Final_BoxOffice

December 5, 2021

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

[438]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import plotly.express as px
import plotly.graph_objects as go
import time
from datetime import datetime
import math
from statistics import median

%matplotlib inline

import warnings
warnings.filterwarnings("ignore")

#Loading the dataset and looking at the data types in the dataset
movies = pd.read_csv('/content/drive/MyDrive/Colab Notebooks/Data/
↪Mojo_budget_update.csv')
movies.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3243 entries, 0 to 3242
Data columns (total 26 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   movie_id        3243 non-null   object
 1   title           3243 non-null   object
 2   year            3243 non-null   int64
 3   trivia          3243 non-null   object
 4   mpaa            3082 non-null   object
 5   release_date    3242 non-null   object
 6   run_time        3243 non-null   object
 7   distributor     3228 non-null   object
 8   director        3243 non-null   object
 9   writer          3234 non-null   object
```

 10 producer   3230 non-null   object
 11 composer   3138 non-null   object
 12 cinematographer 3129 non-null   object
 13 main_actor_1   3243 non-null   object
 14 main_actor_2   3243 non-null   object
 15 main_actor_3   3243 non-null   object
 16 main_actor_4   3240 non-null   object
 17 budget   3243 non-null   float64
 18 domestic   3224 non-null   float64
 19 international   2833 non-null   float64
 20 worldwide   3236 non-null   float64
 21 genre_1   3243 non-null   object
 22 genre_2   2962 non-null   object
 23 genre_3   2221 non-null   object
 24 genre_4   1123 non-null   object
 25 html   3243 non-null   object
dtypes: float64(4), int64(1), object(21)
memory usage: 658.9+ KB

[439]:

```
#Looking at the first 3 rows of the dataset
movies.head(3)
```

[439]:

```
    movie_id  ...                                           html
0  tt0099088  ...  https://www.boxofficemojo.com/title/tt0099088/...
1  tt0099165  ...  https://www.boxofficemojo.com/title/tt0099165/...
2  tt0099348  ...  https://www.boxofficemojo.com/title/tt0099348/...

[3 rows x 26 columns]
```

Date Cleaning & EDA

[440]:

```
#Checking for duplicates
print('Number of duplicate Movie_ID: {}'.format(movies['movie_id'].duplicated().
 ↪sum()))
```

```
Number of duplicate Movie_ID: 0
```

[441]:

```
# Checking for null values and their percentage
num_null_values = movies.isnull().sum()
print(num_null_values)
print('----------------------------')
percentage = num_null_values / len(movies)
print(percentage)
```

```
movie_id             0
title                0
year                 0
```

```
trivia                 0
mpaa                 161
release_date           1
run_time               0
distributor           15
director               0
writer                 9
producer              13
composer             105
cinematographer      114
main_actor_1           0
main_actor_2           0
main_actor_3           0
main_actor_4           3
budget                 0
domestic              19
international        410
worldwide              7
genre_1                0
genre_2              281
genre_3             1022
genre_4             2120
html                   0
dtype: int64
----------------------------
movie_id            0.000000
title               0.000000
year                0.000000
trivia              0.000000
mpaa                0.049645
release_date        0.000308
run_time            0.000000
distributor         0.004625
director            0.000000
writer              0.002775
producer            0.004009
composer            0.032377
cinematographer     0.035153
main_actor_1        0.000000
main_actor_2        0.000000
main_actor_3        0.000000
main_actor_4        0.000925
budget              0.000000
domestic            0.005859
international       0.126426
worldwide           0.002158
genre_1             0.000000
genre_2             0.086648
```

```
genre_3           0.315140
genre_4           0.653716
html              0.000000
dtype: float64
```

[442]:
```
#Since there is very few null values for worldwide & distributor, then I will␣
↪remove these rows and create a new dataframe

moviesNew = movies.dropna(subset=['worldwide', 'distributor'])
num_null_values = moviesNew.isnull().sum()
num_null_values
```

[442]:
```
movie_id             0
title                0
year                 0
trivia               0
mpaa               156
release_date         0
run_time             0
distributor          0
director             0
writer               9
producer            12
composer           105
cinematographer    114
main_actor_1         0
main_actor_2         0
main_actor_3         0
main_actor_4         3
budget               0
domestic            12
international      403
worldwide            0
genre_1              0
genre_2            271
genre_3           1008
genre_4           2101
html                 0
dtype: int64
```

[443]:
```
#Let us replace the NaN in the domestic and international with 0

moviesNew['domestic'] = moviesNew['domestic'].fillna(0)
moviesNew['international'] = moviesNew['international'].fillna(0)
num_null_values = moviesNew.isnull().sum()
num_null_values
```

[443]:
```
movie_id             0
title                0
```

```
year                 0
trivia               0
mpaa               156
release_date         0
run_time             0
distributor          0
director             0
writer               9
producer            12
composer           105
cinematographer    114
main_actor_1         0
main_actor_2         0
main_actor_3         0
main_actor_4         3
budget               0
domestic             0
international        0
worldwide            0
genre_1              0
genre_2            271
genre_3           1008
genre_4           2101
html                 0
dtype: int64
```

[444]:

```
#I will then replace the NaN in the mpaa with the most common PG-13

print(moviesNew['mpaa'].value_counts().head())        #Printing the MPAA counts␣
 ↪before replacement
moviesNew['mpaa'] = moviesNew['mpaa'].fillna('PG-13')
print('-----------------------------------')
print(moviesNew['mpaa'].value_counts().head())        #Printing the MPAA counts␣
 ↪after replacement
```

```
R        1340
PG-13    1221
PG        476
G          22
NC-17       6
Name: mpaa, dtype: int64
----------------------------------
PG-13    1377
R        1340
PG        476
G          22
NC-17       6
Name: mpaa, dtype: int64
```

[445]:
```
#### I can delete the following columns as they are irrelvant to my analysis
#### writer, producer, composer, cinematographer & html as well as domestic &␣
↪international as I am predicting Wordlwide Revenue

moviesNew.drop(['trivia','writer','producer','composer', 'cinematographer',␣
↪'html', 'domestic', 'international'], axis='columns', inplace=True)
moviesNew.head(3)
```

[445]:
```
    movie_id                         title  year  ... genre_2  genre_3  genre_4
0  tt0099088  Back to the Future Part III  1990  ...  Comedy   Sci-Fi  Western
1  tt0099165  The Bonfire of the Vanities  1990  ...   Drama  Romance      NaN
2  tt0099348            Dances with Wolves  1990  ...   Drama  Western      NaN

[3 rows x 18 columns]
```

[446]:
```
# Since there is only 3 missing names under main_actor_4, then I can fill them␣
↪with 'No Actor'

moviesNew['main_actor_4'] = moviesNew['main_actor_4'].fillna('No Actor')
moviesNew[moviesNew['main_actor_4'] == 'No Actor']
```

[446]:
```
       movie_id                         title  ...   genre_3  genre_4
2769  tt2276023  The United States of Autism  ...    Family     News
2812  tt2401878                     Anomalisa  ...     Drama  Romance
3026  tt4218572                        Widows  ...  Thriller      NaN

[3 rows x 18 columns]
```

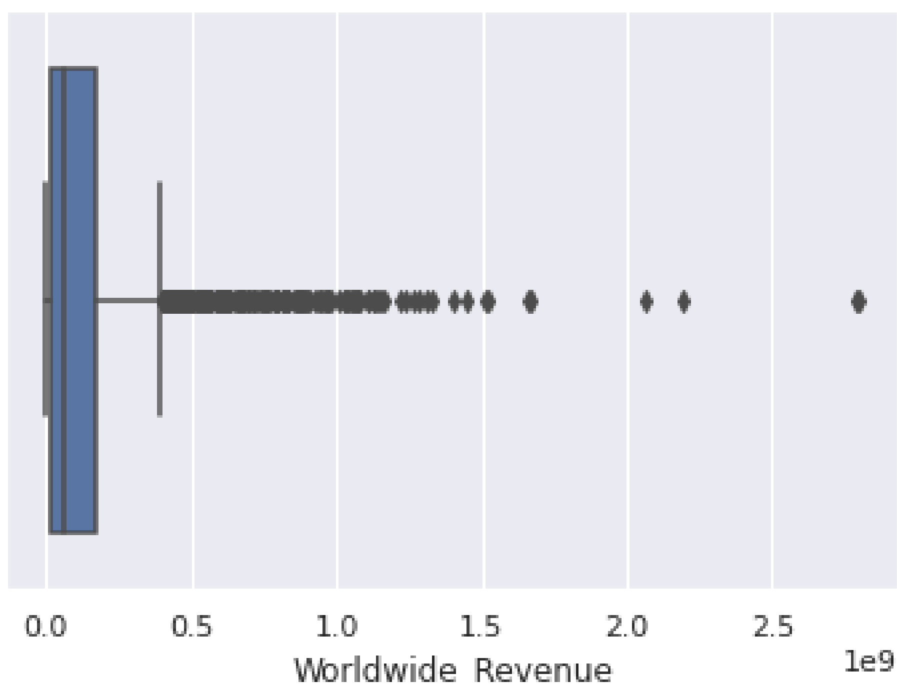
[447]:
```
#Renaming some columns to improve the readability of the dataset

#pd.set_option('display.float_format', '${0:,.2f}'.format)
moviesNew = moviesNew.rename(columns={"domestic": "Domestic_Revenue",␣
↪"international": "International_Revenue", "worldwide": "Worldwide_Revenue"})
moviesNew.head(3)
```

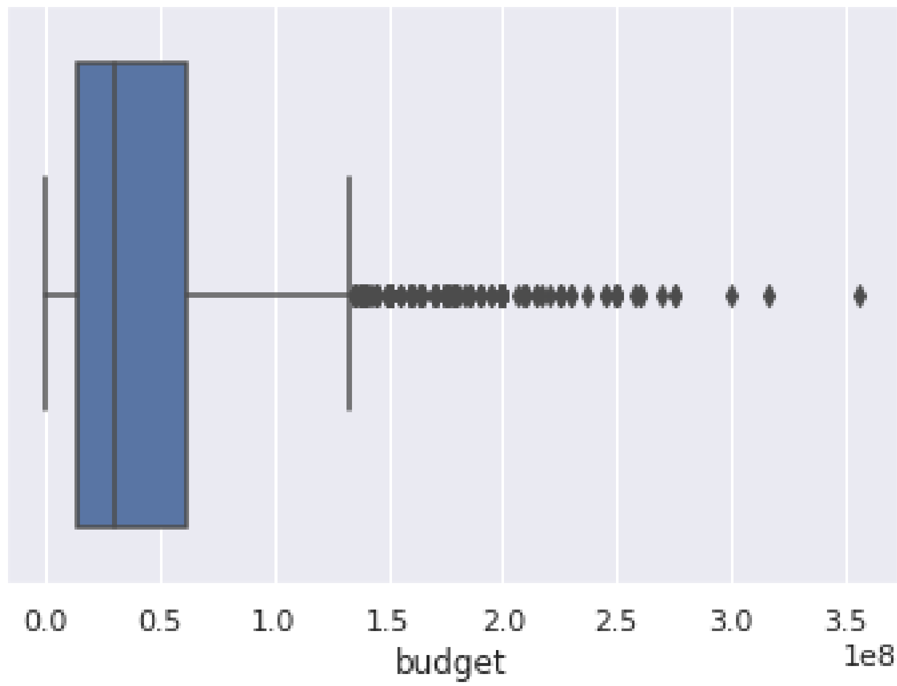
[447]:
```
    movie_id                         title  year  ... genre_2  genre_3  genre_4
0  tt0099088  Back to the Future Part III  1990  ...  Comedy   Sci-Fi  Western
1  tt0099165  The Bonfire of the Vanities  1990  ...   Drama  Romance      NaN
2  tt0099348            Dances with Wolves  1990  ...   Drama  Western      NaN

[3 rows x 18 columns]
```

[448]:
```
moviesNew.describe()

# Some findings:
# 1. The average Worldwide Revenue is $139,757,500
# 2. The highest Worldwide Revenue is $2,797,801,000
# 3. The average Budget is $46,396,300
# 4. The highest Budget is $356,000,000
# 5. The movies in the dataset are between the year 1990 and 2020
```

[448]:
```
             year        budget  Worldwide_Revenue
count  3221.000000  3.221000e+03       3.221000e+03
mean   2006.656007  4.639630e+07       1.397575e+08
std       7.221364  4.714060e+07       2.165638e+08
min    1990.000000  2.200000e+02       3.000000e+01
25%    2001.000000  1.400000e+07       1.912640e+07
50%    2007.000000  3.000000e+07       6.267510e+07
75%    2012.000000  6.200000e+07       1.698528e+08
max    2020.000000  3.560000e+08       2.797801e+09
```

[449]:
```python
sns.boxplot(x=moviesNew['Worldwide_Revenue'])
plt.show()
sns.boxplot(x=moviesNew['budget'])
plt.show()
```





[450]:
```
# 6. The lowest Worldwide Revenue is $30, which is very low, so let us␣
↪investigate more and look at the lowest 10 Grossing movies
cols = ['movie_id', 'title', 'year', 'Worldwide_Revenue']
lowestRev = moviesNew.sort_values('Worldwide_Revenue', ascending=True)[cols].
↪set_index('movie_id')
lowestRev.head(10)
```

[450]:

movie_id	title	year	Worldwide_Revenue
tt0429277	Zyzzyx Rd	2006	30.0
tt1019449	The Rise and Fall of Miss Thang	2007	581.0
tt1235168	Redneck Carnage	2009	706.0
tt0431155	Issues	2005	783.0
tt0387057	Beat the Drum	2003	895.0
tt0102032	High Strung	1992	904.0
tt1735485	The Tunnel	2011	1532.0
tt0396587	FAQs	2005	1967.0
tt2382420	Split: A Deeper Divide	2012	2000.0
tt0120878	The Velocity of Gary	1998	2143.0

[451]:
```
# Findings from the above table
# 1. The first movie title dosen't seem correct, so we can delete this record
# 2. After searching the 'www.the-numbers.com' for the rest of the above list:
#   a. The following movies doesn't exist: 'Redneck Carnage', 'Beat the Drum',␣
↪'High Strung from 1992', 'The Tunnel from 2011'
```

```
#   b. 'The Velocity of Gary' movie has an incorrect Worldwide Revenue
# 3. So to fix these problems, I chose to delete all records that has Worldwide␣
↪Revenue less than $100,000

# Get indexes where Revenue column is less than $100,000
indexRev = moviesNew[ moviesNew['Worldwide_Revenue'] < 100000 ].index

# Delete these row indexes from the dataframe

moviesNew.drop(indexRev, inplace=True)

cols = ['movie_id', 'title', 'year', 'Worldwide_Revenue', 'budget']
lowestRev = moviesNew.sort_values('Worldwide_Revenue', ascending=True)[cols].
↪set_index('movie_id')
lowestRev.head(10)
```

[451]:

```
                                            title  ...      budget
movie_id                                           ...
tt2276023             The United States of Autism  ...     65000.0
tt1247662                            The Good Guy  ...  10000000.0
tt0478262  Return with Honor: A Missionary Homecoming  ...    300000.0
tt0262911                          World Traveler  ...   2000000.0
tt0119506                               Lawn Dogs  ...   8000000.0
tt1210039                    Blood Done Sign My Name  ...  10000000.0
tt0102898                        Shakes the Clown  ...   1400000.0
tt0156096                          Spring Forward  ...   2000000.0
tt1161418                       Gentlemen Broncos  ...  10000000.0
tt0252223                     All the Queen's Men  ...  15000000.0

