Predicting IMDb Scores Using Machine Learning

Phase 2 Submission Document

Team Members

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Project: Predicting IMDb Scores

Introduction

Predicting IMDb scores is valuable for movie studios, distributors, and viewers. It assists in understanding a movie's potential success, guiding marketing strategies, and aiding investment decisions. This report details the process of building an IMDb score prediction model.

Content for Project Phase 2

Data Overview

Data Pre-processing

Feature Engineering

Model Selection

Model Training

Model Evaluation

Data Source

A good data source for house price prediction using machine learning should beAccurate, Complete, Covering the geographic area of interest, Accessible.

Dataset Link: (https://www.kaggle.com/code/imdb-score-prediction-for-movies)

Data Overview

We collected a comprehensive dataset of movies, including various features such as genres, cast, director, budget, and release year. The dataset also includes IMDb scores, which serve as our target variable

Data Processing

To prepare the data for modelling, we executed the following preprocessing tasks

- Handling missing data
- Encoding categorical variables
- Normalizing or scaling numeric features
- Addressing outliers, if necessary

Feature Engineering

Feature engineering involved extracting valuable features from the dataset, including

- Genre-based features
- Actor and director-related features
- Budget normalization
- Release year transformation

Model Selection

We experimented with several machine learning models suitable for regression tasks, including

- Linear Regression
- Random Forest
- Gradient Boosting
- Neural Networks

Model Training

The selected model was trained on a portion of the dataset, and hyperparameters were tuned for optimal performance

Model Evaluation

The model's performance was assessed using various evaluation metrics, including

- Mean Absolute Error (MAE)
- Root Mean Squared Error (RMSE)
- R-squared (R2)

These metrics provided insights into the model's predictive accuracy and its ability to estimate IMDb scores effectively

Program:

Predicting IMDb Scores

In[1]:

```
import numpy as np

import pandas as pd

import matplotlib.pyplot as plt

import seaborn as sns
```

```
from plotnine import *
```

Introduction

To Predict an IMDb Scores using Machine Language

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 factors to measure the movie's success.

Description of dataset attributes

- Color :- Movie is black or coloured
- Director_name:- Name of the movie director
- num_critic_for_reviews :- No of critics for the movie
- duration:- movie duration in minutes
- director_facebook_likes:-Number of likes for the Director on his Facebook Page
- actor_3_facebook_likes:- No of likes for the actor 3 on his/her facebook Page
- actor2_name:- name of the actor 2
- actor_1_facebook_likes:- No of likes for the actor 1 on his/her facebook Page

- gross:- Gross earnings of the movie in Dollars
- genres:- Film categorization like ‘Animation’, ‘Comedy’, ‘Romance’, ‘Horror’, ‘Sci-Fi’, ‘Action’, ‘Family’
- actor_1_name:- Name of the actor 1
- movie_title:-Title of the movie
- num_voted_users:-No of people who voted for the movie
- cast_total_facebook_likes:- Total facebook like for the movie
- actor_3_name:- Name of the actor 3
- facenumber_in_poster:- No of actors who featured in the movie poster
- plot_keywords:-Keywords describing the movie plots
- movie_imdb_link:-Link of the movie link
- num_user_for_reviews:- Number of users who gave a review
- language:- Language of the movie
- country:- Country where movie is produced
- content_rating:- Content rating of the movie
- budget:- Budget of the movie in Dollars
- title_year:- The year in which the movie is released
- actor_2_facebook_likes:- facebook likes for the actor 2
- imdb_score:- IMDB score of the movie
- aspect_ratio :- Aspect ratio the movie was made in
- movie_facebook_likes:- Total no of facebook likes for the movie

Case Study

The dataset here gives the massive information about the movies and their IMDB scores respectively. We are going to analyze each and every factor 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.

Data Processing

In[2]:

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

In[3]:

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

Out[3]:

	color	director_name	num_critic_for_reviews	duration	director_facebook_likes	actor_3_facebook_likes	actor_2_name	actor_1_facebook_likes	gross	genres
0	Color	James Cameron	723.0	178.0	0.0	855.0	Joel David Moore	1000.0	760505847.0	Action|Advent
1	Color	Gore Verbinski	302.0	169.0	563.0	1000.0	Orlando Bloom	40000.0	309404152.0	Action|Advent
2	Color	Sam Mendes	602.0	148.0	0.0	161.0	Rory Kinnear	11000.0	200074175.0	Action|Advent
3	Color	Christopher Nolan	813.0	164.0	22000.0	23000.0	Christian Bale	27000.0	448130642.0	Action|Thriller
4	NaN	Doug Walker	NaN	NaN	131.0	NaN	Rob Walker	131.0	NaN	Documentary
5	Color	Andrew Stanton	462.0	132.0	475.0	530.0	Samantha Morton	640.0	73058679.0	Action|Advent
6	Color	Sam Raimi	392.0	156.0	0.0	4000.0	James Franco	24000.0	336530303.0	Action|Advent
7	Color	Nathan Greno	324.0	100.0	15.0	284.0	Donna Murphy	799.0	200807262.0	Adventure|Ani
8	Color	Joss Whedon	635.0	141.0	0.0	19000.0	Robert Downey Jr.	26000.0	458991599.0	Action|Advent
9	Color	David Yates	375.0	153.0	282.0	10000.0	Daniel Radcliffe	25000.0	301956980.0	Adventure|Far

In[4]:

```
movie_df.shape
```

Out[4]:

```
(5043, 28)
```

In[5]:

```
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
```

In[6]:

```
movie_df.describe().T
```

Out[6]:

	count	mean	std	min	25%	50%	75%	max
num_critic_for_reviews	4993.0	1.401943e+02	1.216017e+02	1.00	50.00	110.00	195.00	8.130000e+02
duration	5028.0	1.072011e+02	2.519744e+01	7.00	93.00	103.00	118.00	5.110000e+02
director_facebook_likes	4939.0	6.865092e+02	2.813329e+03	0.00	7.00	49.00	194.50	2.300000e+04
actor_3_facebook_likes	5020.0	6.450098e+02	1.665042e+03	0.00	133.00	371.50	636.00	2.300000e+04
actor_1_facebook_likes	5036.0	6.560047e+03	1.502076e+04	0.00	614.00	988.00	11000.00	6.400000e+05
gross	4159.0	4.846841e+07	6.845299e+07	162.00	5340987.50	25517500.00	62309437.50	7.605058e+08
num_voted_users	5043.0	8.366816e+04	1.384853e+05	5.00	8593.50	34359.00	96309.00	1.689764e+06
cast_total_facebook_likes	5043.0	9.699064e+03	1.816380e+04	0.00	1411.00	3090.00	13756.50	6.567300e+05
facenumber_in_poster	5030.0	1.371173e+00	2.013576e+00	0.00	0.00	1.00	2.00	4.300000e+01
num_user_for_reviews	5022.0	2.727708e+02	3.779829e+02	1.00	65.00	156.00	326.00	5.060000e+03
budget	4551.0	3.975262e+07	2.061149e+08	218.00	6000000.00	20000000.00	45000000.00	1.221550e+10
title_year	4935.0	2.002471e+03	1.247460e+01	1916.00	1999.00	2005.00	2011.00	2.016000e+03
actor_2_facebook_likes	5030.0	1.651754e+03	4.042439e+03	0.00	281.00	595.00	918.00	1.370000e+05
imdb_score	5043.0	6.442138e+00	1.125116e+00	1.60	5.80	6.60	7.20	9.500000e+00
aspect_ratio	4714.0	2.220403e+00	1.385113e+00	1.18	1.85	2.35	2.35	1.600000e+01
movie_facebook_likes	5043.0	7.525965e+03	1.932045e+04	0.00	0.00	166.00	3000.00	3.490000e+05

