Box Office Movie Analysis

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Overview

This project aims to analyze performance of movies in the box office to get a clear picture of what makes a good movie. Through Exploratory Data Analysis (EDA) of movies and reviews data can get a better understanding of the features that contribute to popularity of films. Microsoft can use this findings to make informed decisions as it plans to enter the films industry.

Business Problem

The movie space has been dominated by streaming services like Netflix, Disney and Hulu. Not so long ago, a close competitor, Apple joined in on the fun producing original video content with amaizing blockbusters i.e SEE. This makes it a question of WHEN not IF. Taking a calculated approach by analyzing the genre,movie durations and revenues will render a better understanding of the film industry. Doing so will increase our chances of success upon entry as well as an additonal source of revenue.

Data Understanding

For this project, I'll be analyzing data from 2 datasets from:

- IMDB database
- BOM csv file `

Importing libraries we might need

In [87]:

```
# Import standard packages
import pandas as pd
import numpy as np
import sqlite3

from collections import OrderedDict
from collections import Counter
import operator
import itertools

import matplotlib.pyplot as plt
import seaborn as sns

%matplotlib inline
```

Loading Datasets

In [88]:

```
# Establishing connection with IMDB database
conn = sqlite3.connect("Data/im.db")

#Converting important tables into DataFrames
#Title, Release, Duration, Genres
movie_basics = pd.read_sql("SELECT * FROM movie_basics",conn)

#movie_id, avgrating, numvotes
movie_ratings = pd.read_sql("SELECT * FROM movie_ratings",conn)

#BOM dataset
BOM = pd.read_csv("Data/bom.movie_gross.csv")
```

Exploring the created DataFrames

In [89]:

```
movie_basics.head()
```

Out[89]:

	movie_id	primary_title	original_title	start_year	runtime_minutes	genres
0	tt0063540	Sunghursh	Sunghursh	2013	175.0	Action,Crime,Drama
1	tt0066787	One Day Before the Rainy Season	Ashad Ka Ek Din	2019	114.0	Biography,Drama
2	tt0069049	The Other Side of the Wind	The Other Side of the Wind	2018	122.0	Drama
3	tt0069204	Sabse Bada Sukh	Sabse Bada Sukh	2018	NaN	Comedy,Drama
4	tt0100275	The Wandering Soap Opera	La Telenovela Errante	2017	80.0	Comedy,Drama,Fantasy

In [90]:

```
movie_ratings.tail()
```

Out[90]:

	movie_id	averagerating	numvotes
73851	tt9805820	8.1	25
73852	tt9844256	7.5	24
73853	tt9851050	4.7	14
73854	tt9886934	7.0	5
73855	tt9894098	6.3	128

In [91]:

```
BOM.head()
```

Out[91]:

	title	studio	domestic_gross	foreign_gross	year
0	Toy Story 3	BV	415000000.0	652000000	2010
1	Alice in Wonderland (2010)	BV	334200000.0	691300000	2010
2	Harry Potter and the Deathly Hallows Part 1	WB	296000000.0	664300000	2010
3	Inception	WB	292600000.0	535700000	2010
4	Shrek Forever After	P/DW	238700000.0	513900000	2010

movie_basics & movie_ratings preperation

To clean the data, we have to find an amicable solution to handle duplicates and null values in our datasets

We'll have to drop some irrelevant columns, rename others and merge dataframes.

Cleaning movie_basics

- Check for duplicated rows and drop if any
- Dropping irrelevant columns for our analysis
- Renaming columns with suitable names
- The movie basics data frame tends to have significant missing values in the 'duration_minutes' and 'genre' columns.

In [92]:

```
# The column 'original_title' isn't relevant in our analysis
movie_basics.drop(labels='original_title',inplace=True,axis=1)
```

In [93]:

```
# Rename the columns with relevant column names
movie_basics.rename(columns={'primary_title':'title', 'duration_minutes':'runtime_m
```

In [94]:

```
# Determining null values
movie_basics.isna().sum()
```

Out[94]:

```
movie_id               0
title                  0
release                0
runtime_minutes    31739
genre               5408
dtype: int64
```

In [95]:

```
# Dropping rows with null values in the genre column
movie_basics.dropna(subset='genre',inplace=True)
```

In [96]:

```
#Mean & Median values of the runtime_minutes column
print("Mean: ",movie_basics['runtime_minutes'].mean())
print("Median: ",movie_basics['runtime_minutes'].median())
```

```
Mean:  86.26190157974928
Median:  87.0
```

In [97]:

```
# Filling missing values in the runtime_minutes column
movie_basics['runtime_minutes'].fillna(movie_basics['runtime_minutes'].mean(),axis=
```

In [98]:

```
# Let's split the genre column into single value rows
movie_basics['genre'] = movie_basics['genre'].str.split(',')
```

Cleaning movie_ratings

- Check for duplicates on movie_id column
- drop numvotes column
- concat with movie basics

In [99]:

```
movie_ratings.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 73856 entries, 0 to 73855
Data columns (total 3 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   movie_id       73856 non-null  object
 1   averagerating  73856 non-null  float64
 2   numvotes       73856 non-null  int64
dtypes: float64(1), int64(1), object(1)
memory usage: 1.7+ MB
```