[10 rows x 4 columns]
```

[452]:

```
moviesNew.describe(include='object')

# Some findings regarding from the table below
# 1. MPAA: There are 5 different movies rating, with the most frequent one is␣
↪PG-13
# 2. Ditributor: There are 157 different production companies, Warner Bros. is␣
↪the top with 388 movies
# 3. Main Actor 1: Adam Sandler top the list with 27 movies
# 4. Main Actor 2: Samuel L. Jackson top this list with 15 movies
# 5. The most frequent Genres are 'Action' and 'Drama'
```

[452]:

```
         movie_id       title   mpaa  ... genre_2   genre_3   genre_4
count        3151        3151   3151  ...    2906      2188      1116
unique       3151        3125      5  ...      20        20        17
top     tt1270286  Robin Hood  PG-13  ...   Drama  Thriller  Thriller
freq            1           2   1343  ...     747       382       356
```

```
[4 rows x 15 columns]
```

[453]:
```
# I will drop the genre_3 and genre_4 columns as they have more than 30%␣
↪missing values.

moviesNew.drop(['genre_3', 'genre_4'], axis='columns', inplace=True)
```

[454]:
```
# Replace NaN in genre_2 with 'No Secondary Genre'

moviesNew['genre_2'] = moviesNew['genre_2'].fillna('No Secondary Genre')
moviesNew[moviesNew['genre_2'] == 'No Secondary Genre'].head(5)
```

[454]:
```
     movie_id                title  ...       genre_1             genre_2
15  tt0100332     Paris Is Burning  ...  Documentary  No Secondary Genre
24  tt0101587        City Slickers  ...       Comedy  No Secondary Genre
39  tt0102303          Life Stinks  ...       Comedy  No Secondary Genre
47  tt0102558  Nothing But Trouble  ...       Comedy  No Secondary Genre
49  tt0102753        Rambling Rose  ...        Drama  No Secondary Genre

[5 rows x 16 columns]
```

Revenue & Budget

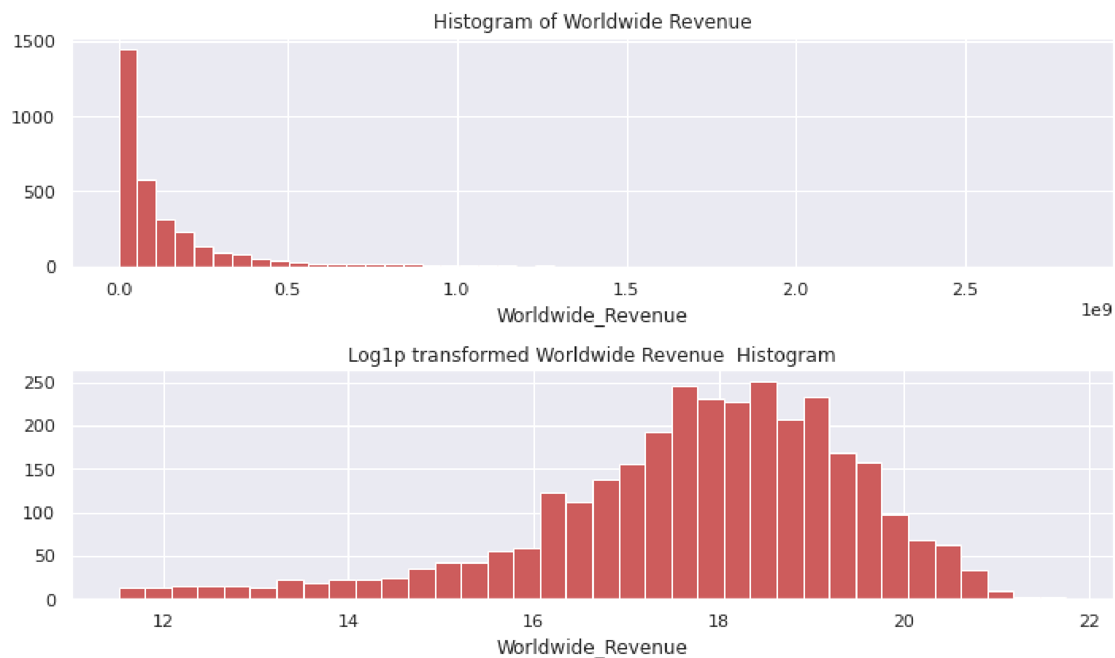
[455]:
```
#Let us look at the Top 20 movies based on Worldwide Revenue with release year

cols = ['title', 'Worldwide_Revenue', 'year']
revenueData = moviesNew.sort_values('Worldwide_Revenue', ascending=False)[cols].
↪set_index('title')
top_20_revenue = revenueData.head(20)

fig = px.bar(top_20_revenue, x=top_20_revenue.index, y='Worldwide_Revenue',␣
↪text='year', title = 'Top 20 Revenue Movies', color = 'Worldwide_Revenue',␣
↪height=700, width=1200,
             labels={'Worldwide_Revenue':'Global Revenue in USD Billion',  'x':
↪''})
fig.update_traces(textposition = 'outside')
fig.update_layout(barmode='group', xaxis_tickangle=-45)
fig.show()

# Avengers:Endgame which was released in 2019 recorded the highest Global␣
↪Revenue in the last 30 years
```

[456]:
```
#Let us look at the Top 20 movies based on Budget with year of release

cols = ['title', 'budget', 'year']
budgetData = moviesNew.sort_values('budget', ascending=False)[cols].
↪set_index('title')
top_20_budget = budgetData.head(20)
```

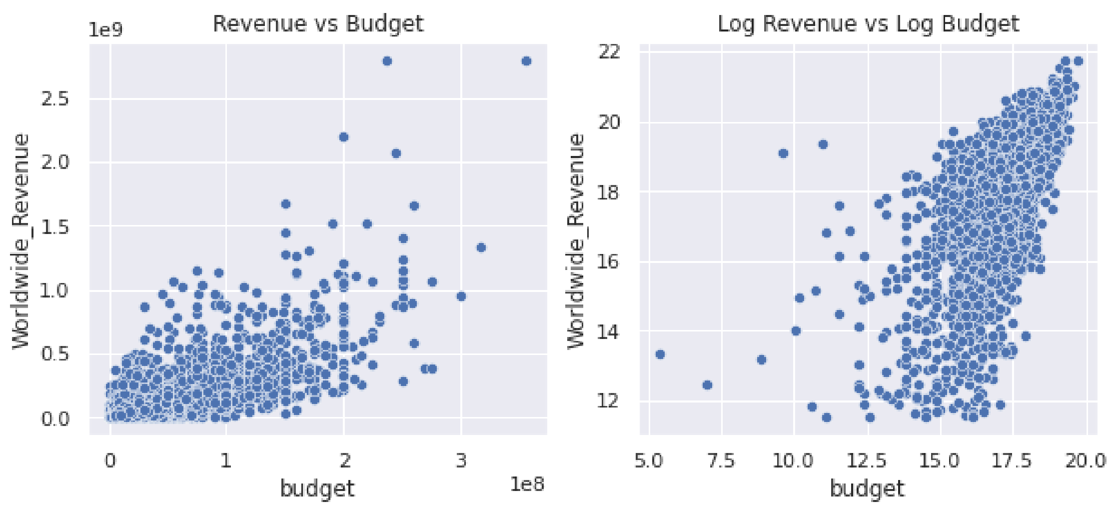
```python
fig = px.bar(top_20_budget, x=top_20_budget.index, y='budget', text='year',␣
 ↪title = 'Top 20 Budget Movies', color = 'budget', height=700, width=1200,
             labels={'budget':'Budget in USD Million', 'x':''})
fig.update_traces(textposition = 'outside')
fig.update_layout(barmode='group', xaxis_tickangle=-45)
fig.show()

# Avengers:Endgame which was released in 2019 had the highest production cost␣
 ↪in the last 30 years
```

[457]:
```python
#Let us look at the Top 10 profitable movies

profitsValue = moviesNew['Worldwide_Revenue'] - moviesNew['budget']
profitsValue.name = 'profit'
profitsData = moviesNew.join(profitsValue)[['title', 'budget',␣
 ↪'Worldwide_Revenue', 'profit']].sort_values('profit', ascending=False)
top_10_profits = profitsData.head(10).set_index('title')

fig = go.Figure()
fig.add_trace(go.Bar(
    x=top_10_profits.index,
    y=profitsData.Worldwide_Revenue,
    name='Global Revenue',
    marker_color='orange'
))
fig.add_trace(go.Bar(
    x=top_10_profits.index,
    y=profitsData.budget,
    name='Budget',
    marker_color='blue'
))
fig.add_trace(go.Bar(
    x=top_10_profits.index,
    y=profitsData.profit,
    name='Profit',
    marker_color='purple'
))

fig.update_layout(
    title = 'Top 10 Profitable Movies'
    )
fig.update_layout(barmode='group', xaxis_tickangle=-45)
fig.show()

# Avatar recorded the highest profitable movie with over $2.5 USD Billion
```

[458]:
```python
## Exploring the Target (Dependent) variable - Worldwide Revenue

f, ax = plt.subplots(2, figsize=(10,6))
sns.set(rc={'figure.figsize':(12,8)})

sns.distplot(a=moviesNew.Worldwide_Revenue, kde = False, ax = ax[0], color='indianred', hist_kws=dict(alpha=1))
ax[0].set_title("Histogram of Worldwide Revenue")
sns.distplot(a=np.log1p(moviesNew.Worldwide_Revenue), kde = False, ax = ax[1], color='indianred', hist_kws=dict(alpha=1))
ax[1].set_title("Log1p transformed Worldwide Revenue  Histogram")
f.tight_layout()
```



[459]:
```python
#Relationship between Revenue and Budget

plt.figure(figsize=(10,4))
plt.subplot(1,2,1)
sns.scatterplot(moviesNew['budget'], moviesNew['Worldwide_Revenue'])
plt.title('Revenue vs Budget');

#Relationship using the log transformation to make the data look more normal
plt.subplot(1,2,2)
sns.scatterplot(np.log1p(moviesNew['budget']), np.log1p(moviesNew['Worldwide_Revenue']))
plt.title('Log Revenue vs Log Budget');
```



[460]:
```
#Adding the Log Worldwide revenue and Log budget to the DataFrame

moviesNew['Log_Worldwide_Revenue'] = np.log1p(moviesNew['Worldwide_Revenue'])
moviesNew['Log_budget'] = np.log1p(moviesNew['budget'])
moviesNew.head(3)
```

[460]:
```
     movie_id                           title  ...  Log_Worldwide_Revenue Log_budget
0  tt0099088  Back to the Future Part III  ...              19.321428  17.504390
1  tt0099165  The Bonfire of the Vanities  ...              16.568610  17.665658
2  tt0099348             Dances with Wolves  ...              19.865736  16.906553

[3 rows x 18 columns]
```

[461]:
```
#Correleation between Revenue and Budget

moviesNew[['Log_Worldwide_Revenue', 'Log_budget']].corr()

## There is a Strong Positive relationship between Budget and Worldwide Revenue
```

[461]:
```
                       Log_Worldwide_Revenue  Log_budget
Log_Worldwide_Revenue                1.00000     0.66538
Log_budget                           0.66538     1.00000
```

[462]:
```
## Creating a subset DataFrame for Budget and Revenue
budget_df = moviesNew[['movie_id', 'Log_Worldwide_Revenue', 'Log_budget']]
```

[463]:
```
## Splitting the data into Traain and Test
from sklearn.model_selection import train_test_split

x = budget_df.drop(['Log_Worldwide_Revenue', 'movie_id'], axis=1)
y = budget_df['Log_Worldwide_Revenue']
X_train, X_test, y_train, y_test = train_test_split(x,y, random_state=1,␣
 ↪test_size=0.20)
```

```
print('Train set: ', X_train.shape, y_train.shape)
print('Test set: ', X_test.shape, y_test.shape)
```

```
Train set:  (2520, 1) (2520,)
Test set:  (631, 1) (631,)
```

[464]:
```
## Creating Linear regression model and testing results

from sklearn.linear_model import LinearRegression
import sklearn.metrics as metrics

lm = LinearRegression()
lm.fit(X_train, y_train)
lm_prediction = lm.predict(X_test)

run_time=time.time()

results = {'Model':['Linear Regression'],
           'Dependent Var':['Budget'],
           'R-Square':[metrics.r2_score(y_test, lm_prediction)],
           'MSE':[metrics.mean_squared_error(y_test, lm_prediction)],
           'RMSE':[np.sqrt(metrics.mean_squared_error(y_test, lm_prediction))],
           'Run Time':[round(((time.time()-run_time)/60),2)]}
results_df = pd.DataFrame(results)
```

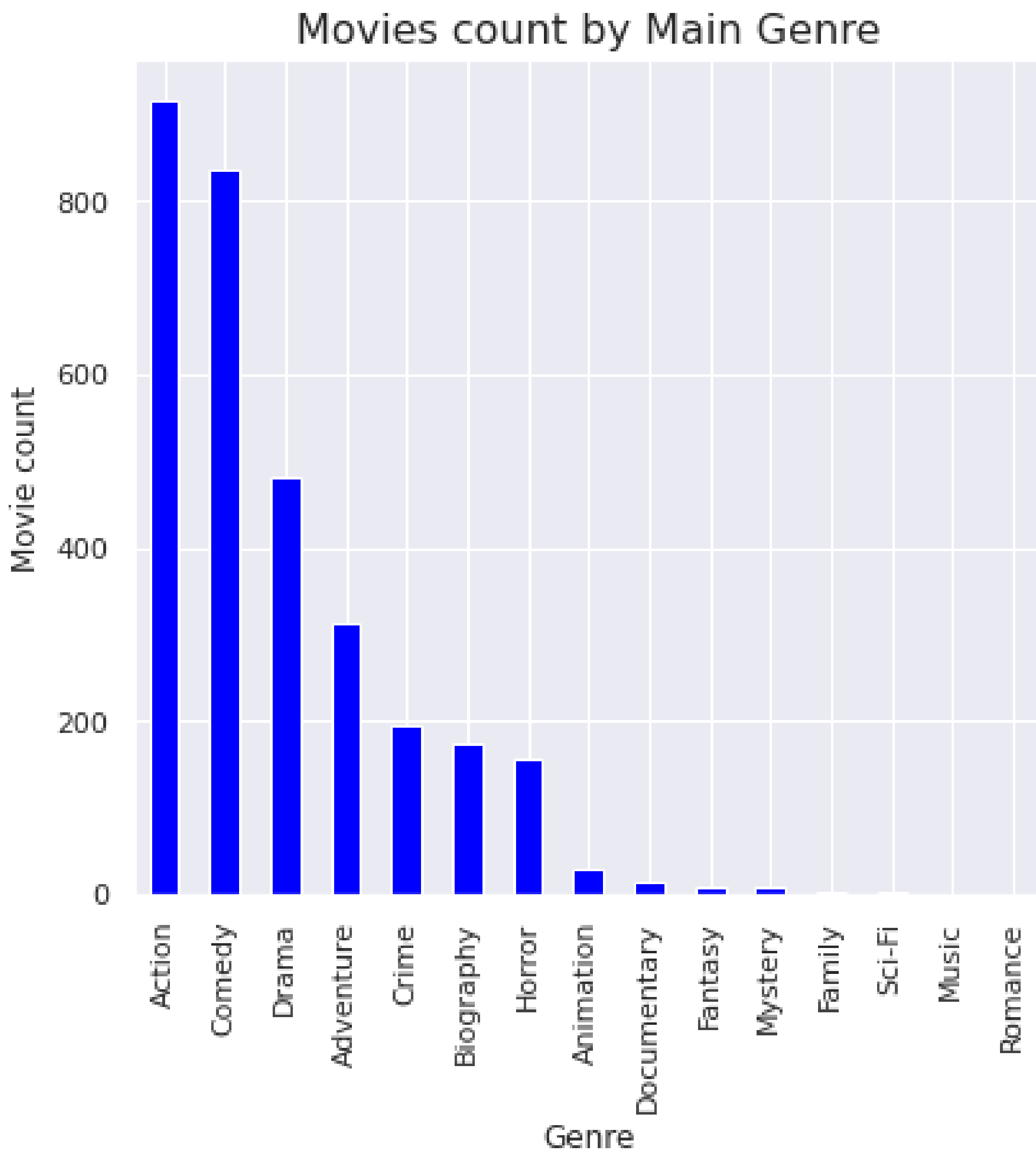
[465]:
```
## Creating LightGBM model and testing results