In[7]:

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

In[8]:

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

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

In[9]:

```
movie_df.columns
```

Out[9]:

```
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')
```

In[10]:

```
movie_df.isna().any()
```

Out[10]:

```
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
```

In[11]:

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

Out[11]:

```
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
```

In[12]:

```
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'],inpl
ace=True)
```

In[13]:

```
movie_df.shape
```

Out[13]:

```
(4737, 26)
```

In[14]:

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

In[15]:

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

In[17]:

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

In[18]:

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

Out[18]:

```
director_name                0
num_critic_for_reviews       0
duration                     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
```

In[19]:

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

Out[19]:

```
(4695, 26)
```

In[20]:

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

Out[20]:

```
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
```

In[21]:

```
plt.figure(figsize=(40,10))

sns.countplot(movie_df["language"])

plt.show()
```

In[22]:

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

In[23]:

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

movie_df.head(5)
```

Out[23]:

	director_name	num_critic_for_reviews	duration	director_facebook_likes	actor_3_facebook_likes	actor_2_name	actor_1_facebook_likes	gross	genres
0	James Cameron	723.0	178.0	0.0	855.0	Joel David Moore	1000.0	760505847.0	Action|Adventure|Fa Fi
1	Gore Verbinski	302.0	169.0	563.0	1000.0	Orlando Bloom	40000.0	309404152.0	Action|Adventure|Fa
2	Sam Mendes	602.0	148.0	0.0	161.0	Rory Kinnear	11000.0	200074175.0	Action|Adventure|Th
3	Christopher Nolan	813.0	164.0	22000.0	23000.0	Christian Bale	27000.0	448130642.0	Action|Thriller
5	Andrew Stanton	462.0	132.0	475.0	530.0	Samantha Morton	640.0	73058679.0	Action|Adventure|Sci

In[24]:

```
movie_df['Profit_Percentage']=(movie_df["Profit"]/movie_df["gross"])*100

movie_df
```

Out[24]:

	director_name	num_critic_for_reviews	duration	director_facebook_likes	actor_3_facebook_likes	actor_2_name	actor_1_facebook_likes	gross	genres
0	James Cameron	723.0	178.0	0.0	855.0	Joel David Moore	1000.0	760505847.0	Action|Adventure
1	Gore Verbinski	302.0	169.0	563.0	1000.0	Orlando Bloom	40000.0	309404152.0	Action|Adventure
2	Sam Mendes	602.0	148.0	0.0	161.0	Rory Kinnear	11000.0	200074175.0	Action|Adventure
3	Christopher Nolan	813.0	164.0	22000.0	23000.0	Christian Bale	27000.0	448130642.0	Action|Thriller
5	Andrew Stanton	462.0	132.0	475.0	530.0	Samantha Morton	640.0	73058679.0	Action|Adventure
...	...	...	...	...	...	...	...	...	...
5034	Neill Dela Llana	35.0	80.0	0.0	0.0	Edgar Tancangco	0.0	70071.0	Thriller
5035	Robert Rodriguez	56.0	81.0	0.0	6.0	Peter Marquardt	121.0	2040920.0	Action|Crime|Dra
5037	Edward Burns	14.0	95.0	0.0	133.0	Caitlin FitzGerald	296.0	4584.0	Comedy|Drama
5038	Scott Smith	1.0	87.0	2.0	318.0	Daphne Zuniga	637.0	26005908.0	Comedy|Drama
5042	Jon Gunn	43.0	90.0	16.0	16.0	Brian Herzlinger	86.0	85222.0	Documentary

In[25]:

value_counts=movie_df["country"].value_counts()

print(value_counts)

Out[25]:

```
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
```

In[26]:

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

In[27]:

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

Out[27]:

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

In[28]:

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

Out[28]:

<table>
<tr><th></th><th>director_name</th><th>num_critic_for_reviews</th><th>duration</th><th>director_facebook_likes</th><th>actor_3_facebook_likes</th><th>actor_2_name</th><th>actor_1_facebook_likes</th><th>gross</th><th>genres</th></tr>
<tr><td>0</td><td>James Cameron</td><td>723.0</td><td>178.0</td><td>0.0</td><td>855.0</td><td>Joel David Moore</td><td>1000.0</td><td>760505847.0</td><td>Action|Adventure|Fa</td></tr>
<tr><td>1</td><td>Gore Verbinski</td><td>302.0</td><td>169.0</td><td>563.0</td><td>1000.0</td><td>Orlando Bloom</td><td>40000.0</td><td>309404152.0</td><td>Action|Adventure|Fa</td></tr>
<tr><td>2</td><td>Sam Mendes</td><td>602.0</td><td>148.0</td><td>0.0</td><td>161.0</td><td>Rory Kinnear</td><td>11000.0</td><td>200074175.0</td><td>Action|Adventure|Th</td></tr>
<tr><td>3</td><td>Christopher Nolan</td><td>813.0</td><td>164.0</td><td>22000.0</td><td>23000.0</td><td>Christian Bale</td><td>27000.0</td><td>448130642.0</td><td>Action|Thriller</td></tr>
<tr><td>5</td><td>Andrew Stanton</td><td>462.0</td><td>132.0</td><td>475.0</td><td>530.0</td><td>Samantha Morton</td><td>640.0</td><td>73058679.0</td><td>Action|Adventure|Sc</td></tr>
<tr><td>6</td><td>Sam Raimi</td><td>392.0</td><td>156.0</td><td>0.0</td><td>4000.0</td><td>James Franco</td><td>24000.0</td><td>336530303.0</td><td>Action|Adventure|Ro</td></tr>
<tr><td>7</td><td>Nathan Greno</td><td>324.0</td><td>100.0</td><td>15.0</td><td>284.0</td><td>Donna Murphy</td><td>799.0</td><td>200807262.0</td><td>Adventure|Animatio</td></tr>
<tr><td>8</td><td>Joss Whedon</td><td>635.0</td><td>141.0</td><td>0.0</td><td>19000.0</td><td>Robert Downey Jr.</td><td>26000.0</td><td>458991599.0</td><td>Action|Adventure|Sc</td></tr>
<tr><td>9</td><td>David Yates</td><td>375.0</td><td>153.0</td><td>282.0</td><td>10000.0</td><td>Daniel Radcliffe</td><td>25000.0</td><td>301956980.0</td><td>Adventure|Family|Fa</td></tr>
<tr><td>10</td><td>Zack Snyder</td><td>673.0</td><td>183.0</td><td>0.0</td><td>2000.0</td><td>Lauren Cohan</td><td>15000.0</td><td>330249062.0</td><td>Action|Adventure|Sc</td></tr>
</table>

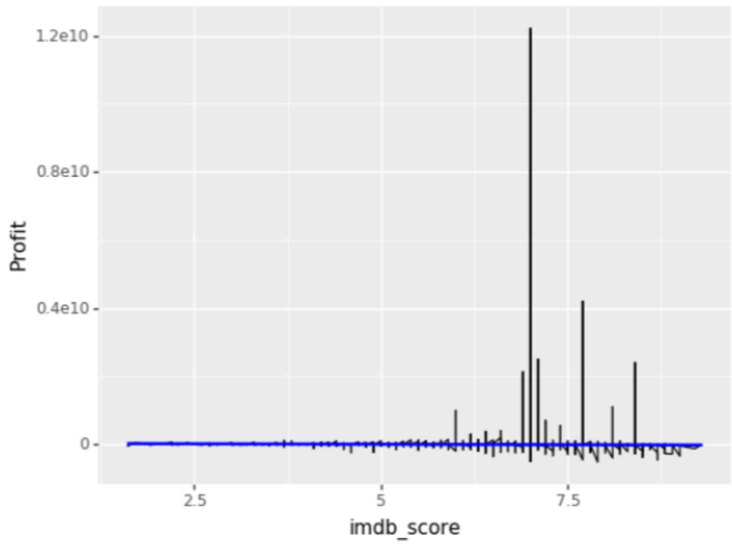
Data Visualization

In[29]:

```
(ggplot(movie_df)
 + aes(x='title_year')
 + geom_bar(size=20)
)
```

In[30]:

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

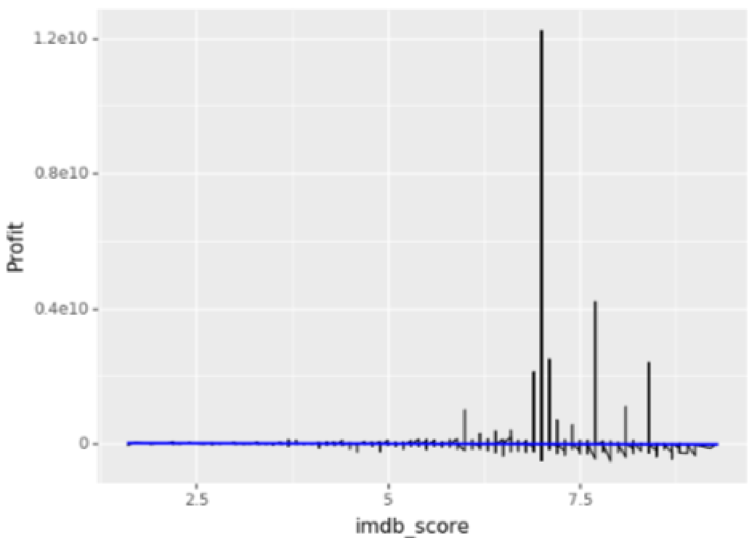


Out[30]:

<ggplot: (8779159653317)>

In[31]:

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

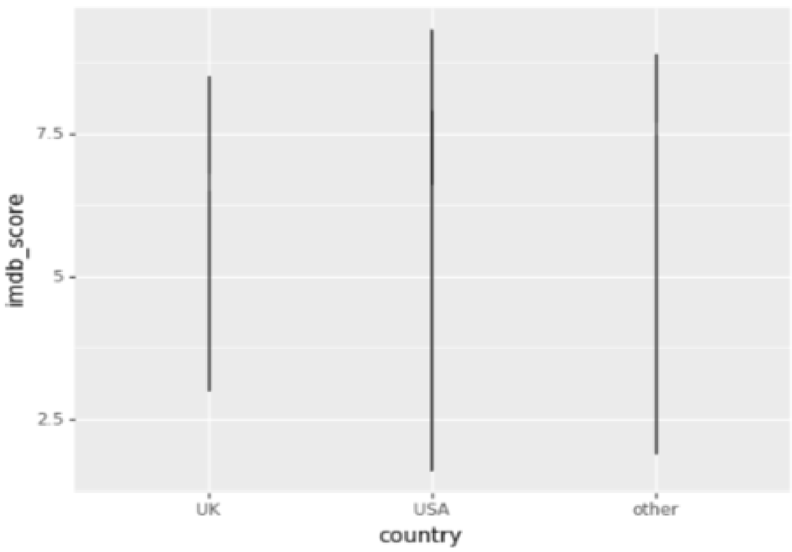


Out[31]:

<ggplot: (8779159577103)>

In[32]:

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



Out[32]:

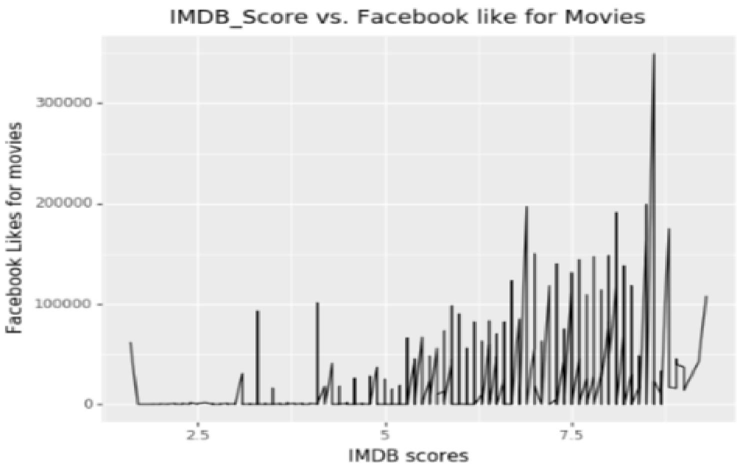
<ggplot: (-9223363257695236576)>

In[33]:

```
(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')

)

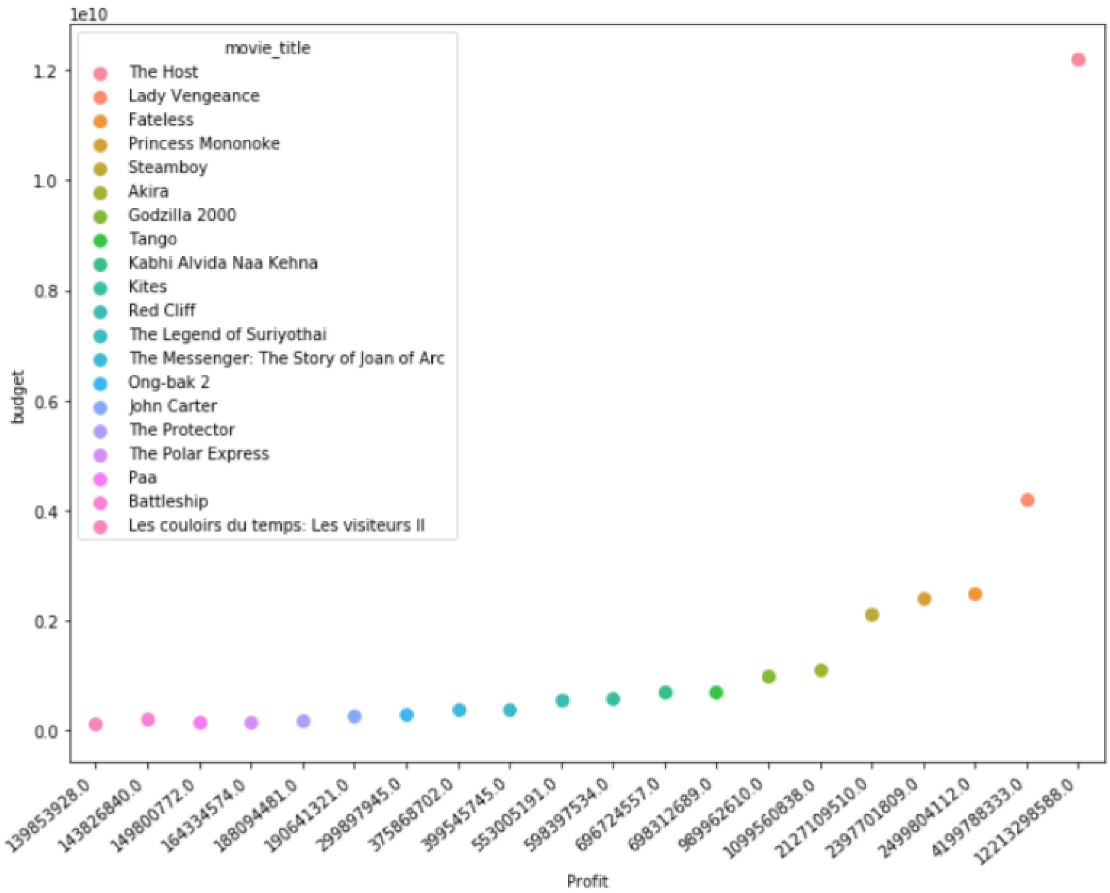


Out[33]:

<ggplot: (8779159517781)>

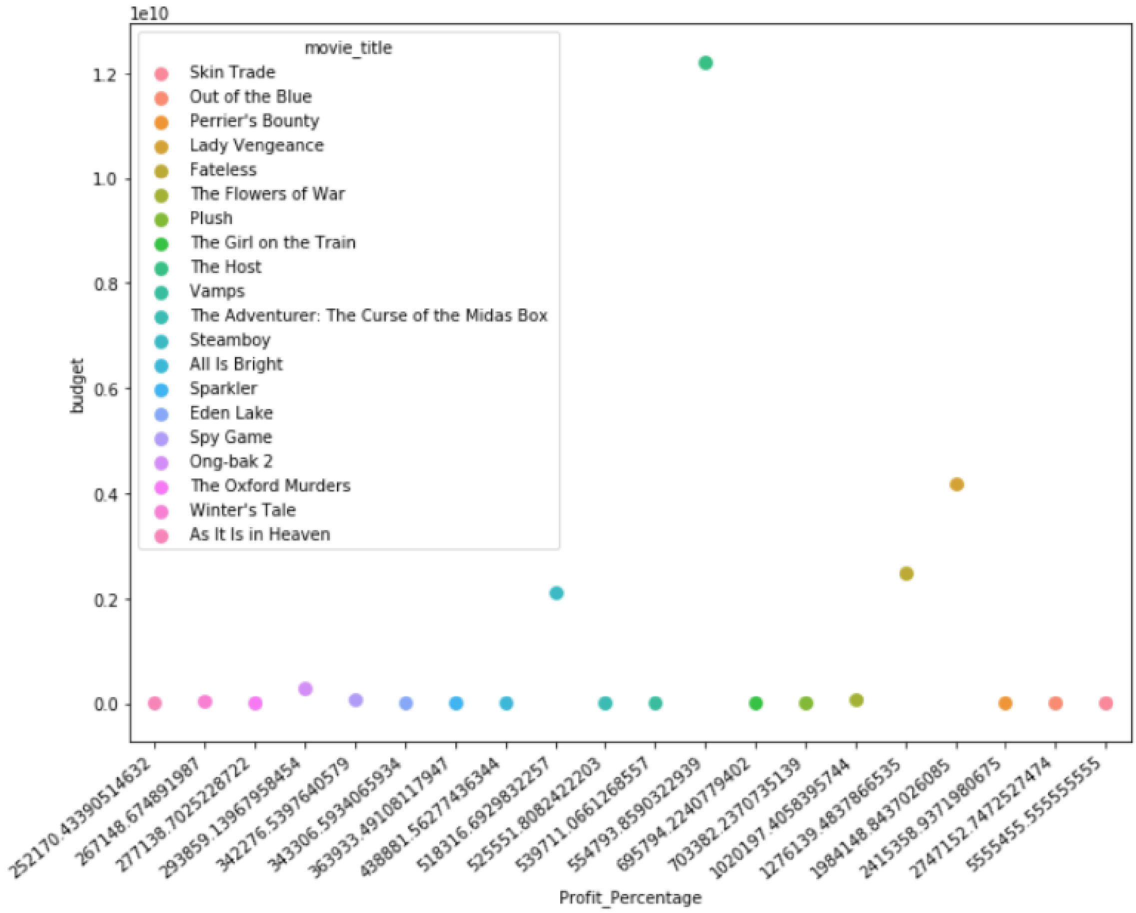
In[34]:

```
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()
```



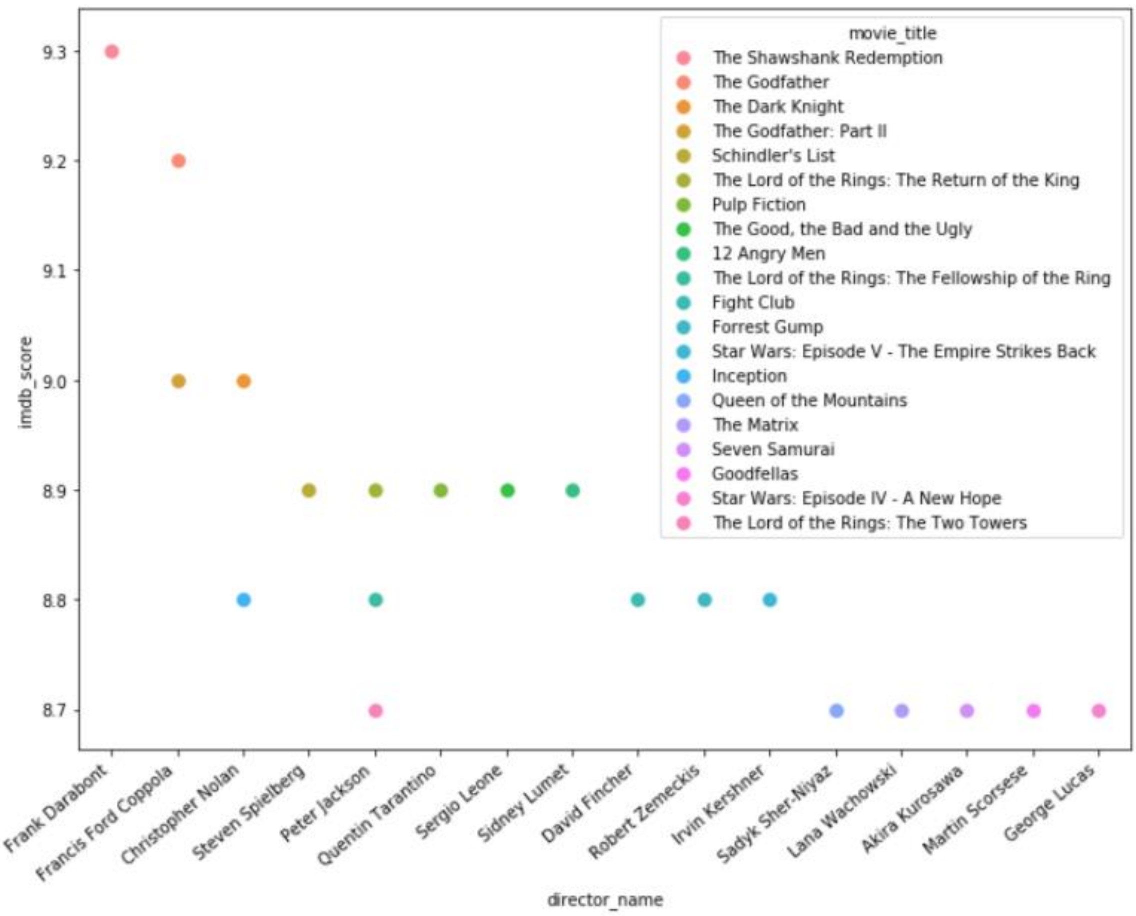
In[35]:

```
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()
```



