.81       924
           4      0.84      0.52      0.65        61

    accuracy                          0.69      1409
   macro avg      0.52      0.42      0.45      1409
weighted avg      0.64      0.69      0.65      1409


KNN Reports
              precision    recall  f1-score   support

           1      0.00      0.00      0.00        46
```

```
         2       0.46      0.41      0.44       378
         3       0.73      0.83      0.78       924
         4       1.00      0.20      0.33        61

   accuracy                          0.67      1409
  macro avg       0.55      0.36      0.39      1409
weighted avg       0.64      0.67      0.64      1409
```

SVC Reports

```
            precision    recall   f1-score   support

         1       0.14      0.02      0.04        46
         2       0.42      0.42      0.42       378
         3       0.74      0.79      0.76       924
         4       0.57      0.33      0.42        61

   accuracy                          0.64      1409
  macro avg       0.47      0.39      0.41      1409
weighted avg       0.62      0.64      0.63      1409
```

Naive BayesReports

```
            precision    recall   f1-score   support

         1       0.05      0.91      0.09        46
         2       0.50      0.00      0.01       378
         3       0.71      0.01      0.01       924
         4       0.11      0.85      0.19        61

   accuracy                          0.07      1409
  macro avg       0.34      0.44      0.07      1409
weighted avg       0.61      0.07      0.02      1409
```

Decision Tree Reports

```
            precision    recall   f1-score   support

         1       0.11      0.11      0.11        46
         2       0.47      0.51      0.49       378
         3       0.78      0.76      0.77       924
         4       0.77      0.59      0.67        61

   accuracy                          0.67      1409
  macro avg       0.53      0.49      0.51      1409
weighted avg       0.67      0.67      0.67      1409
```

Ada Boosting

```
            precision    recall  f1-score   support

         1       0.17      0.15      0.16        46
         2       0.46      0.51      0.48       378
         3       0.77      0.75      0.76       924
         4       0.65      0.51      0.57        61

   accuracy                          0.65      1409
  macro avg       0.51      0.48      0.49      1409
weighted avg       0.66      0.65      0.66      1409
```

```
Random Forests Reports
              precision    recall  f1-score   support

           1       1.00      0.04      0.08        46
           2       0.62      0.47      0.53       378
           3       0.77      0.92      0.84       924
           4       0.96      0.44      0.61        61

    accuracy                           0.75      1409
   macro avg       0.84      0.47      0.52      1409
weighted avg       0.75      0.75      0.72      1409

Bagging Clasifier 0.7429179978700745
Gradient Boosting               precision    recall  f1-score   support

           1       0.25      0.02      0.04        46
           2       0.60      0.56      0.58       378
           3       0.80      0.88      0.84       924
           4       0.86      0.49      0.62        61

    accuracy                           0.75      1409
   macro avg       0.63      0.49      0.52      1409
weighted avg       0.73      0.75      0.74      1409



XGBoosting
              precision    recall   f1-score   support

           1       0.25      0.02      0.04        46
           2       0.59      0.52      0.55       378
           3       0.79      0.89      0.84       924
           4       0.89      0.54      0.67        61

    accuracy                           0.75      1409
   macro avg       0.63      0.49      0.53      1409
weighted avg       0.72      0.75      0.73      1409

opt/conda/lib/python3.6/site-packages/sklearn/metrics/classification.py:1437: UndefinedMetric
Warning: Precision and F-score are ill-defined and being set to 0.0 in labels with no predicted samp
les.
  'precision', 'predicted', average, warn_for
```

10.Conclusion

The conclusion is that Random Forest Algorithm along with the gradient boosting have the accuracy of 74.5 and 75.5 respectively

Done by:

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