import lightgbm as lgb

model_lgb=lgb.LGBMRegressor(n_estimators=10000,
                            objective="regression",
                            metric="mse",
                            min_child_samples=100,
                            use_best_model=True)
```

[466]:
```
model_lgb.fit(X_train.values,y_train)

lgb_pred_train=model_lgb.predict(X_test.values)
#run_time=time.time()

results1 = {'Model':'LGBMReg','Dependent Var':'Budget', 'R-Square':metrics.
 ↪r2_score(y_test, lgb_pred_train), 'MSE':metrics.mean_squared_error(y_test,␣
 ↪lgb_pred_train),
            'RMSE':np.sqrt(metrics.mean_squared_error(y_test,␣
 ↪lgb_pred_train)),'Run Time':round(((time.time()-run_time)/60),2)}
results_df = results_df.append(results1, ignore_index=True)
```

[467]:
```
from sklearn.ensemble import RandomForestRegressor, RandomForestClassifier

rf_model = RandomForestRegressor(n_estimators=40, min_samples_leaf=10,␣
 ↪max_features=0.5, n_jobs=-1, oob_score=True)
rf_model.fit(X_train, y_train)

rf_model=rf_model.predict(X_test.values)
#run_time=time.time()

results2 = {'Model':'RandomForest','Dependent Var':'Budget', 'R-Square':metrics.
 ↪r2_score(y_test, rf_model), 'MSE':metrics.mean_squared_error(y_test,␣
 ↪rf_model),
            'RMSE':np.sqrt(metrics.mean_squared_error(y_test, rf_model)), 'Run␣
 ↪Time':round(((time.time()-run_time)/60),2)}
results_df = results_df.append(results2, ignore_index=True)
```

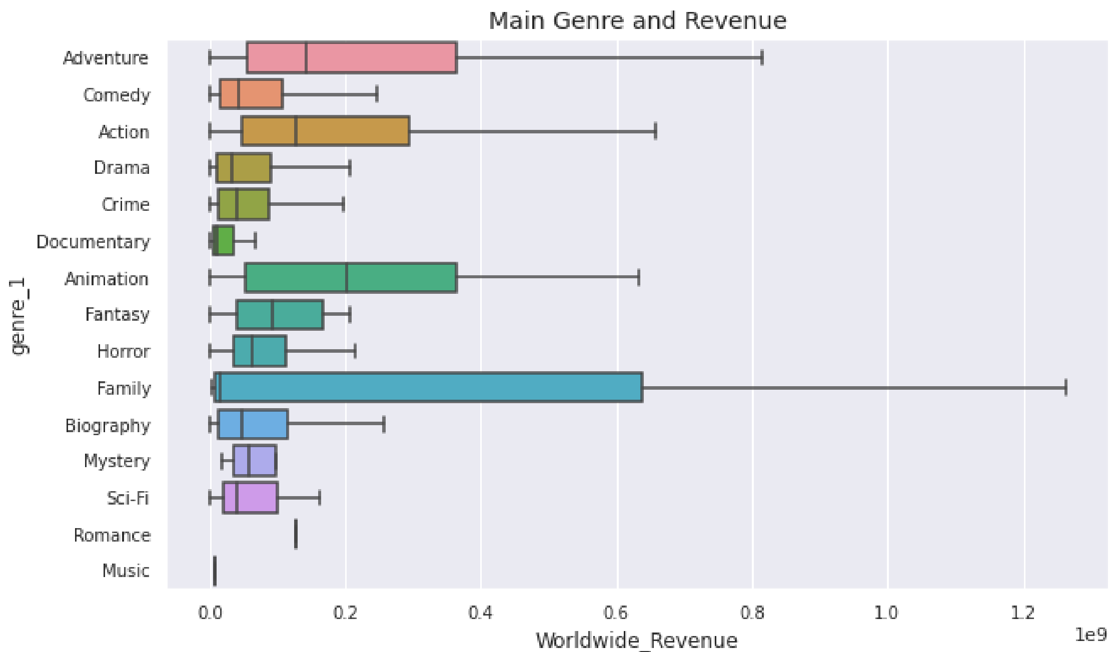
MAIN GENRE

[468]:
```
## Checking the movies count per Main Genre

plt.figure(figsize=(14,6))
plt.subplot(1,2,1)
moviesNew['genre_1'].value_counts().plot(kind='bar', color='blue');
plt.title('Movies count by Main Genre', size=16)
plt.xlabel('Genre', size=12)
plt.ylabel('Movie count', size=12);

## Top movies released was for Genre 'Action', 'Comedy', 'Drama', and␣
 ↪'Adventure
```



[469]:
```
## Looking at Main Genre and Revenue

fig, ax = plt.subplots(figsize=(10, 6))
ax.tick_params(axis='both', labelsize=10)
plt.title('Main Genre and Revenue', fontsize=14)
plt.xlabel('Worldwide Revenue', fontsize=12)
plt.ylabel('Main Genre', fontsize=12)
sns.boxplot(ax=ax, x=moviesNew.Worldwide_Revenue, y=moviesNew.genre_1,
 ↪showfliers=False, orient='h')
plt.show();
```

```
## Main genres 'Family, Adventure, Animation and Action' generated the highest␣
↪worldwide revenue
```



[470]:
```
## Creating a list of the TOP 5 Genre by movies released
genre_mask = ['Action', 'Comedy', 'Drama', 'Adventure', 'Crime']
movies_genre = moviesNew[moviesNew['genre_1'].isin(genre_mask)]
movies_genre.head(3)     ## Looking at the DataFrame with records has the TOP 5␣
↪Genre
```

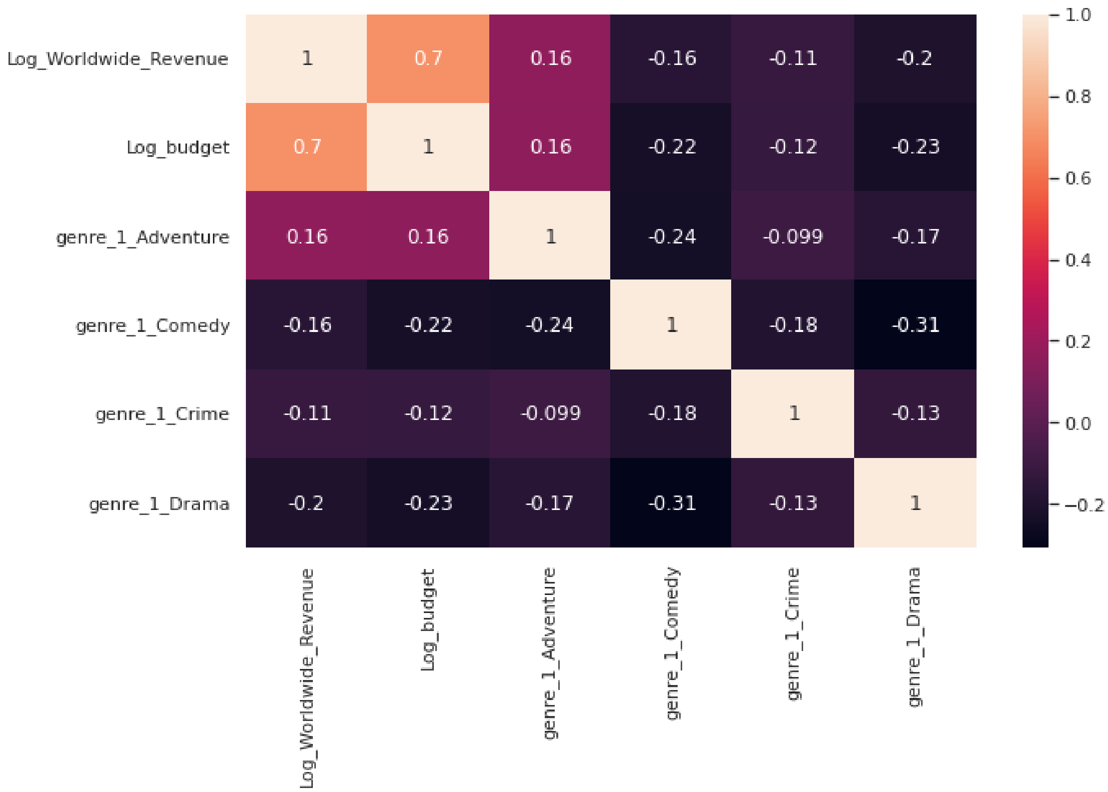
[470]:
```
    movie_id                        title  ...  Log_Worldwide_Revenue Log_budget
0  tt0099088  Back to the Future Part III  ...              19.321428  17.504390
1  tt0099165  The Bonfire of the Vanities  ...              16.568610  17.665658
2  tt0099348           Dances with Wolves  ...              19.865736  16.906553

[3 rows x 18 columns]
```

[471]:
```
## Creating dummy variables for Genre
genre_df = movies_genre[['movie_id', 'Log_Worldwide_Revenue', 'Log_budget',␣
↪'genre_1']]
genre_df = pd.get_dummies(genre_df, columns=['genre_1'], drop_first=True)
genre_df.head(5)
```

[471]:
```
    movie_id  Log_Worldwide_Revenue  ...  genre_1_Crime  genre_1_Drama
0  tt0099088              19.321428  ...              0              0
1  tt0099165              16.568610  ...              0              0
2  tt0099348              19.865736  ...              0              0
```

```
3  tt0099422          18.907657  ...          0          0
4  tt0099423          19.297180  ...          0          0

[5 rows x 7 columns]
```

[472]:
```python
#Relationship between Revenue and Top 5 Genre

corrMatrix_genre = genre_df.corr()
plt.subplots(figsize = (10,6))
sns.heatmap(corrMatrix_genre, annot=True)
plt.show()

## There is a very weak relationship between Main Genre and Worldwide Revenue
```



[473]:
```python
from sklearn.model_selection import train_test_split

x1 = genre_df.drop(['Log_Worldwide_Revenue', 'movie_id'], axis=1)
y1 = genre_df['Log_Worldwide_Revenue']
X1_train, X1_test, y1_train, y1_test = train_test_split(x1,y1, random_state=1,␣
↪test_size=0.20)
print('Train set: ', X1_train.shape, y1_train.shape)
print('Test set: ', X1_test.shape, y1_test.shape)
```

```
Train set:  (2196, 5) (2196,)
Test set:  (550, 5) (550,)
```

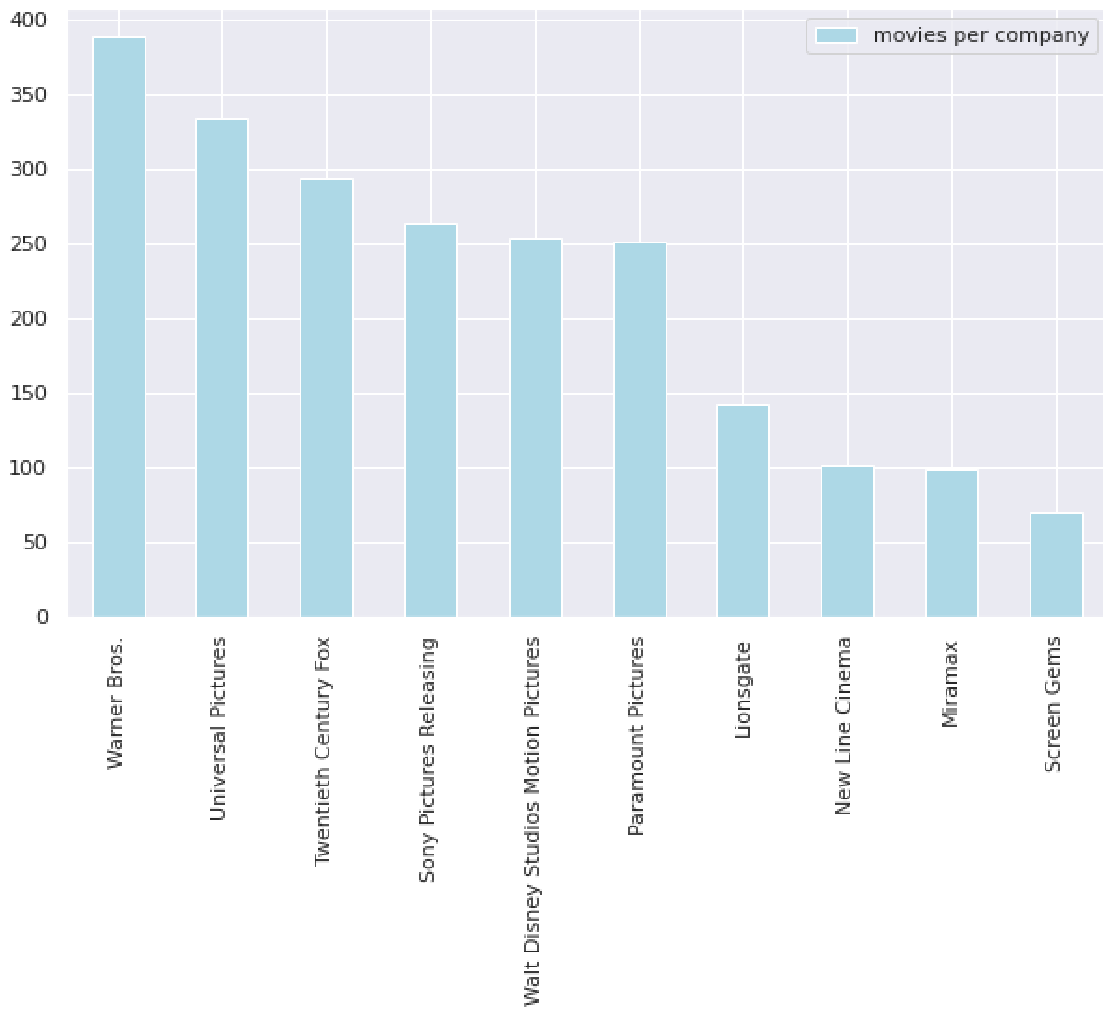
[474]:
```
from sklearn.linear_model import LinearRegression
import sklearn.metrics as metrics

lm1 = LinearRegression()
lm1.fit(X1_train, y1_train)
lm1_prediction = lm1.predict(X1_test)
#run_time=time.time()