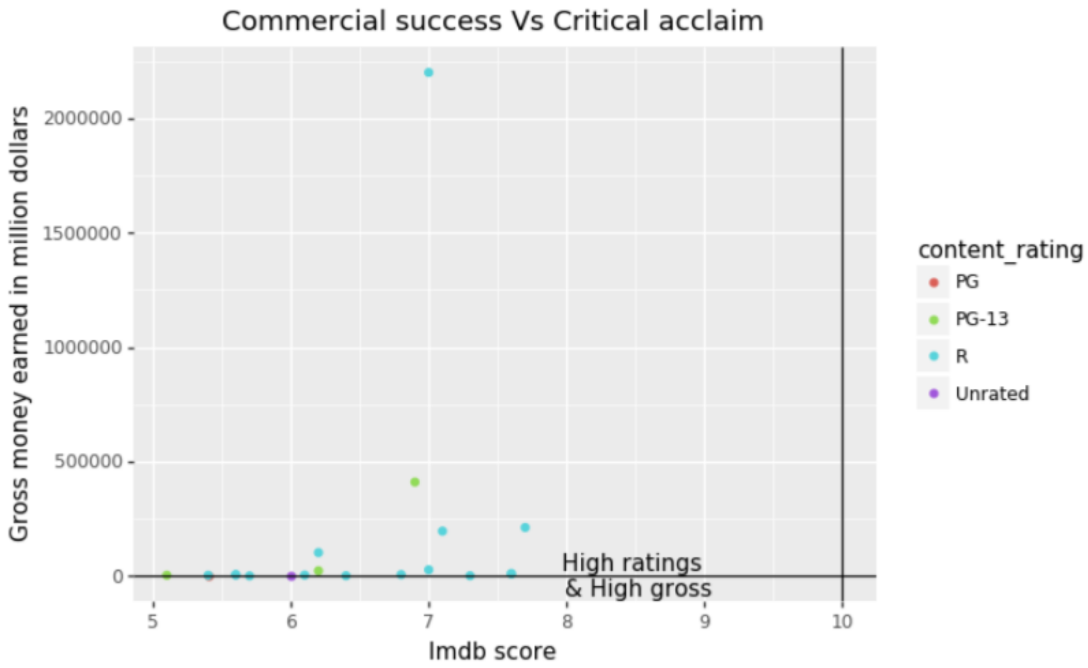
In[36]:

```
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()
```



In[37]:

```
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"))
```

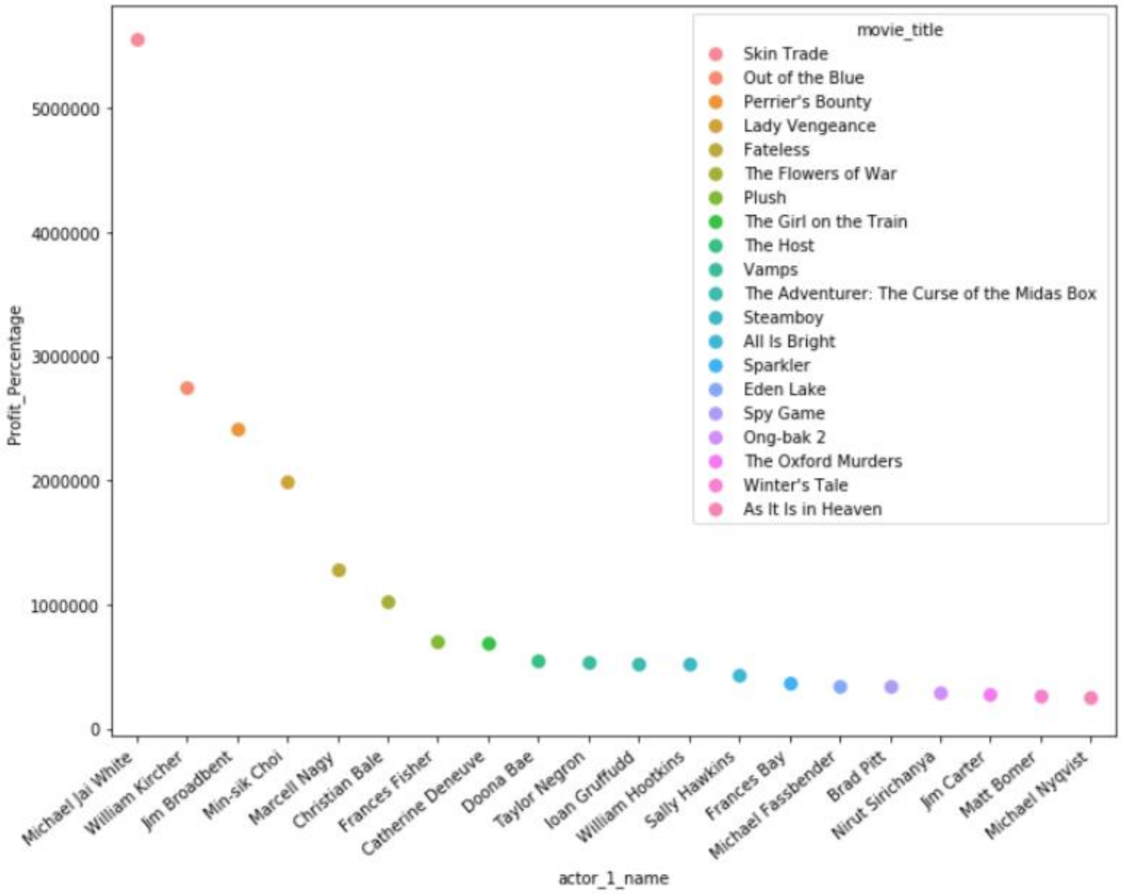


Out[37]:

ggplot: (8779159511195)>

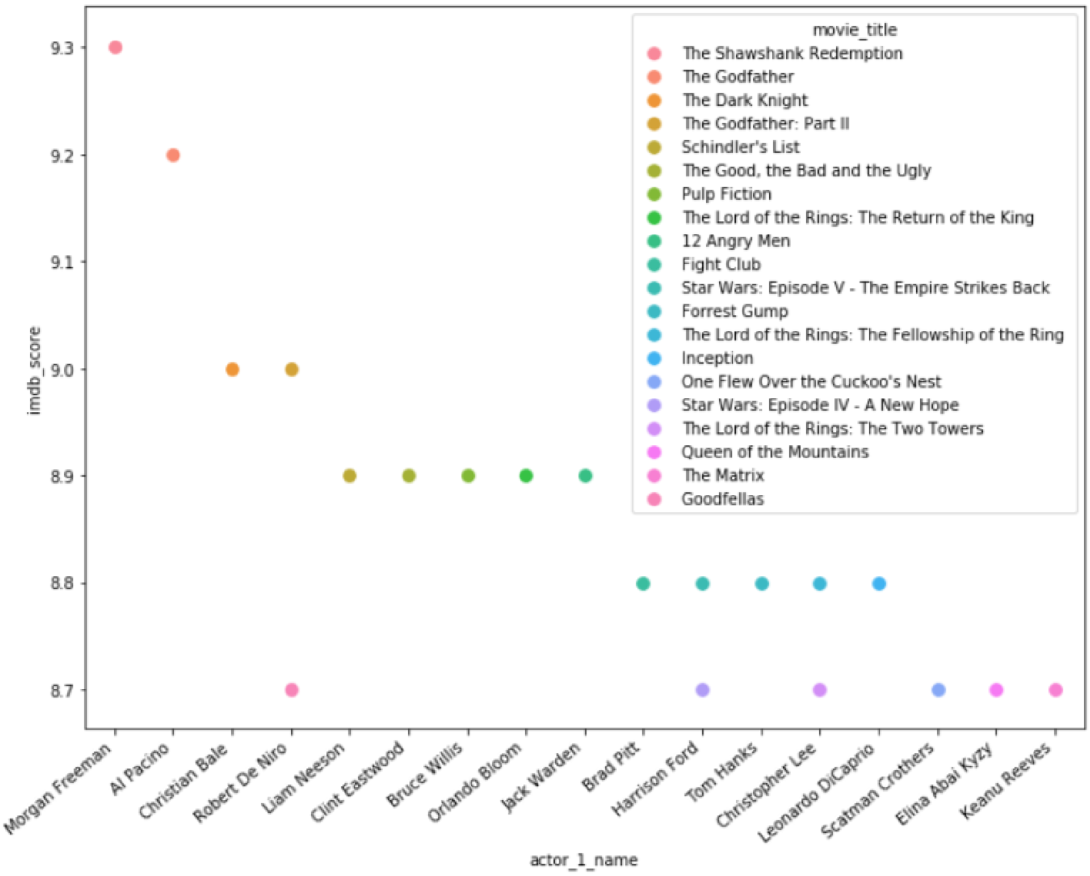
In[38]:

```
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()
```



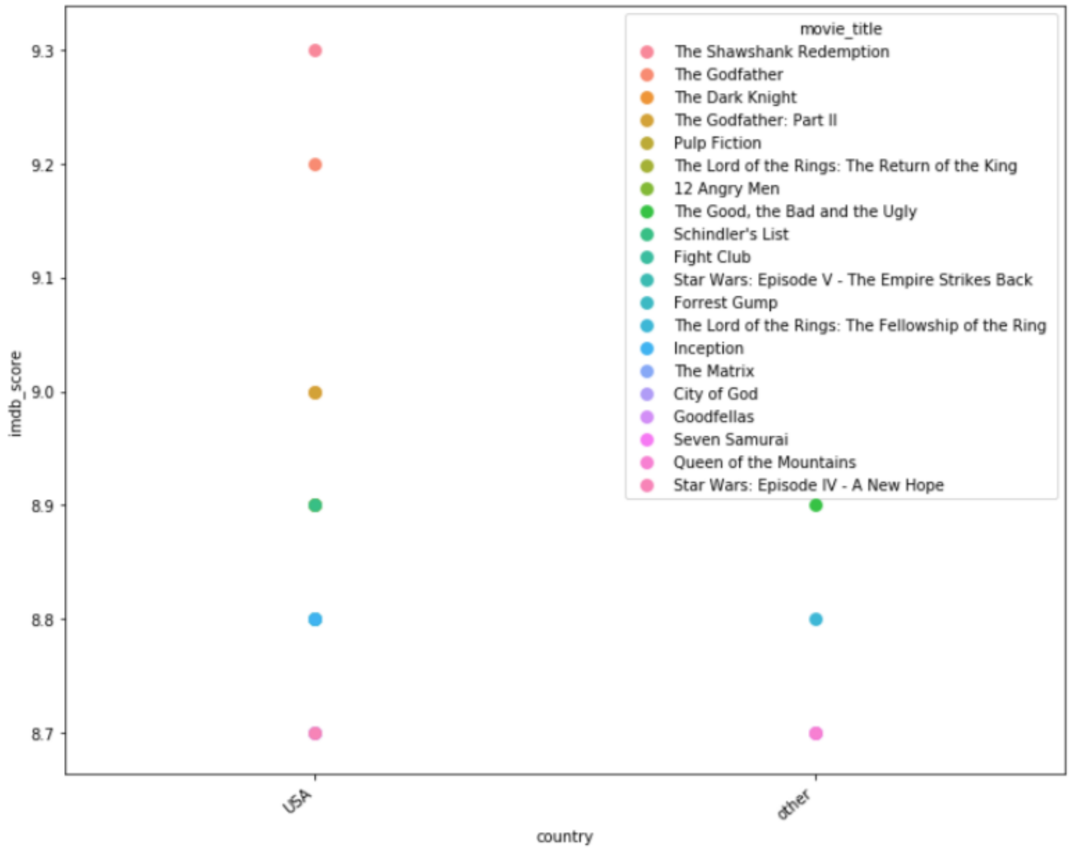
In[39]:

```
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['actor_1_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()
```



In[40]:

```
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['country'], 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()
```



Data Preparation for the models

Removing Columns with names

In[41]:

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

In[42]:

```
movie_df.drop('actor_1_name',axis=1,inplace=True)
```

In[43]:

```
movie_df.drop('actor_2_name',axis=1,inplace=True)
```

In[44]:

```
movie_df.drop('actor_3_name',axis=1,inplace=True)
```

In[45]:

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

In[46]:

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

In[47]:

```
movie_df['genres'].value_counts()
```

Out[47]:

```
Drama                               209
Comedy                              186
Comedy|Drama|Romance                182
Comedy|Drama                        180
Comedy|Romance                      149
                                   ...
Comedy|Drama|Horror                   1
Mystery|Western                       1
Animation|Comedy|Drama|Romance        1
Adventure|Drama|Romance|Western       1
Drama|War|Western                     1
Name: genres, Length: 875, dtype: int64
```

In[48]:

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

Remove the Linear dependent variables

In[49]:

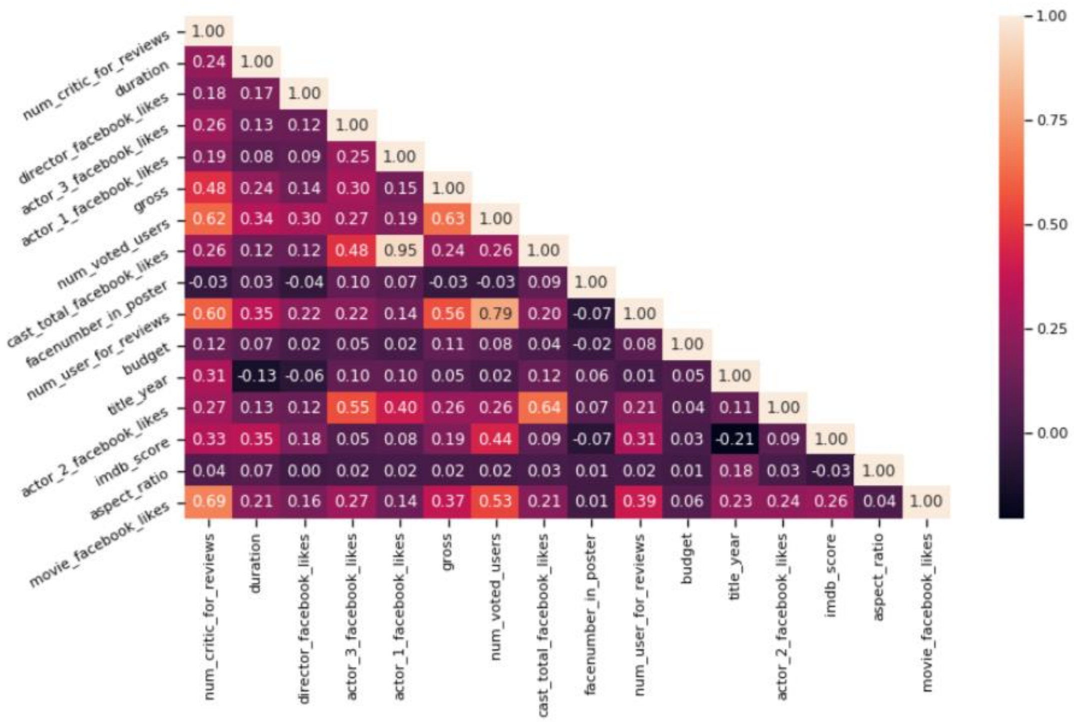
```
movie_df.drop('Profit',axis=1,inplace=True)
```