results3 = {'Model':'Linear Regression','Dependent Var':'Budget & Genre',␣
 ↪'R-Square':metrics.r2_score(y1_test, lm1_prediction),
            'MSE':metrics.mean_squared_error(y1_test, lm1_prediction),
            'RMSE':np.sqrt(metrics.mean_squared_error(y1_test,␣
 ↪lm1_prediction)), 'Run Time':round(((time.time()-run_time)/60),2)}
results_df = results_df.append(results3, ignore_index=True)
```

[475]:
```
model1_lgb=lgb.LGBMRegressor(n_estimators=10000,
                              objective="regression",
                              metric="mse",
                              min_child_samples=100,
                              use_best_model=True)
model1_lgb.fit(X1_train.values,y1_train)
lgb1_pred_train=model1_lgb.predict(X1_test.values)
#run_time=time.time()

results4 = {'Model':'LGBMReg','Dependent Var':'Budget & Genre', 'R-Square':
 ↪metrics.r2_score(y1_test, lgb1_pred_train),
            'MSE':metrics.mean_squared_error(y1_test, lgb1_pred_train),
            'RMSE':np.sqrt(metrics.mean_squared_error(y1_test,␣
 ↪lgb1_pred_train)),'Run Time':round(((time.time()-run_time)/60),2)}
results_df = results_df.append(results4, ignore_index=True)
```

[476]:
```
rf1_model  = RandomForestRegressor(n_estimators=40, min_samples_leaf=10,␣
 ↪max_features=0.5, n_jobs=-1, oob_score=True)
rf1_model.fit(X1_train, y1_train)

rf1_model=rf1_model.predict(X1_test.values)
#run_time=time.time()
results5 = {'Model':'RandomForest','Dependent Var':'Budget & Genre', 'R-Square':
 ↪metrics.r2_score(y1_test, rf1_model),
            'MSE':metrics.mean_squared_error(y1_test, rf1_model),
            'RMSE':np.sqrt(metrics.mean_squared_error(y1_test, rf1_model)),␣
 ↪'Run Time':round(((time.time()-run_time)/60),2)}
results_df = results_df.append(results5, ignore_index=True)
```

DISTRIBUTOR

[477]:
```
## Looking at the Number of movies per Distributor (TOP 10)

distributorDict = {}
for elem in moviesNew["distributor"].values:
    #for dist in element:
    if elem not in distributorDict:
      distributorDict[elem] = 1
    else:
      distributorDict[elem] += 1

dist_df = pd.DataFrame.from_dict(distributorDict, orient='index',␣
 ↪columns=["movies per company"])
dist_df.sort_values(by="movies per company", ascending=False).head(10).plot.
 ↪bar(color='lightblue', figsize=(10,6))

dist_df.columns = ["num_of_movies"]

# We can see that 'Warner Bros.' has the highest number of movies produced.
```



[478]:
```
## Looking at the Total Revenue per Distributor

## Creating an index for Distributors
dist_df.index.values
for d in dist_df.index.values:
    moviesNew[d] = moviesNew['distributor'].apply(lambda x: 1 if d in x else 0)

## Total Revenue per Distributor
for i, d in enumerate(dist_df.index.values):
    dist_df.loc[d, "total_revenue"] = moviesNew[moviesNew[d]==1].
 ↪Worldwide_Revenue.sum()

dist_df.sort_values(by=["total_revenue", "num_of_movies"], ascending=False).
 ↪head(5)
```

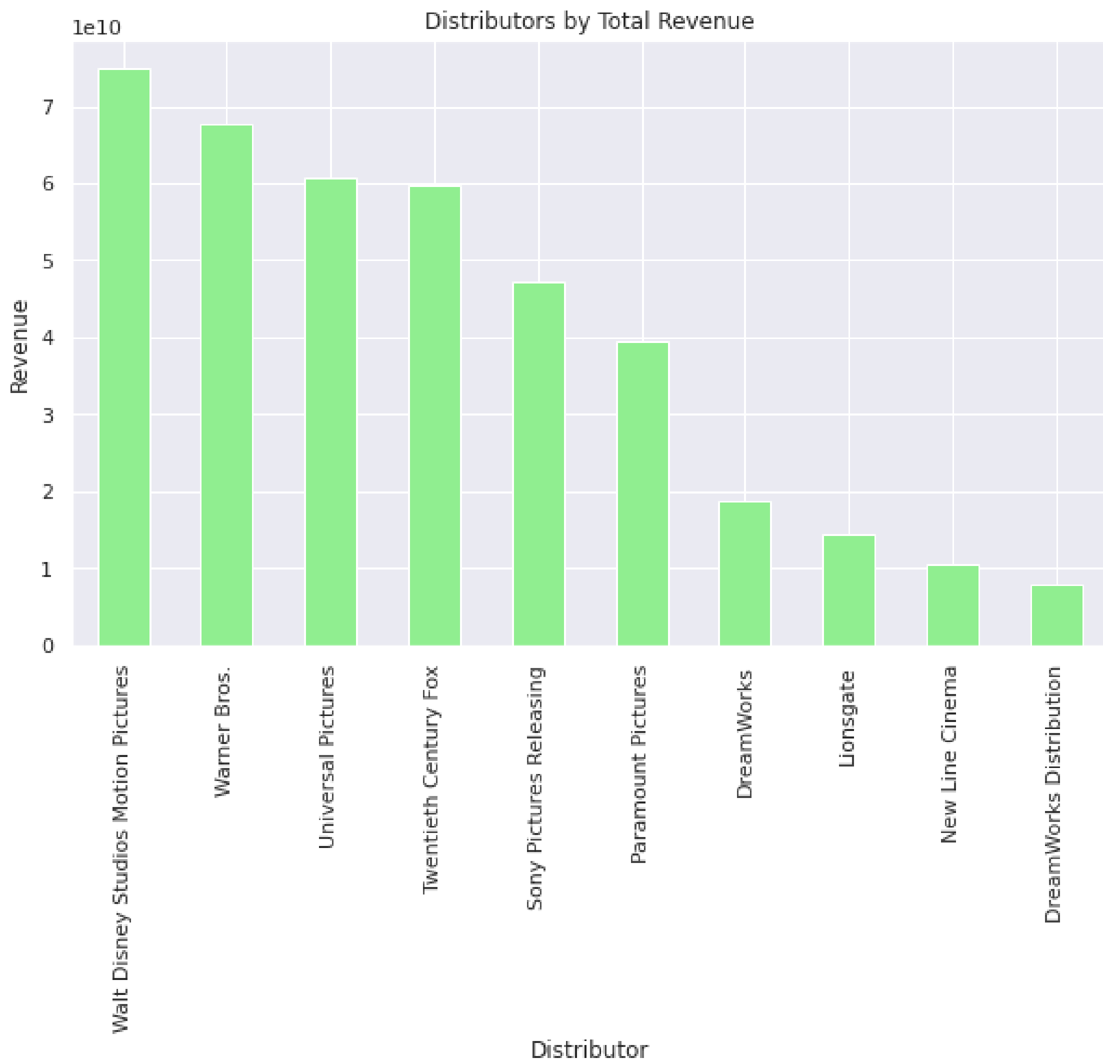
[478]:

```
                                      num_of_movies  total_revenue
Walt Disney Studios Motion Pictures             253   7.487085e+10
Warner Bros.                                    388   6.761542e+10
Universal Pictures                              334   6.083843e+10
Twentieth Century Fox                           294   5.987527e+10
Sony Pictures Releasing                         263   4.732572e+10
```

[479]:

```python
# TOP 10 Distributors by Total Revenue

dist_df.sort_values(by=["total_revenue"], ascending=False).total_revenue.
 ↪head(10).plot.bar(color='lightgreen', figsize=(10,6))
plt.title("Distributors by Total Revenue")
plt.ylabel("Revenue")
plt.xlabel("Distributor")

#'Walt Disney Studios' has the highest total revenue earner
```

[479]: Text(0.5, 0, 'Distributor')



[480]:
```
## Will group the TOP 10 distributors and the rest will be OTHER

top10_dist = moviesNew['distributor'].value_counts()[:10].index
top10_dist
```

[480]:
```
Index(['Warner Bros.', 'Universal Pictures', 'Twentieth Century Fox',
       'Sony Pictures Releasing', 'Walt Disney Studios Motion Pictures',
       'Paramount Pictures', 'Lionsgate', 'New Line Cinema', 'Miramax',
       'Screen Gems'],
      dtype='object')
```

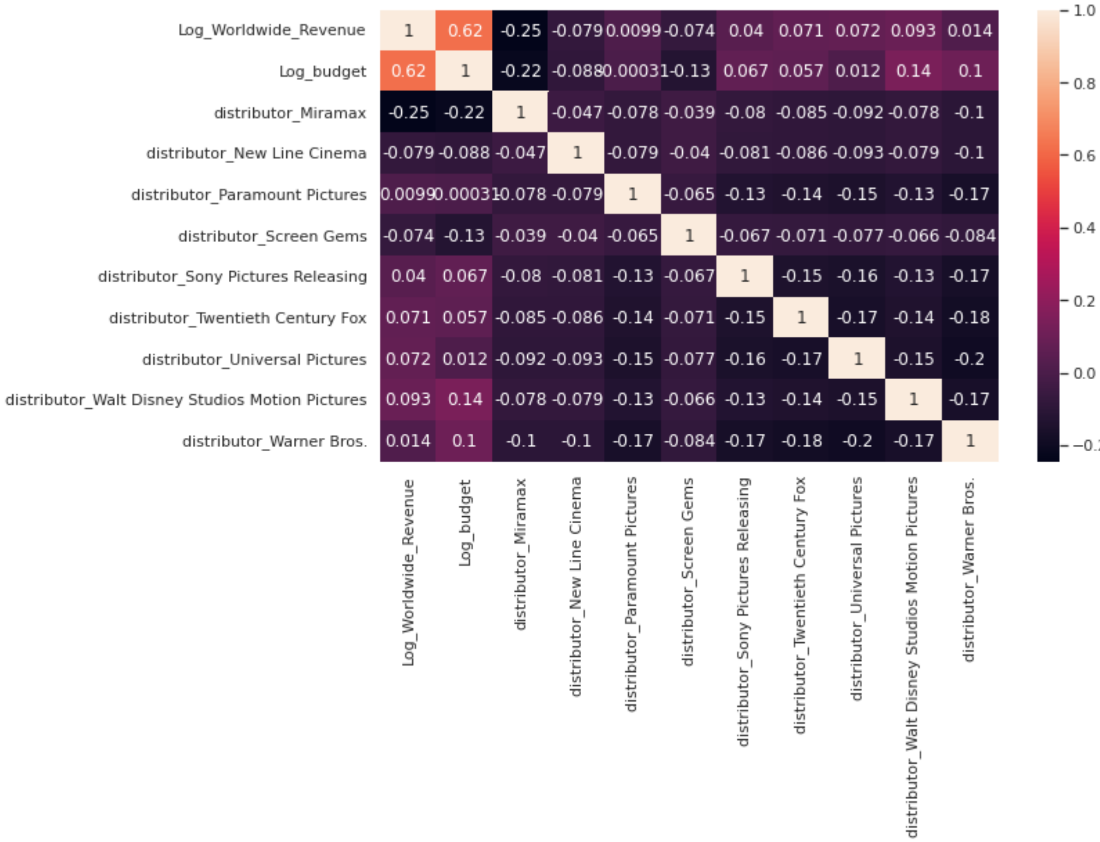
[481]:
```
## Creating a subset DataFrame for TOP 10 Distributors

dist_df = moviesNew[moviesNew['distributor'].isin(top10_dist)]
dist_df = dist_df[['movie_id', 'Log_Worldwide_Revenue', 'Log_budget',␣
 ↪'distributor']]
dist_df.head(3)
```

[481]:
```
    movie_id  ...                          distributor
0  tt0099088  ...                   Universal Pictures
1  tt0099165  ...                         Warner Bros.
3  tt0099422  ...  Walt Disney Studios Motion Pictures

[3 rows x 4 columns]
```

[482]:
```
## Creating dummys for TOP 10 Distributors

dist_df = pd.get_dummies(dist_df, columns=['distributor'], drop_first=True)
dist_df.head(5)
```

[482]:
```
    movie_id  ...  distributor_Warner Bros.
0  tt0099088  ...                         0
1  tt0099165  ...                         1
3  tt0099422  ...                         0
4  tt0099423  ...                         0
5  tt0099587  ...                         0

[5 rows x 12 columns]
```

[483]:
```
## Correlation between Revenue and TOP 10 Distributor

corrMatrix_dist = dist_df.corr()
plt.subplots(figsize = (10,6))
sns.heatmap(corrMatrix_dist, annot=True)
plt.show()

## Also there is a very little correlation between Distributor and Worldwide␣
 ↪Revenue
```



[484]:
```
x2 = dist_df.drop(['Log_Worldwide_Revenue', 'movie_id'], axis=1)
y2 = dist_df['Log_Worldwide_Revenue']
X2_train, X2_test, y2_train, y2_test = train_test_split(x2,y2, random_state=1,␣
↪test_size=0.20)
print('Train set: ', X2_train.shape, y2_train.shape)
print('Test set: ', X2_test.shape, y2_test.shape)
```