In[50]:

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

In[51]:

```
import matplotlib.pyplot as plt

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)
```



In[52]:

```
movie_df['Other_actor_facebbok_likes']=movie_df["actor_2_facebook_likes"] +
movie_df['actor_3_facebook_likes']
```

In[53]:

```
movie_df.drop('actor_2_facebook_likes',axis=1,inplace=True)
```

In[54]:

```
movie_df.drop('actor_3_facebook_likes',axis=1,inplace=True)
```

In[55]:

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

In[56]:

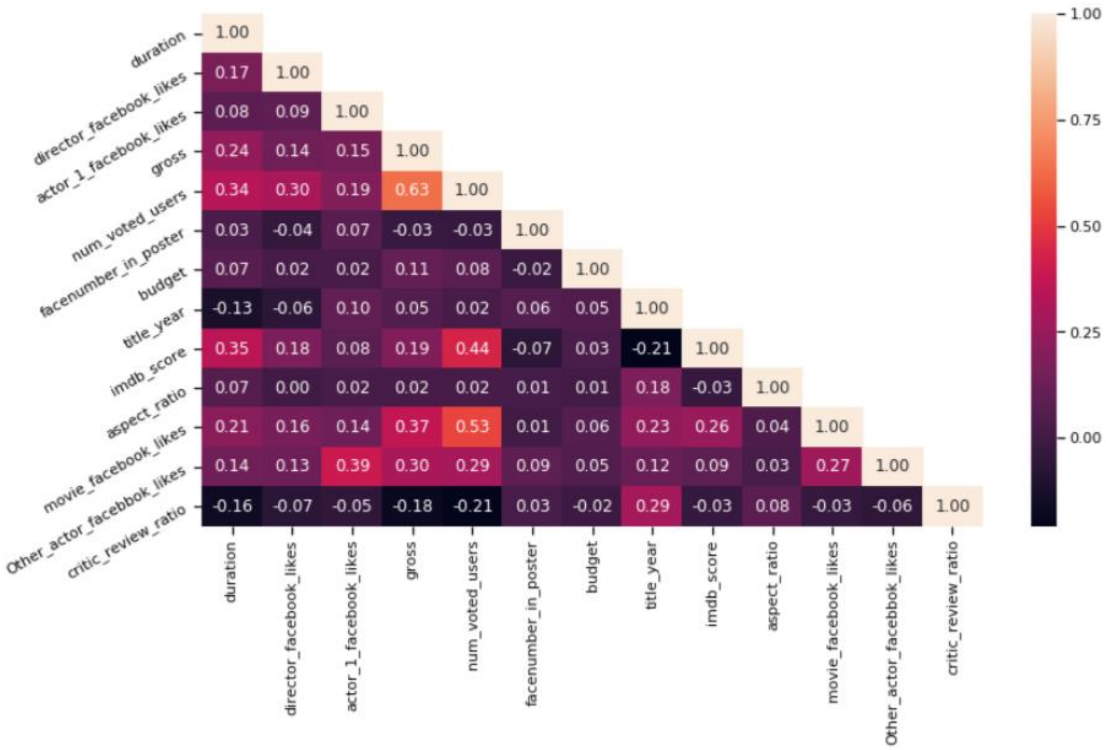
```
movie_df['critic_review_ratio']=movie_df['num_critic_for_reviews']/movie_df['num_user_fo
r_reviews']
```

In[57]:

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

In[58]:

```
import matplotlib.pyplot as plt

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))

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)
```



In[59]:

movie_df["imdb_binned_score"]=pd.cut(movie_df['imdb_score'], bins=[0,4,6,8,10], right=True, labels=False)+1

In[60]:

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

In[61]:

movie_df.head(5)

Out[61]:

	duration	director_facebook_likes	actor_1_facebook_likes	gross	num_voted_users	facenumber_in_poster	country	content_rating	budget	title_year
1937	142.0	0.0	11000.0	28341469.0	1689764	0.0	USA	R	25000000.0	1994.0
3466	175.0	0.0	14000.0	134821952.0	1155770	1.0	USA	R	6000000.0	1972.0
66	152.0	22000.0	23000.0	533316061.0	1676169	0.0	USA	PG-13	185000000.0	2008.0
2837	220.0	0.0	22000.0	57300000.0	790926	1.0	USA	R	13000000.0	1974.0
3355	178.0	16000.0	13000.0	107930000.0	1324680	1.0	USA	R	8000000.0	1994.0

Handling the categorical Data

In[62]:

movie_df = pd.get_dummies(data = movie_df, columns = ['country'] , prefix = ['country'] , drop_first = True)

movie_df = pd.get_dummies(data = movie_df, columns = ['content_rating'] , prefix = ['content_rating'] , drop_first = True)

In[63]:

movie_df.columns

Out[63]:

```
Index(['duration', 'director_facebook_likes', 'actor_1_facebook_likes',
       'gross', 'num_voted_users', 'facenumber_in_poster', 'budget',
       'title_year', 'aspect_ratio', 'movie_facebook_likes',
       'Other_actor_facebbok_likes', 'critic_review_ratio',
       'imdb_binned_score', 'country_USA', 'country_other', 'content_rating_G',
       'content_rating_GP', 'content_rating_M', 'content_rating_NC-17',
       'content_rating_Not Rated', 'content_rating_PG', 'content_rating_PG-13',
       'content_rating_Passed', 'content_rating_R', 'content_rating_TV-14',
       'content_rating_TV-G', 'content_rating_TV-PG', 'content_rating_Unrated',
       'content_rating_X'],
      dtype='object')
```

Splitting the Data into Training and test Data

In[64]:

X=pd.DataFrame(columns=['duration','director_facebook_likes','actor_1_facebook_likes','gross','num_voted_users','facenumber_in_poster','budget','title_year','aspect_ratio','movie_facebook_likes','Other_actor_facebbok_likes','critic_review_ratio','country_USA','country_other','content_rating_G','content_rating_GP','content_rating_M','content_rating_NC-17','content_rating_Not Rated','content_rating_PG','content_rating_PG-13','content_rating_Passed','content_rating_R','content_rating_TV-14','content_rating_TV-G','content_rating_TV-PG','content_rating_Unrated','content_rating_X'],data=movie_df)

y=pd.DataFrame(columns=['imdb_binned_score'],data=movie_df)

from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test=train_test_split(X,y,test_size=0.3,random_state=100)