```
Train set:  (1755, 10) (1755,)
Test set:  (439, 10) (439,)
```

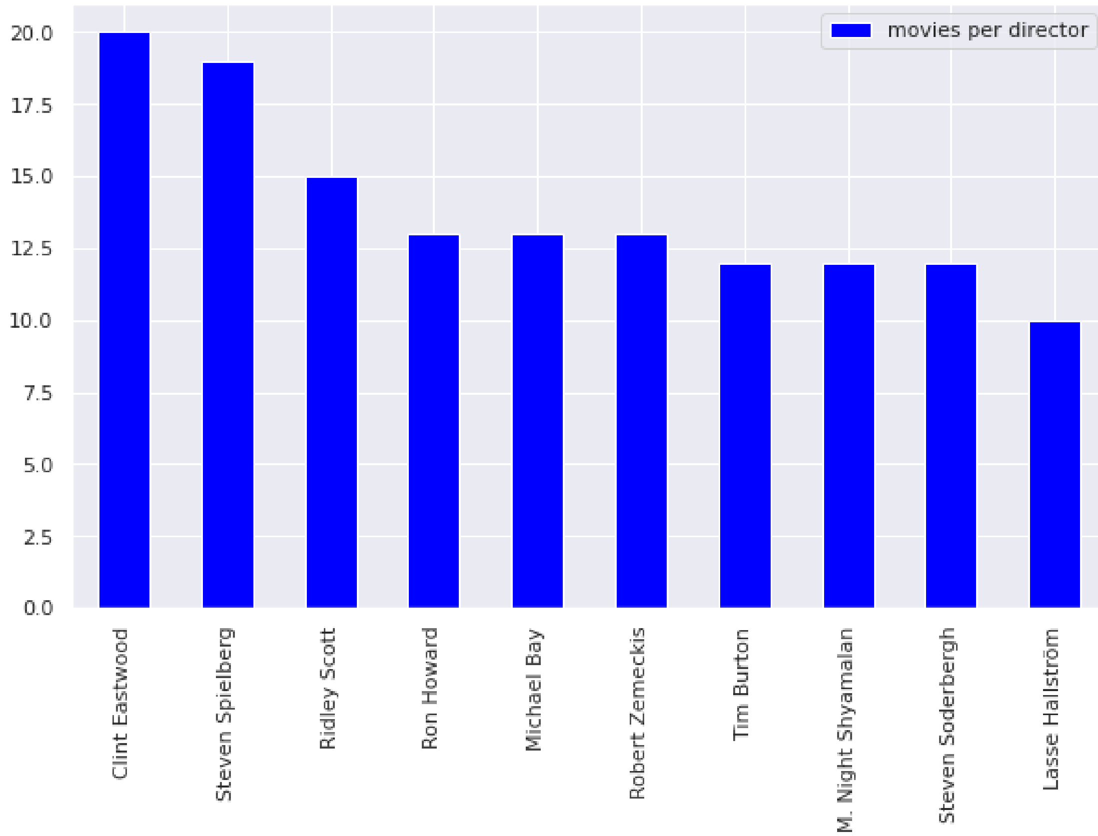
[485]:
```
lm2 = LinearRegression()
lm2.fit(X2_train, y2_train)
lm2_prediction = lm2.predict(X2_test)
#run_time=time.time()
results6 = {'Model':'Linear Regression','Dependent Var':'Budget & Distributor',␣
↪'R-Square':metrics.r2_score(y2_test, lm2_prediction),
            'MSE':metrics.mean_squared_error(y2_test, lm2_prediction),
            'RMSE':np.sqrt(metrics.mean_squared_error(y2_test,␣
↪lm2_prediction)), 'Run Time':round(((time.time()-run_time)/60),2)}
results_df = results_df.append(results6, ignore_index=True)
```

[486]:
```
model2_lgb=lgb.LGBMRegressor(n_estimators=10000,
                             objective="regression",
                             metric="mse",
                             min_child_samples=100,
                             use_best_model=True)
model2_lgb.fit(X2_train.values,y2_train)
lgb2_pred_train=model2_lgb.predict(X2_test.values)
#run_time=time.time()
results7 = {'Model':'LGBMReg','Dependent Var':'Budget & Distributor',␣
 ↪'R-Square':metrics.r2_score(y2_test, lgb2_pred_train),
            'MSE':metrics.mean_squared_error(y2_test, lgb2_pred_train),
            'RMSE':np.sqrt(metrics.mean_squared_error(y2_test,␣
 ↪lgb2_pred_train)), 'Run Time':round(((time.time()-run_time)/60),2)}
results_df = results_df.append(results7, ignore_index=True)
```

[487]:
```
rf2_model = RandomForestRegressor(n_estimators=40, min_samples_leaf=10,␣
 ↪max_features=0.5, n_jobs=-1, oob_score=True)
rf2_model.fit(X2_train, y2_train)

rf2_model=rf2_model.predict(X2_test.values)
#run_time=time.time()
results8 = {'Model':'RandomForest','Dependent Var':'Budget & Distributor',␣
 ↪'R-Square':metrics.r2_score(y2_test, rf2_model),
            'MSE':metrics.mean_squared_error(y2_test, rf2_model),
            'RMSE':np.sqrt(metrics.mean_squared_error(y2_test, rf2_model)),␣
 ↪'Run Time':round(((time.time()-run_time)/60),2)}
results_df = results_df.append(results8, ignore_index=True)
```

DIRECTOR

[488]:
```
## Looking at the Top 10 director by the number of movies

directorDict = {}
for elem in moviesNew["director"].values:
    if elem not in directorDict:
      directorDict[elem] = 1
    else:
      directorDict[elem] += 1

director_df = pd.DataFrame.from_dict(directorDict, orient='index',␣
 ↪columns=["movies per director"])
director_df.sort_values(by="movies per director", ascending=False).head(10).
 ↪plot.bar(color='Blue', figsize=(10,6))

director_df.columns = ["num_of_movies"]

## The most popular director based on the number of titles is Clint Eastwood
```



[489]:
```
## Creating an index for Directors

director_df.index.values
for d in director_df.index.values:
    moviesNew[d] = moviesNew['director'].apply(lambda x: 1 if d in x else 0)

## Total Revenue per Director
for i, d in enumerate(director_df.index.values):
    director_df.loc[d, "total_revenue"] = moviesNew[moviesNew[d]==1].
 ↪Worldwide_Revenue.sum()

director_df.sort_values(by=["total_revenue", "num_of_movies"], ascending=False).
 ↪head(10)
```

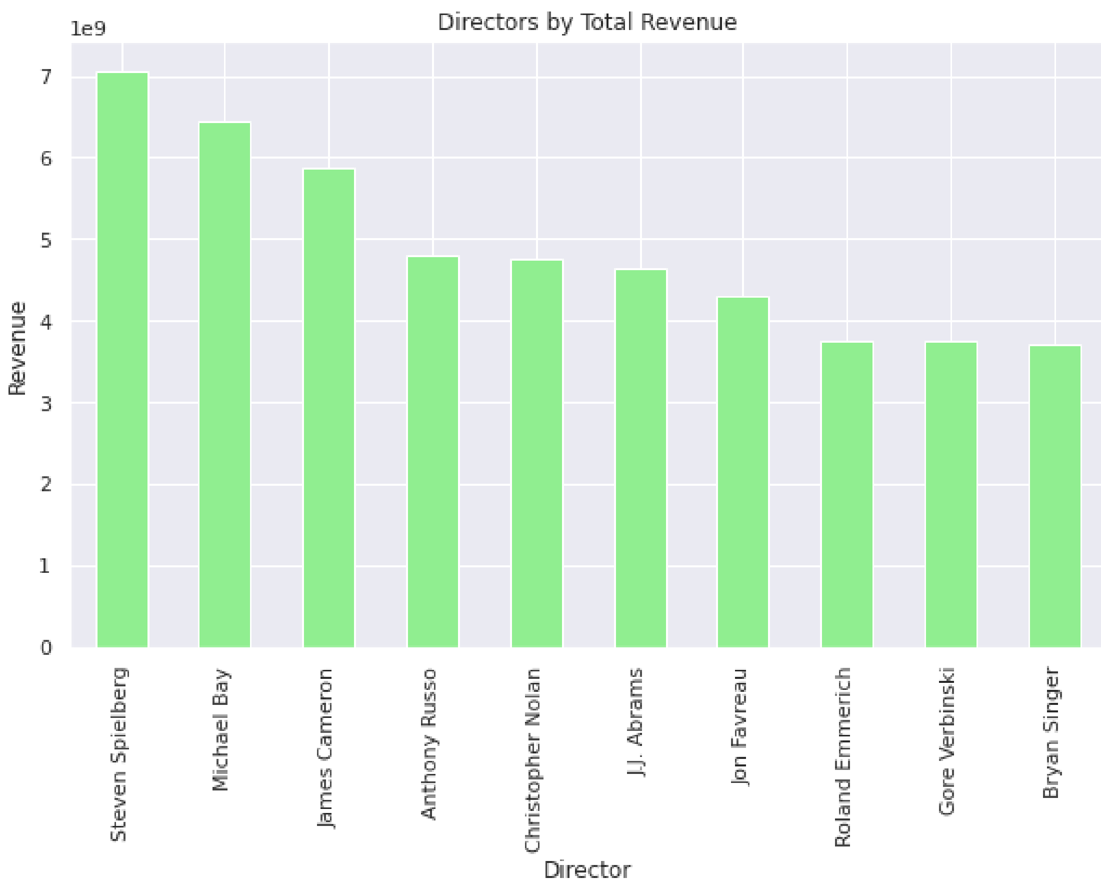
[489]:

	num_of_movies	total_revenue
Steven Spielberg	19	7.067664e+09
Michael Bay	13	6.451693e+09
James Cameron	4	5.884646e+09
Anthony Russo	4	4.796147e+09
Christopher Nolan	9	4.756854e+09
J.J. Abrams	6	4.653989e+09

```
Jon Favreau                      7    4.294367e+09
Roland Emmerich                 10    3.761203e+09
Gore Verbinski                  10    3.753025e+09
Bryan Singer                     9    3.711342e+09
```

[490]:
```
## Directors by Total Revenue

director_df.sort_values(by=["total_revenue"], ascending=False).total_revenue.
 ↪head(10).plot.bar(color='lightgreen', figsize=(10,6))
plt.title("Directors by Total Revenue")
plt.ylabel("Revenue")
plt.xlabel("Director")

## The top director based on the total revenue earned is Steven Spielberg with␣
 ↪a total of $7,067,664,000
```

[490]:
```
Text(0.5, 0, 'Director')
```



[491]:
```
## Will group the TOP 10 directors and the rest will be OTHER

top10_direct = moviesNew['director'].value_counts()[:10].index
```

```
top10_direct
```

[491]:
```
Index(['Clint Eastwood', 'Steven Spielberg', 'Ridley Scott', 'Ron Howard',
       'Michael Bay', 'Robert Zemeckis', 'M. Night Shyamalan', 'Tim Burton',
       'Steven Soderbergh', 'Peter Berg'],
      dtype='object')
```

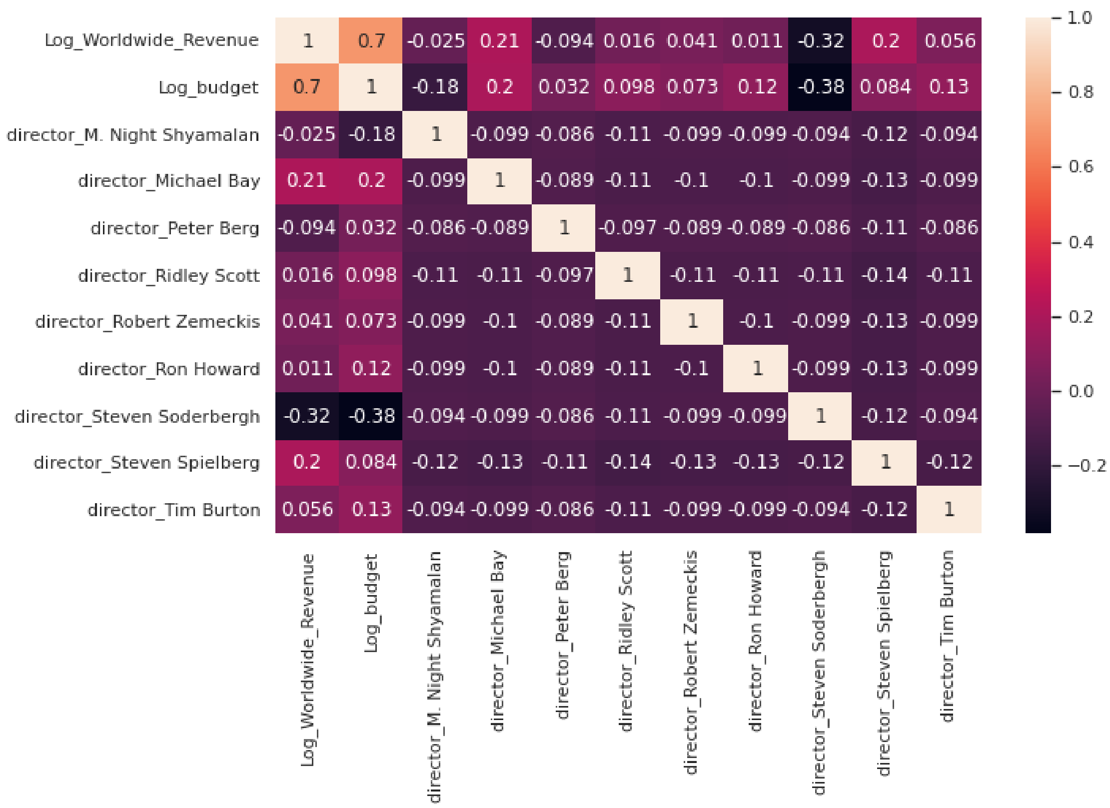
[492]:
```
## Creating a subset DataFrame for TOP 10 Directors

director_df = moviesNew[moviesNew['director'].isin(top10_direct)]
director_df = director_df[['movie_id', 'Log_Worldwide_Revenue', 'Log_budget',
 ↪'director']]
director_df.head(3)
```

[492]:
```
     movie_id  Log_Worldwide_Revenue  Log_budget          director
0   tt0099088              19.321428   17.504390   Robert Zemeckis
34  tt0102057              19.522138   18.064006  Steven Spielberg
62  tt0103074              17.631789   16.618871      Ridley Scott
```

[493]:
```
## Creating dummys for the TOP 10 Directors

director_df = pd.get_dummies(director_df, columns=['director'], drop_first=True)
director_df.head(3)
```

[493]:
```
     movie_id  ...  director_Tim Burton
0   tt0099088  ...                    0
34  tt0102057  ...                    0
62  tt0103074  ...                    0

[3 rows x 12 columns]
```

[494]:
```
#Relationship between Revenue and TOP 10 Directors

corrMatrix_direct = director_df.corr()
plt.subplots(figsize = (10,6))
sns.heatmap(corrMatrix_direct, annot=True)
plt.show()

## There is a very weak correlation between Director and Worldwide Revenue
```



[495]:
```
x3 = director_df.drop(['Log_Worldwide_Revenue', 'movie_id'], axis=1)
y3 = director_df['Log_Worldwide_Revenue']
X3_train, X3_test, y3_train, y3_test = train_test_split(x3,y3, random_state=1,␣
 ↪test_size=0.20)
print('Train set: ', X3_train.shape, y3_train.shape)
print('Test set: ', X3_test.shape, y3_test.shape)
```