Feature Scaling

In[65]:

```
from sklearn.preprocessing import StandardScaler
sc_X = StandardScaler()
X_train = sc_X.fit_transform(X_train)
X_test = sc_X.transform(X_test)
```

Classification Model Selection

Logistic Regression

In[66]:

```
from sklearn.linear_model import LogisticRegression
logit =LogisticRegression()
logit.fit(X_train,np.ravel(y_train,order='C'))
y_pred=logit.predict(X_test)
```

In[67]:

```
from sklearn import metrics
cnf_matrix = metrics.confusion_matrix(y_test, y_pred)
print(cnf_matrix)

print("Accuracy:",metrics.accuracy_score(y_test, y_pred))
```

Out[67]:

```
[[  0  24  22   0]
 [  0  93 285   0]
 [  0  67 851   6]
 [  0   1  28  32]]
Accuracy: 0.6926898509581263
```

KNN

In[68]:

```
from sklearn.neighbors import KNeighborsClassifier
knn = KNeighborsClassifier(n_neighbors=22)
knn.fit(X_train, np.ravel(y_train,order='C'))
knnpred = knn.predict(X_test)
cnf_matrix = metrics.confusion_matrix(y_test, knnpred)
print(cnf_matrix)
print("Accuracy:",metrics.accuracy_score(y_test, knnpred))
```

Out[68]:

```
[[  0  24  22   0]
 [  0 155 223   0]
 [  0 153 771   0]
 [  0   2  47  12]]
Accuracy: 0.6657203690560681
```

SVC

In[69]:

```
from sklearn.svm import SVC
svc= SVC(kernel = 'sigmoid')
svc.fit(X_train, np.ravel(y_train,order='C'))
svcpred = svc.predict(X_test)
cnf_matrix = metrics.confusion_matrix(y_test, svcpred)
print(cnf_matrix)
print("Accuracy:",metrics.accuracy_score(y_test, svcpred))
```

Out[69]:

```
[[  1  36   9   0]
 [  2 157 219   0]
 [  4 175 730  15]
 [  0   8  33  20]]
Accuracy: 0.6444286728176012
```

Naive Bayes

In[70]:

```
from sklearn.naive_bayes import GaussianNB
gaussiannb= GaussianNB()
gaussiannb.fit(X_train, np.ravel(y_train,order='C'))
gaussiannbpred = gaussiannb.predict(X_test)
cnf_matrix = metrics.confusion_matrix(y_test, gaussiannbpred)
print(cnf_matrix)
print("Accuracy:",metrics.accuracy_score(y_test, gaussiannbpred))
```

Out[70]:

```
[[ 42   0   1   3]
 [326   1   1  50]
 [530   0   5 389]
 [  8   1   0  52]]
Accuracy: 0.07097232079488999
```

Decision Tree

In[71]:

```
from sklearn.tree import DecisionTreeClassifier
dtree = DecisionTreeClassifier(criterion='gini')
dtree.fit(X_train, np.ravel(y_train,order='C'))
dtreepred = dtree.predict(X_test)
cnf_matrix = metrics.confusion_matrix(y_test, dtreepred)
print(cnf_matrix)
print("Accuracy:",metrics.accuracy_score(y_test, dtreepred))
```

Out[71]:

```
[[  5  24  17   0]
 [ 24 194 160   0]
 [ 15 192 706  11]
 [  0   2  23  36]]
Accuracy: 0.6678495386799148
```

ADA Boosting

In[72]:

```
from sklearn.ensemble import AdaBoostClassifier
abcl = AdaBoostClassifier(base_estimator=dtree, n_estimators=60)
abcl=abcl.fit(X_train,np.ravel(y_train,order='C'))
```

abcl_pred=abcl.predict(X_test)

cnf_matrix = metrics.confusion_matrix(y_test, abcl_pred)

print(cnf_matrix)

print("Accuracy:",metrics.accuracy_score(y_test, abcl_pred))

Out[72]:

```
[[  7  25  14   0]
 [ 20 194 164   0]
 [ 13 205 689  17]
 [  0   1  29  31]]
Accuracy: 0.6536550745209369
```

Random Forest

In[73]:

from sklearn.ensemble import RandomForestClassifier

rfc = RandomForestClassifier(n_estimators = 200)*#criterion = entopy,gini*

rfc.fit(X_train, np.ravel(y_train,order='C'))

rfcpred = rfc.predict(X_test)

cnf_matrix = metrics.confusion_matrix(y_test, rfcpred)

print(cnf_matrix)

print("Accuracy:",metrics.accuracy_score(y_test, rfcpred))

Out[73]:

```
[[  2  31  13   0]
 [  0 177 201   0]
 [  0  77 846   1]
 [  0   0  34  27]]
Accuracy: 0.7466288147622427
```

Bagging Classifier

In[74]:

```
new_movie_df=movie_df.pop("imdb_binned_score")
```

In[75]:

```
from sklearn.ensemble import BaggingClassifier
bgcl = BaggingClassifier(n_estimators=60, max_samples=.7 , oob_score=True)

bgcl = bgcl.fit(movie_df, new_movie_df)
print(bgcl.oob_score_)
```

Out[75]:

0.7429179978700745

Gradient Boosting

In[76]:

```
from sklearn.ensemble import GradientBoostingClassifier
gbcl = GradientBoostingClassifier(n_estimators = 50, learning_rate = 0.09, max_depth=5)
gbcl = gbcl.fit(X_train,np.ravel(y_train,order='C'))
test_pred = gbcl.predict(X_test)
cnf_matrix = metrics.confusion_matrix(y_test, test_pred)
print(cnf_matrix)
print("Accuracy:",metrics.accuracy_score(y_test, test_pred))
```

Out[76]:

```
[[  1  38   7   0]
 [  0 211 167   0]
 [  2 100 817   5]
 [  1   0  30  30]]
Accuracy: 0.751596877217885
```

XG Boosting

In[77]:

```
from xgboost import XGBClassifier
xgb = XGBClassifier()
xgb.fit(X_train, np.ravel(y_train,order='C'))
xgbprd = xgb.predict(X_test)
cnf_matrix = metrics.confusion_matrix(y_test, xgbprd)
print(cnf_matrix)
print("Accuracy:",metrics.accuracy_score(y_test, xgbprd))
```

Out[77]:

```
[[  1  36   9   0]
 [  2 198 178   0]
 [  1 101 818   4]
 [  0   2  26  33]]
Accuracy: 0.7452093683463449
```

Model Comparison

In[78]:

```
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))
```

Out[78]:

```
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
```

Conclusion

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

This analysis compares certain attributes regarding Facebook and IMDB site against the gross revenue of a film. The higher number of Facebook likes from the primary actor and supporting actors plays a significant role in generating revenue from a film. Through both models and the sensitivity analysis, someone can easily see the support in this conclusion. Directors and producers can take this dataset and implement it into their thought process when planning their movie. Movie-goers can use this dataset to make the same predictions once the movie is announced with primary and supporting actors/actresses. It could possibly save movie-goers money when debating on whether to go see a movie or not.

This project has helped me substantially in practicing with running analysis on certain topics and generating a result. It has developed my skill in Excel and XL Miner by using the Missing Data handle, the Reduce Categories handle, the Data Partition handle, the Multiple Linear Regression handle, and a sensitivity analysis. Overall, the effectiveness of this project was very useful for me in the preparation for my career. I can take this project as proof of knowledge in these areas as well as knowing associated terms.