```
Train set:  (111, 10) (111,)
Test set:  (28, 10) (28,)
```

[496]:
```
lm3 = LinearRegression()
lm3.fit(X3_train, y3_train)
lm3_prediction = lm3.predict(X3_test)
#run_time=time.time()
results9 = {'Model':'Linear Regression','Dependent Var':'Budget & Director',␣
 ↪'R-Square':metrics.r2_score(y3_test, lm3_prediction),
            'MSE':metrics.mean_squared_error(y3_test, lm3_prediction),
            'RMSE':np.sqrt(metrics.mean_squared_error(y3_test,␣
 ↪lm3_prediction)), 'Run Time':round(((time.time()-run_time)/60),2)}
results_df = results_df.append(results9, ignore_index=True)
```

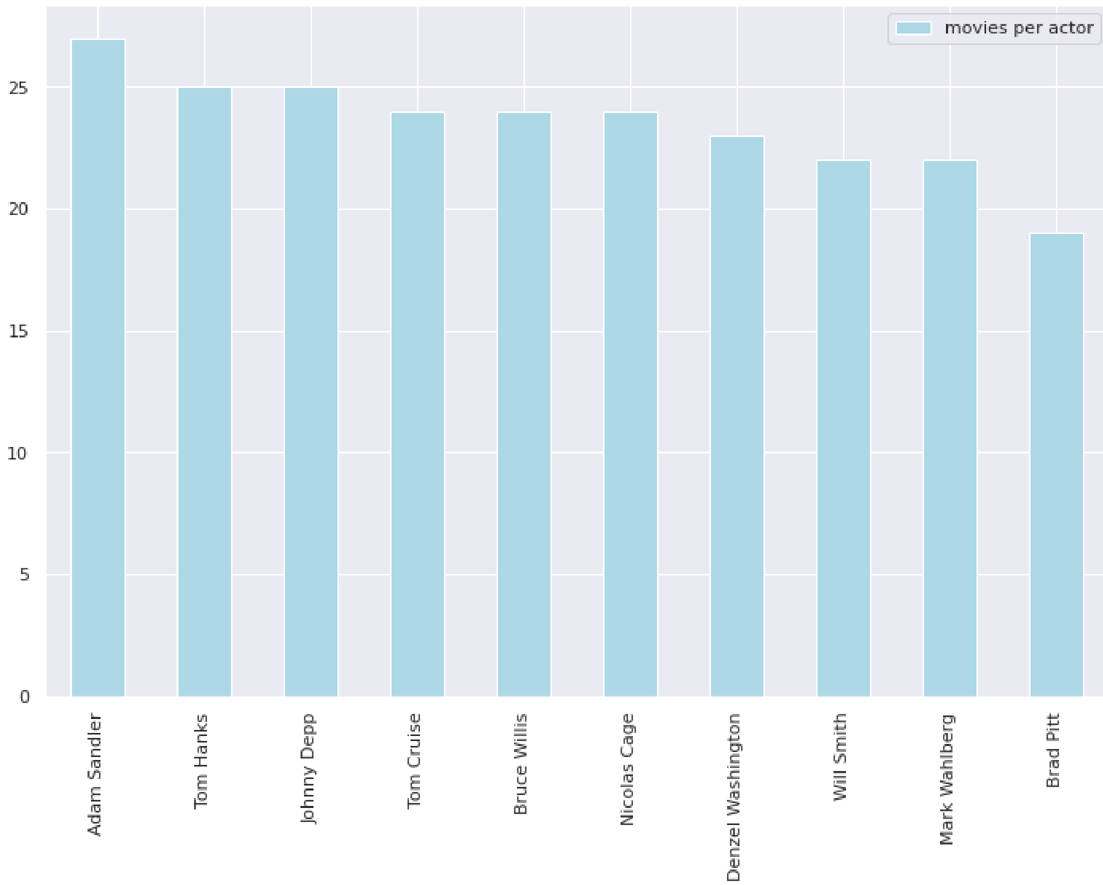
[497]:
```
model3_lgb=lgb.LGBMRegressor(n_estimators=10000,
                             objective="regression",
                             metric="mse",
                             min_child_samples=100,
                             use_best_model=True)
model3_lgb.fit(X3_train.values,y3_train)
lgb3_pred_train=model3_lgb.predict(X3_test.values)
#run_time=time.time()
results_10 = {'Model':'LGBMReg','Dependent Var':'Budget & Director', 'R-Square':
↪metrics.r2_score(y3_test, lgb3_pred_train),
            'MSE':metrics.mean_squared_error(y3_test, lgb3_pred_train),
            'RMSE':np.sqrt(metrics.mean_squared_error(y3_test,␣
↪lgb3_pred_train)), 'Run Time':round(((time.time()-run_time)/60),2)}
results_df = results_df.append(results_10, ignore_index=True)
```

[498]:
```
rf3_model = RandomForestRegressor(n_estimators=40, min_samples_leaf=10,␣
↪max_features=0.5, n_jobs=-1, oob_score=True)
rf3_model.fit(X3_train, y3_train)

rf3_model=rf3_model.predict(X3_test.values)
#run_time=time.time()
results_11 = {'Model':'RandomForest','Dependent Var':'Budget & Director',␣
↪'R-Square':metrics.r2_score(y3_test, rf3_model),
            'MSE':metrics.mean_squared_error(y3_test, rf3_model),
            'RMSE':np.sqrt(metrics.mean_squared_error(y3_test, rf3_model)),␣
↪'Run Time':round(((time.time()-run_time)/60),2)}
results_df = results_df.append(results_11, ignore_index=True)
```

MAIN ACTOR

[499]:
```
## Looking at the Top 10 Main Actor by the number of movies

actorDict = {}
for elem in moviesNew["main_actor_1"].values:
    if elem not in actorDict:
      actorDict[elem] = 1
    else:
      actorDict[elem] += 1

actor_df = pd.DataFrame.from_dict(actorDict, orient='index', columns=["movies␣
↪per actor"])
actor_df.sort_values(by="movies per actor", ascending=False).head(10).plot.
↪bar(color = 'lightblue', figsize=(12,8))

actor_df.columns = ["num_of_movies"]
```

```
# We can see that the most popular actor based on the number of titles is Adam␣
↪Sandler
```



[500]:
```
## Looking at TOP 10 Main Actor by Worlwide Revenue

## Creating an index for Actors
actor_df.index.values
for d in actor_df.index.values:
    moviesNew[d] = moviesNew['main_actor_1'].apply(lambda x: 1 if d in x else 0)

## Total Revenue per Actor
for i, d in enumerate(actor_df.index.values):
    actor_df.loc[d, "total_revenue"] = moviesNew[moviesNew[d]==1].
↪Worldwide_Revenue.sum()

actor_df.sort_values(by=["total_revenue", "num_of_movies"], ascending=False).
↪head(10)
```

[500]:

	num_of_movies	total_revenue
Robert Downey Jr.	12	9.206894e+09

```
Tom Hanks                  25   8.491896e+09
Tom Cruise                 24   8.125249e+09
Will Smith                 22   7.933443e+09
Johnny Depp                25   7.268864e+09
Leonardo DiCaprio          16   6.615727e+09
Vin Diesel                 16   6.064423e+09
Daniel Radcliffe            6   5.426364e+09
Dwayne Johnson             18   5.394877e+09
Chris Pratt                 6   5.275768e+09
```

[501]:
```python
# Top 20 Main Actor by Total Revenue

top_20_actor = actor_df.sort_values(by=["total_revenue"], ascending=False).
 ↪head(20)
fig = px.bar(top_20_actor, x=top_20_actor.index, y='total_revenue', title =␣
 ↪'Top 20 Actors by Movies Revenue', color = 'total_revenue', height=700,␣
 ↪width=900,
             labels={'Worldwide_Revenue':'Global Revenue in USD Billion', 'x':
 ↪''})
fig.update_layout(barmode='group', xaxis_tickangle=-45)
fig.show()

# The top actor/actress based on the total revenue earned is Robert Downey Jr.␣
 ↪with a total of $9,206,893,682
```

[502]:
```python
## Will group the TOP 10 actors and the rest will be OTHER

top10_actor = moviesNew['main_actor_1'].value_counts()[:10].index
top10_actor
```

[502]:
```
Index(['Adam Sandler', 'Johnny Depp', 'Tom Hanks', 'Nicolas Cage',
       'Tom Cruise', 'Bruce Willis', 'Denzel Washington', 'Will Smith',
       'Mark Wahlberg', 'Ben Stiller'],
      dtype='object')
```

[503]:
```python
## Creating a subset DataFrame for TOP 10 Directors

actor_df = moviesNew[moviesNew['main_actor_1'].isin(top10_actor)]
actor_df = actor_df[['movie_id', 'Log_Worldwide_Revenue', 'Log_budget',␣
 ↪'main_actor_1']]
actor_df.head(3)
```

[503]:

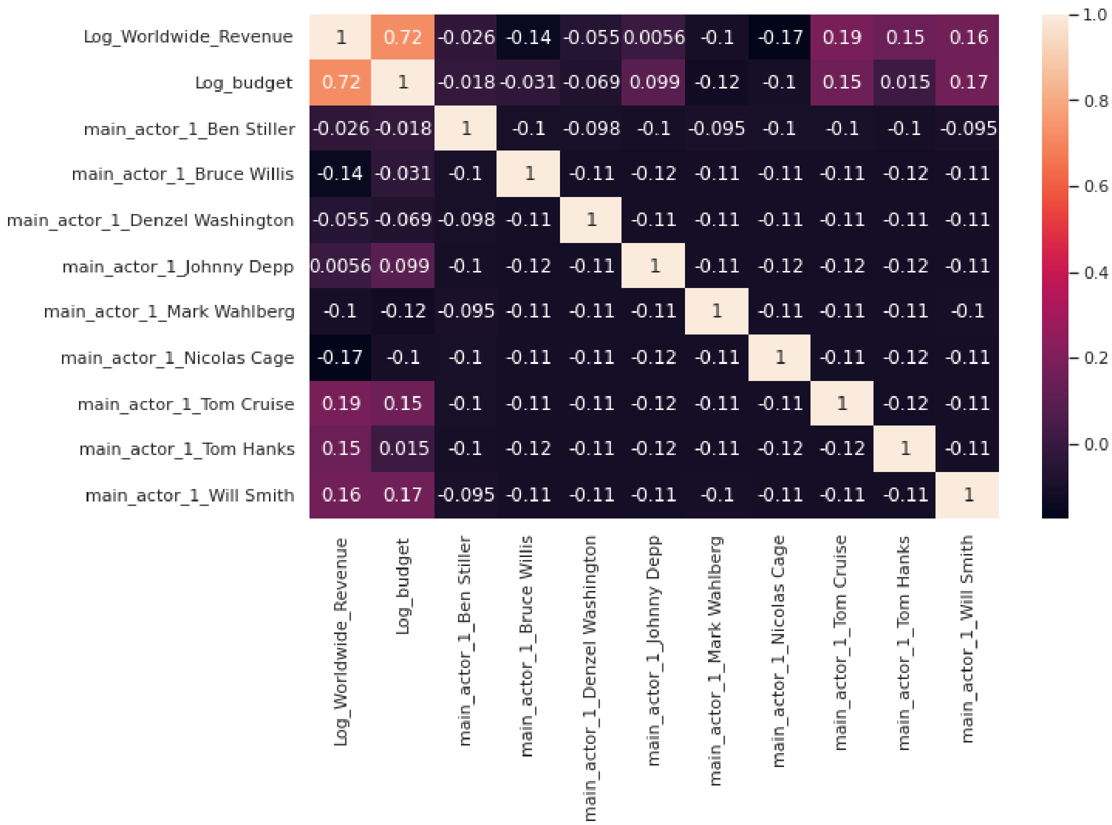
	movie_id	Log_Worldwide_Revenue	Log_budget	main_actor_1
1	tt0099165	16.568610	17.665658	Tom Hanks
4	tt0099423	19.297180	18.064006	Bruce Willis
37	tt0102070	16.661471	17.989898	Bruce Willis

[504]:
```python
## Creating dummys for the TOP 10 Main Actors

actor_df = pd.get_dummies(actor_df, columns=['main_actor_1'], drop_first=True)
```

```python
actor_df.head(3)
```

[504]:
```
      movie_id  ...  main_actor_1_Will Smith
1   tt0099165  ...                        0
4   tt0099423  ...                        0
37  tt0102070  ...                        0

[3 rows x 12 columns]
```

[505]:
```python
#Relationship between Revenue and TOP 10 Main Actors

corrMatrix_actor = actor_df.corr()
plt.subplots(figsize = (10,6))
sns.heatmap(corrMatrix_actor, annot=True)
plt.show()

## There is a very weak correlation between Main Actor and Worldwide Revenue
```



[506]:
```python
x4 = actor_df.drop(['Log_Worldwide_Revenue', 'movie_id'], axis=1)
y4 = actor_df['Log_Worldwide_Revenue']
X4_train, X4_test, y4_train, y4_test = train_test_split(x4,y4, random_state=1,␣
↪test_size=0.20)
```

```python
print('Train set: ', X4_train.shape, y4_train.shape)
print('Test set: ', X4_test.shape, y4_test.shape)
```

```
Train set:  (188, 10) (188,)
Test set:  (47, 10) (47,)
```

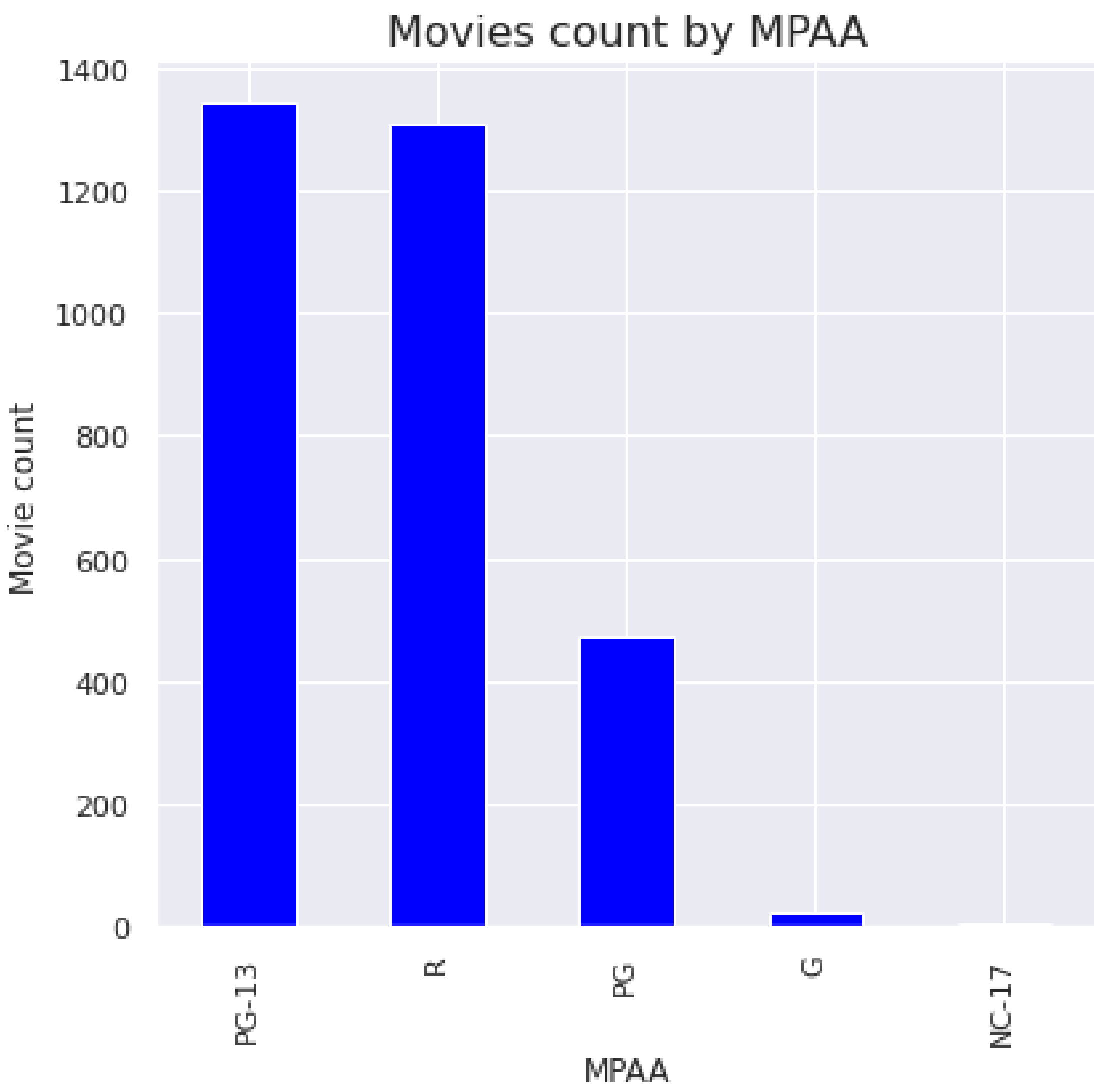
[507]:
```python
lm4 = LinearRegression()
lm4.fit(X4_train, y4_train)
lm4_prediction = lm4.predict(X4_test)
#run_time=time.time()
results_12 = {'Model':'Linear Regression','Dependent Var':'Budget & Actor',␣
↪'R-Square':metrics.r2_score(y4_test, lm4_prediction),
            'MSE':metrics.mean_squared_error(y4_test, lm4_prediction),
            'RMSE':np.sqrt(metrics.mean_squared_error(y4_test,␣
↪lm4_prediction)), 'Run Time':round(((time.time()-run_time)/60),2)}
results_df = results_df.append(results_12, ignore_index=True)
```

[508]:
```python
model4_lgb=lgb.LGBMRegressor(n_estimators=10000,
                             objective="regression",
                             metric="mse",
                             min_child_samples=100,
                             use_best_model=True)
model4_lgb.fit(X4_train.values,y4_train)
lgb4_pred_train=model4_lgb.predict(X4_test.values)
#run_time=time.time()
results_13 = {'Model':'LGBMReg','Dependent Var':'Budget & Actor', 'R-Square':
↪metrics.r2_score(y4_test, lgb4_pred_train),
            'MSE':metrics.mean_squared_error(y4_test, lgb4_pred_train),
            'RMSE':np.sqrt(metrics.mean_squared_error(y4_test,␣
↪lgb4_pred_train)), 'Run Time':round(((time.time()-run_time)/60),2)}
results_df = results_df.append(results_13, ignore_index=True)
```

[509]:
```python
rf4_model = RandomForestRegressor(n_estimators=40, min_samples_leaf=10,␣
↪max_features=0.5, n_jobs=-1, oob_score=True)
rf4_model.fit(X4_train, y4_train)

rf4_model=rf4_model.predict(X4_test.values)
#run_time=time.time()
results_14 = {'Model':'RandomForest','Dependent Var':'Budget & Actor',␣
↪'R-Square':metrics.r2_score(y4_test, rf4_model),
            'MSE':metrics.mean_squared_error(y4_test, rf4_model),
            'RMSE':np.sqrt(metrics.mean_squared_error(y4_test, rf4_model)),␣
↪'Run Time':round(((time.time()-run_time)/60),2)}
results_df = results_df.append(results_14, ignore_index=True)
```

MPAA

[510]:
```python
## MPAA
## Checking the movies count per MPAA

plt.figure(figsize=(14,6))
plt.subplot(1,2,1)
moviesNew['mpaa'].value_counts().plot(kind='bar', color='blue');
plt.title('Movies count by MPAA', size=16)
plt.xlabel('MPAA', size=12)
plt.ylabel('Movie count', size=12);

## Top movies released was PG-13 rating
```



[511]:
```python
## Looking at MPAA and Revenue
```

```
fig, ax = plt.subplots(figsize=(10, 6))
ax.tick_params(axis='both', labelsize=10)
plt.title('MPAA and Revenue', fontsize=14)
plt.xlabel('Worldwide Revenue', fontsize=12)
plt.ylabel('MPAA', fontsize=12)
sns.boxplot(ax=ax, x=moviesNew.Worldwide_Revenue, y=moviesNew.mpaa,␣
 ↪showfliers=False, orient='h')
plt.show();

## Movies rating G have higer revenue than other ratings
```

[512]:
```
mpaa_df = moviesNew[['movie_id', 'Log_Worldwide_Revenue', 'Log_budget', 'mpaa']]
mpaa_df.head(3)
```

[512]:

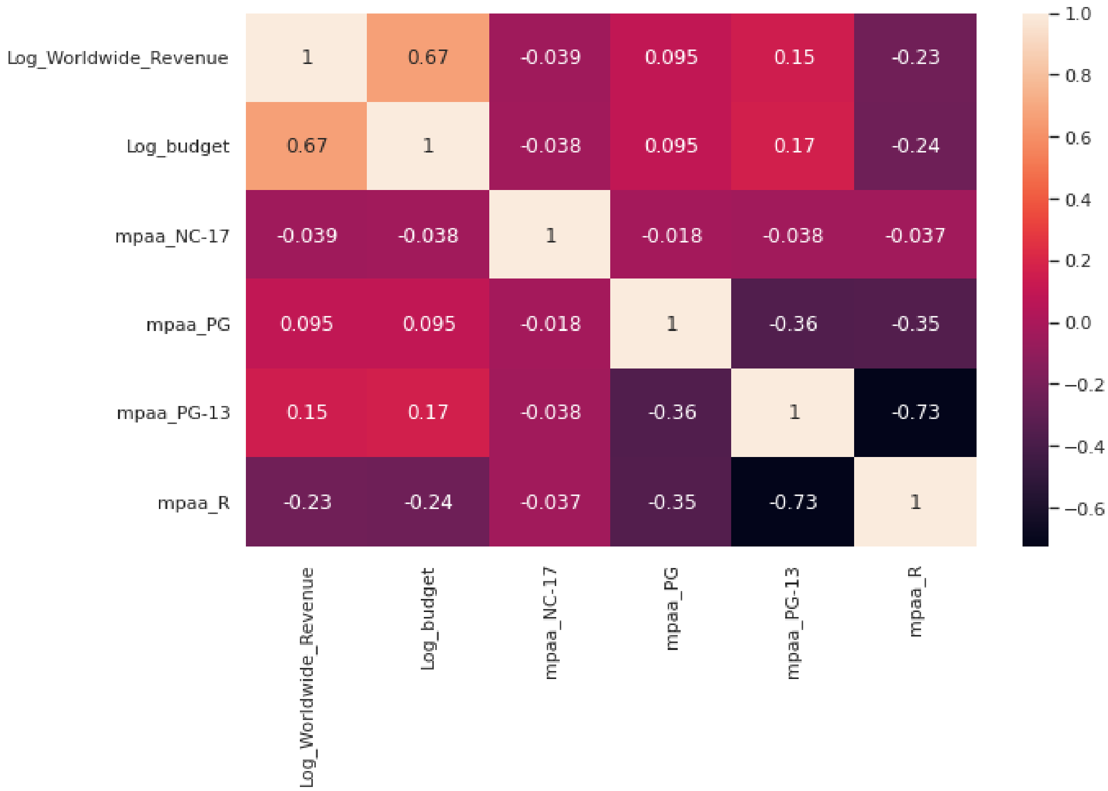
	movie_id	Log_Worldwide_Revenue	Log_budget	mpaa
0	tt0099088	19.321428	17.504390	PG-13
1	tt0099165	16.568610	17.665658	R
2	tt0099348	19.865736	16.906553	PG-13

[513]:
```
## Creating dummys for MPAA

mpaa_df = pd.get_dummies(mpaa_df, columns=['mpaa'], drop_first=True)
mpaa_df.head(3)
```

[513]:
```
    movie_id  Log_Worldwide_Revenue  Log_budget  ...  mpaa_PG  mpaa_PG-13
mpaa_R
```

```
0  tt0099088              19.321428   17.504390  ...         0            1
0
1  tt0099165              16.568610   17.665658  ...         0            0
1
2  tt0099348              19.865736   16.906553  ...         0            1
0

[3 rows x 7 columns]
```

[514]:
```
#Relationship between Revenue and MPAA

corrMatrix_mpaa = mpaa_df.corr()
plt.subplots(figsize = (10,6))
sns.heatmap(corrMatrix_mpaa, annot=True)
plt.show()

## There is a very weak correlation between MPAA and Worldwide Revenue
```



[515]:
```
x5 = mpaa_df.drop(['Log_Worldwide_Revenue', 'movie_id'], axis=1)
y5 = mpaa_df['Log_Worldwide_Revenue']
X5_train, X5_test, y5_train, y5_test = train_test_split(x5,y5, random_state=1,␣
↪test_size=0.20)
print('Train set: ', X5_train.shape, y5_train.shape)
```

```
print('Test set: ', X5_test.shape, y5_test.shape)
```

```
Train set:  (2520, 5) (2520,)
Test set:  (631, 5) (631,)
```

[516]:
```
lm5 = LinearRegression()
lm5.fit(X5_train, y5_train)
lm5_prediction = lm5.predict(X5_test)
#run_time=time.time()
results_15 = {'Model':'Linear Regression','Dependent Var':'Budget & MPAA',␣
↪'R-Square':metrics.r2_score(y5_test, lm5_prediction),
            'MSE':metrics.mean_squared_error(y5_test, lm5_prediction),
            'RMSE':np.sqrt(metrics.mean_squared_error(y5_test,␣
↪lm5_prediction)), 'Run Time':round(((time.time()-run_time)/60),2)}
results_df = results_df.append(results_15, ignore_index=True)
```

[517]:
```
model5_lgb=lgb.LGBMRegressor(n_estimators=10000,
                             objective="regression",
                             metric="mse",
                             min_child_samples=100,
                             use_best_model=True)
model5_lgb.fit(X5_train.values,y5_train)
lgb5_pred_train=model5_lgb.predict(X5_test.values)
#run_time=time.time()
results_16 = {'Model':'LGBMReg','Dependent Var':'Budget & MPAA', 'R-Square':
↪metrics.r2_score(y5_test, lgb5_pred_train),
            'MSE':metrics.mean_squared_error(y5_test, lgb5_pred_train),
            'RMSE':np.sqrt(metrics.mean_squared_error(y5_test,␣
↪lgb5_pred_train)), 'Run Time':round(((time.time()-run_time)/60),2)}
results_df = results_df.append(results_16, ignore_index=True)
```

[518]:
```
rf5_model = RandomForestRegressor(n_estimators=40, min_samples_leaf=10,␣
↪max_features=0.5, n_jobs=-1, oob_score=True)
rf5_model.fit(X5_train, y5_train)

rf5_model=rf5_model.predict(X5_test.values)
#run_time=time.time()
results_17 = {'Model':'RandomForest','Dependent Var':'Budget & MPAA',␣
↪'R-Square':metrics.r2_score(y5_test, rf5_model),
            'MSE':metrics.mean_squared_error(y5_test, rf5_model),
            'RMSE':np.sqrt(metrics.mean_squared_error(y5_test, rf5_model)),␣
↪'Run Time':round(((time.time()-run_time)/60),2)}
results_df = results_df.append(results_17, ignore_index=True)
```

Release Date

[519]:
```
## First, splitting the release_date into Month and Day
```

```
moviesNew[["Release_month", "Release_day"]] = moviesNew["release_date"].str.
 ↪split(" ", expand = True)
moviesNew.head(3)
```

[519]:
```
     movie_id                          title  ... Release_month Release_day
0  tt0099088  Back to the Future Part III  ...           May          25
1  tt0099165  The Bonfire of the Vanities  ...      December          22
2  tt0099348           Dances with Wolves  ...      November           9

[3 rows x 2799 columns]
```

[520]:
```
## Combine year, month and day in one Object

moviesNew['releaseDate'] = moviesNew['Release_month'] + '-' +␣
 ↪moviesNew['Release_day'] + '-' + moviesNew['year'].astype(str)
moviesNew.drop(['Release_month', 'Release_day'], axis='columns', inplace=True)
moviesNew.head(3)
```

[520]:
```
     movie_id                          title  ...  Ashley Bratcher
releaseDate
0  tt0099088  Back to the Future Part III  ...                0
May-25-1990
1  tt0099165  The Bonfire of the Vanities  ...                0
December-22-1990
2  tt0099348           Dances with Wolves  ...                0
November-9-1990

[3 rows x 2798 columns]
```

[521]:
```
moviesNew.drop(['year', 'release_date'], axis='columns', inplace=True)
moviesNew.head(2)
```

[521]:
```
     movie_id                          title  ... Ashley Bratcher       releaseDate
0  tt0099088  Back to the Future Part III  ...               0       May-25-1990
1  tt0099165  The Bonfire of the Vanities  ...               0  December-22-1990

[2 rows x 2796 columns]
```

[522]:
```
## Changing the type of the Release Date

moviesNew['releaseDate'] = pd.to_datetime(moviesNew['releaseDate'],␣
 ↪format='%B-%d-%Y')
moviesNew.head(2)
```

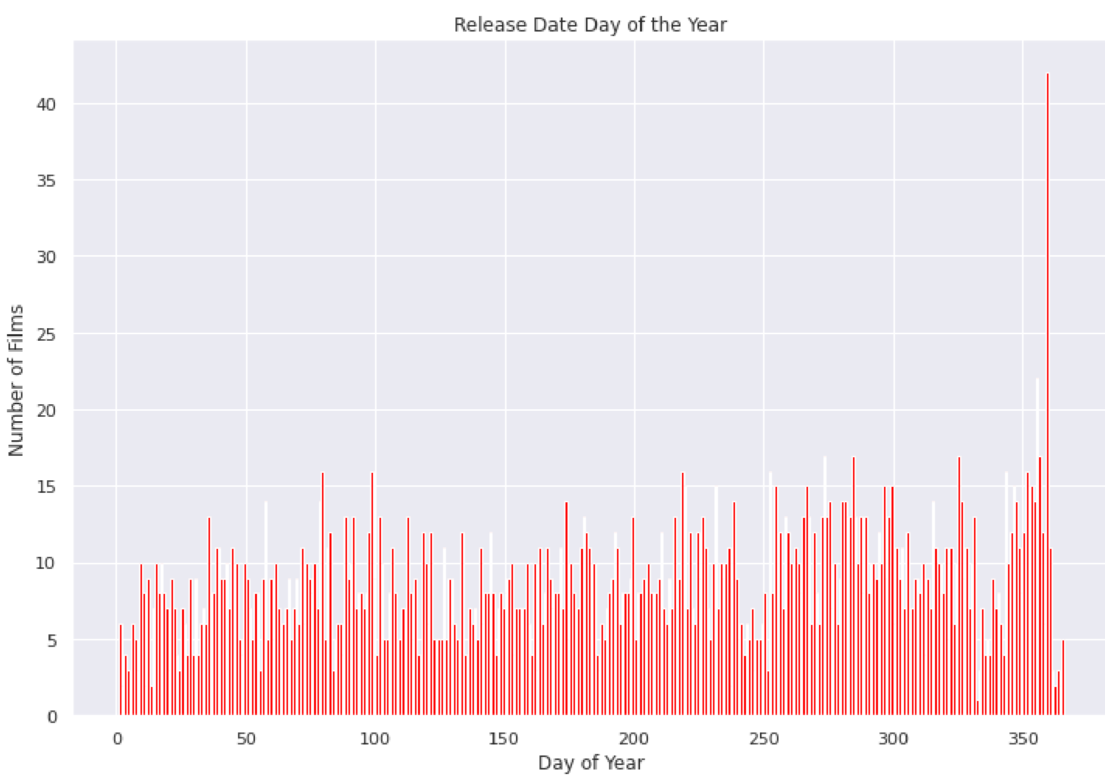
[522]:
```
     movie_id                          title  ... Ashley Bratcher releaseDate
0  tt0099088  Back to the Future Part III  ...               0  1990-05-25
1  tt0099165  The Bonfire of the Vanities  ...               0  1990-12-22

[2 rows x 2796 columns]
```

[523]:
```
moviesNew['releaseDay'] = moviesNew['releaseDate'].dt.day
moviesNew['releaseMth'] = moviesNew['releaseDate'].dt.month
moviesNew['releaseYear'] = moviesNew['releaseDate'].dt.year
moviesNew.head(2)
```

[523]:
```
    movie_id                        title  ... releaseMth releaseYear
0  tt0099088  Back to the Future Part III  ...          5        1990
1  tt0099165  The Bonfire of the Vanities  ...         12        1990

[2 rows x 2799 columns]
```

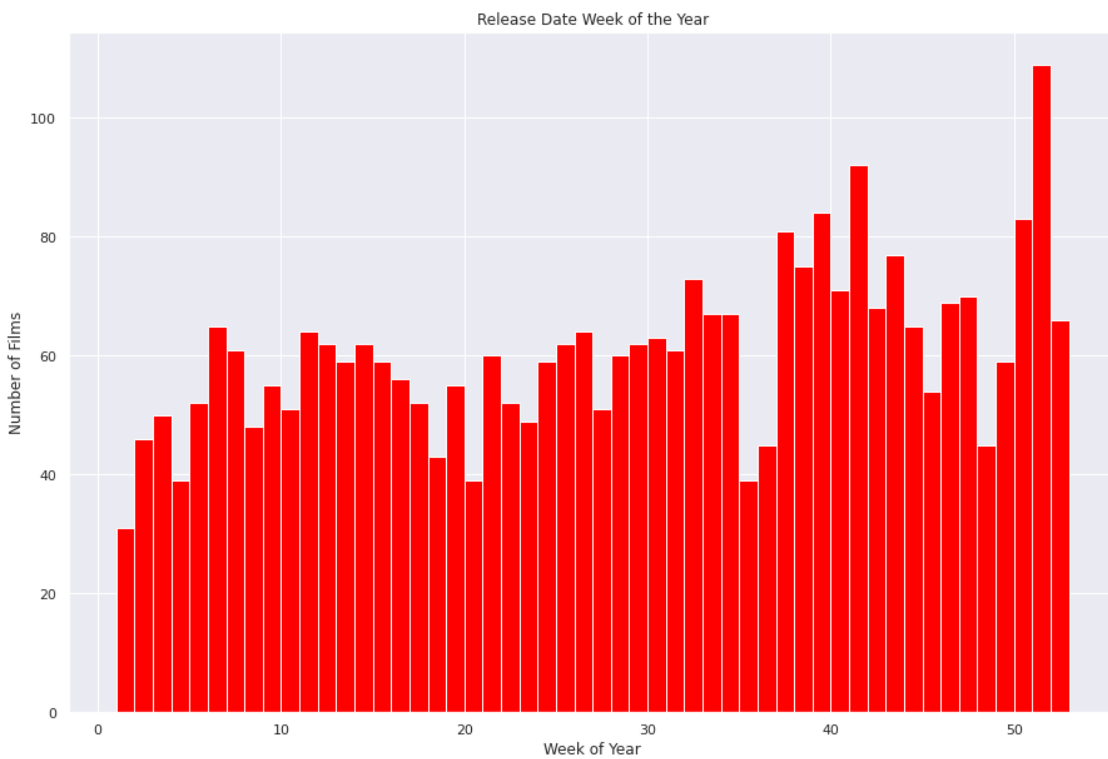
[524]:
```
## Plotting Movies release Day of the Year
fig, fx = plt.subplots()
sns.distplot(moviesNew['releaseDate'].dt.dayofyear, bins=365, kde=False,␣
 ↪color='red', hist_kws=dict(alpha=1))
sns.set(rc={'figure.figsize':(15,10)})

fx.set_xlabel("Day of Year")
fx.set_ylabel("Number of Films")
fx.set_title("Release Date Day of the Year")

## It is a very crowded graph, but it is clear to notice Christmas time has the␣
 ↪highest number of movies released.
```

[524]: Text(0.5, 1.0, 'Release Date Day of the Year')



[525]:
```python
## Plotting Movies release Week of the Year
fig, gx = plt.subplots()
sns.distplot(moviesNew['releaseDate'].dt.weekofyear, bins=52, kde=False,␣
 ↪color='red', hist_kws=dict(alpha=1))
sns.set(rc={'figure.figsize':(15,10)})

gx.set_xlabel("Week of Year")
gx.set_ylabel("Number of Films")
gx.set_title("Release Date Week of the Year")

## Another graph showing Christmas week has the highest number of movies␣
 ↪released due to the popularity of going to the movies during the holiday
## season. The second largest spike is during the first week of October.
```

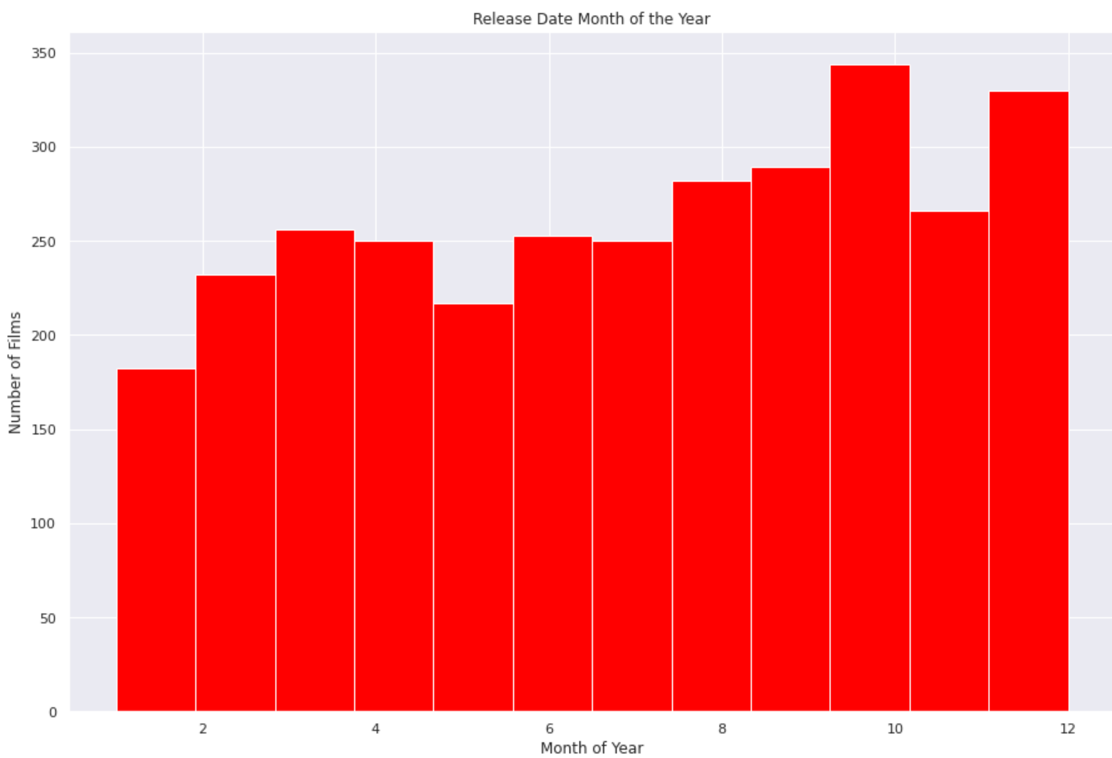
[525]: Text(0.5, 1.0, 'Release Date Week of the Year')



[526]:
```python
## Plotting Movies release Month of the Year
fig, hx = plt.subplots()
sns.distplot(moviesNew['releaseDate'].dt.month, bins=12, kde=False,␣
 ↪color='red', hist_kws=dict(alpha=1))
sns.set(rc={'figure.figsize':(12,6)})

hx.set_xlabel("Month of Year")
```

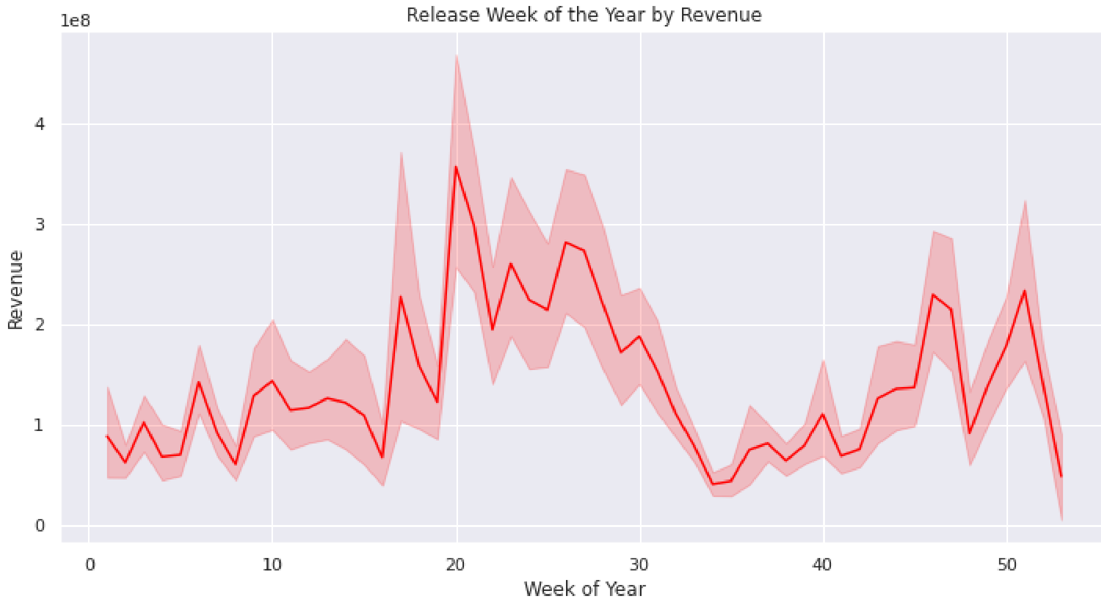
```
hx.set_ylabel("Number of Films")
hx.set_title("Release Date Month of the Year")

## This graph shows October and December have the highest number of movies␣
↪released
```

[526]: Text(0.5, 1.0, 'Release Date Month of the Year')



[527]:
```
## Week of release with Revenue

fig, fx = plt.subplots()
sns.lineplot(x=moviesNew['releaseDate'].dt.weekofyear,␣
↪y=moviesNew['Worldwide_Revenue'], color='red')
sns.set(rc={'figure.figsize':(12, 6)})

fx.set_xlabel("Week of Year")
fx.set_ylabel("Revenue")
fx.set_title("Release Week of the Year by Revenue")

## There is a high peak in Revenue during the last week of May and through out␣
↪the weeks of summer followed by the Christmas week.
```

[527]: Text(0.5, 1.0, 'Release Week of the Year by Revenue')



[528]:
```
#Relationship between Revenue and Week of Release

moviesNew['releaseWeek'] = moviesNew['releaseDate'].dt.weekofyear
releaseWeek_df = moviesNew[['Worldwide_Revenue', 'releaseWeek']]

corrMatrix_week = releaseWeek_df.corr()
plt.subplots(figsize = (10,6))
sns.heatmap(corrMatrix_week, annot=True)
plt.show()
```

[529]:
```
#Relationship between Revenue and Day of Release

releaseDay_df = moviesNew[['Worldwide_Revenue', 'releaseDay']]

corrMatrix_day = releaseDay_df.corr()
plt.subplots(figsize = (8,6))
sns.heatmap(corrMatrix_day, annot=True)
plt.show()
```

[530]:
```
## There is a very little correlation between Released Day, Released Week and␣
↪Revenue. In summary, the number of movies released in a given month
## or day during the year is not as important as some months that has special␣
↪events happening, for example, January amd February could be generating
## more revenue with less movies released because of the Oscar season.
```

SUMMARY & PREDICTION

[531]:
```
results_df = results_df.sort_values(by='R-Square', ascending=False)
results_df.head(5)
```

[531]:

	Model	Dependent Var	R-Square	MSE	RMSE	Run Time
3	Linear Regression	Budget & Genre	0.509896	1.576106	1.255431	0.22
5	RandomForest	Budget & Genre	0.500352	1.606799	1.267596	0.28
2	RandomForest	Budget	0.488950	1.505534	1.227002	0.06
15	Linear Regression	Budget & MPAA	0.487490	1.509833	1.228753	0.81
14	RandomForest	Budget & Actor	0.484366	0.616926	0.785446	0.73

[532]:
```
## My best model ended up being the Linear Regression model, with Budget and␣
↪Genre as the 2 dependent varibales. The model scores an RMSE of 1.2554 and
## the Random Forest model was a second close with RMSE value of 1.2680
```

[533]:
```python
## Predictions using Budget and Genre

rev_prediction = np.expm1(lm1.predict(X1_test))
lm1_predict = pd.DataFrame(rev_prediction, columns=['Predicted_Revenue'])
lm1_predict.head(5)
```

[533]:
```
   Predicted_Revenue
0       4.164916e+06
1       2.327033e+07
2       5.753357e+06
3       9.628572e+07
4       2.199198e+08
```

[534]:
```python
## Comparing Predicted Revenue and Original Revenue

test_result = pd.concat([moviesNew, lm1_predict], axis = 1, sort=True)

#look at the first 5 values
test_result = test_result[['title','budget', 'releaseYear',␣
↪'Worldwide_Revenue', 'Predicted_Revenue']]
test_result.head()
```

[534]:
```
                        title  ...  Predicted_Revenue
0  Back to the Future Part III  ...       4.164916e+06
1  The Bonfire of the Vanities  ...       2.327033e+07
2           Dances with Wolves  ...       5.753357e+06
3                  Dick Tracy  ...       9.628572e+07
4                  Die Hard 2  ...       2.199198e+08

[5 rows x 5 columns]
```

[535]:
```python
test_result['Revenue_diff'] = test_result['Predicted_Revenue'] -␣
↪test_result['Worldwide_Revenue']
test_result['Diff_percentage'] = test_result['Revenue_diff'] /␣
↪test_result['Worldwide_Revenue']
test_result.head(5)
```

[535]:
```
                        title      budget  ...  Revenue_diff  Diff_percentage
0  Back to the Future Part III  40000000.0  ... -2.419793e+08        -0.983079
1  The Bonfire of the Vanities  47000000.0  ...  7.579139e+06         0.483019
2           Dances with Wolves  22000000.0  ... -4.184555e+08        -0.986437
3                  Dick Tracy  47000000.0  ... -6.645301e+07        -0.408342
4                  Die Hard 2  70000000.0  ... -2.032768e+07        -0.084611

[5 rows x 7 columns]
```

[536]:
```python
test_result.to_csv('submission.csv', index=False)
```

[537]:
```python
from statistics import mean
```

```
print('Average error of Linear Regression: ${:.2f}'.format(mean(abs(np.
 ↪expm1(lm1.predict(X1_test)) - np.expm1(y1_test.values)))))
```

```
Average error of Linear Regression: $79662817.41
```

[538]:
```
## From the above information, with my best model used for the prediction with␣
 ↪accuracy only at 50%, we can see that Revenue is off by an average of $76␣
 ↪million on each
## prediction.## It is a very significant amount, but if we look at the data on␣
 ↪hand, for a blockbuster movies that makes over $800 million in revenue,
## being off by $76 million is very close and a good starting point for␣
 ↪prediction.
```

[539]:
```
print("Intercept:", lm1.intercept_)
print("Coefficients:")
list(zip(x1, lm1.coef_))
```

```
Intercept: 1.3556088018606758
Coefficients:
```

[539]:
```
[('Log_budget', 0.9602199620713926),
 ('genre_1_Adventure', 0.21451196826244034),
 ('genre_1_Comedy', -0.137625708091583),
 ('genre_1_Crime', -0.2899168514079639),
 ('genre_1_Drama', -0.25917193020212925)]
```

[540]:
```
## Regression equation:
## Revenue = 1.3556 + (0.9602 * Log_budget) + (0.2145 * Adventure) + (-0.1376 *␣
 ↪Comedy) + (-0.2899 * Crime) + (-0.2591 * Drama)
## From the above Multiple Linear Regression equation, I can conclude that for␣
 ↪an increase in Budget the Revenue increases by 0.9602,
## and movies with Genre Adventure increases Revenue by 0.2145
```

[ ]:
```
%%capture
!wget -nc https://raw.githubusercontent.com/brpy/colab-pdf/master/colab_pdf.py
from colab_pdf import colab_pdf
colab_pdf('Final BoxOffice_Rev_Prediction.ipynb')
```