In [100]:

```
movie_ratings['movie_id'].duplicated().sum()
```

Out[100]:

```
0
```

movie_ratings seems to be ready for manipulation as it lacks duplicates and all values are present

Merging movie_basics & movie_ratings

In [101]:

```
df3 = movie_basics.merge(movie_ratings, on='movie_id', how='inner', suffixes=('B',
```

In [102]:

```
df3.sort_values(by='averagerating',ascending=False).head(20)
```

Out[102]:

	movie_id	title	release	runtime_minutes	genre	averagerating	numvotes
9664	tt1770682	Freeing Bernie Baran	2010	100.000000	[Crime, Documentary]	10.0	5
53165	tt5390098	The Paternal Bond: Barbary Macaques	2015	59.000000	[Documentary]	10.0	5
65246	tt7259300	Calamity Kevin	2019	77.000000	[Adventure, Comedy]	10.0	6
42553	tt4109192	I Was Born Yesterday!	2015	31.000000	[Documentary]	10.0	6
49589	tt4960818	Revolution Food	2015	70.000000	[Documentary]	10.0	8
868	tt10378660	The Dark Knight: The Ballad of the N Word	2018	129.000000	[Comedy, Drama]	10.0	5
52884	tt5344358	All Around Us	2019	86.261902	[Documentary]	10.0	6
70796	tt8730716	Pick It Up! - Ska in the '90s	2019	99.000000	[Documentary]	10.0	5
49431	tt4944240	Dog Days in the Heartland	2017	86.261902	[Drama]	10.0	5
693	tt10176328	Exteriores: Mulheres Brasileiras na Diplomacia	2018	52.000000	[Documentary]	10.0	5
60199	tt6295832	Requiem voor een Boom	2016	48.000000	[Documentary]	10.0	5
65059	tt7227500	Ellis Island: The Making of a Master Race in A...	2018	70.000000	[Documentary, History]	10.0	6
72817	tt9715646	Renegade	2019	86.261902	[Documentary]	10.0	20
50601	tt5089804	Fly High: Story of the Disc Dog	2019	65.000000	[Documentary]	10.0	7
27072	tt2632430	Hercule contre Hermès	2012	72.000000	[Documentary]	10.0	5

	movie_id	title	release	runtime_minutes	genre	averagerating	numvotes
63957	tt6991826	A Dedicated Life: Phoebe Brand Beyond the Group	2015	93.000000	[Documentary]	10.0	5
72848	tt9743544	The Wedding Present: Something Left Behind	2018	87.000000	[Documentary]	9.9	8
72549	tt9537008	Gini Helida Kathe	2019	138.000000	[Drama]	9.9	417
72996	tt9866708	Wild Karnataka	2019	53.000000	[Documentary]	9.9	10
72941	tt9820678	Moscow we will lose	2019	51.000000	[Documentary]	9.9	18

In [103]:

```
Q1 = np.percentile(df3['runtime_minutes'],25)
Q3 = np.percentile(df3['runtime_minutes'],75)
IQR = Q3 - Q1
print('IQR:', IQR)

upper_limit = Q3 + 1.5 * IQR
lower_limit = Q1 - 1.5 * IQR

print('upper limit:', upper_limit)
print('lower limit:', lower_limit)
```

```
IQR: 19.0
upper limit: 130.5
lower limit: 54.5
```

In [104]:

```
#Removing outliers
lower_outliers = df3['runtime_minutes'] < lower_limit
upper_outliers = df3['runtime_minutes']  > upper_limit

outliers = df3[lower_outliers | upper_outliers].index
df3.drop(outliers, inplace=True)
```

BOM DataFrame preparation

In [105]:

```
BOM.head()
```

Out[105]:

	title	studio	domestic_gross	foreign_gross	year
0	Toy Story 3	BV	415000000.0	652000000	2010
1	Alice in Wonderland (2010)	BV	334200000.0	691300000	2010
2	Harry Potter and the Deathly Hallows Part 1	WB	296000000.0	664300000	2010
3	Inception	WB	292600000.0	535700000	2010
4	Shrek Forever After	P/DW	238700000.0	513900000	2010

In [106]:

```
BOM.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3387 entries, 0 to 3386
Data columns (total 5 columns):
 #   Column          Non-Null Count  Dtype  
---  ------          --------------  -----  
 0   title           3387 non-null   object 
 1   studio          3382 non-null   object 
 2   domestic_gross  3359 non-null   float64
 3   foreign_gross   2037 non-null   object 
 4   year            3387 non-null   int64  
dtypes: float64(1), int64(1), object(3)
memory usage: 132.4+ KB
```

In [107]:

```
#Checking for duplicated entries
BOM['title'].duplicated().sum()
```

Out[107]:

```
1
```

In [108]:

```
#Dropping duplicated rows
BOM.drop_duplicates('title',inplace=True)
```

In [109]:

```
#Checking for null values
BOM.isna().sum()
```

Out[109]:

```
title                0
studio               5
domestic_gross      28
foreign_gross     1349
year                 0
dtype: int64
```

We have a signifacant number of missing values in BOM columns, which have to be dealt with for further manipulation

In [110]:

```
BOM['studio'].value_counts()
```

Out[110]:

```
IFC           166
Uni.          147
WB            140
Fox           136
Magn.         136
             ...
E1              1
PI              1
ELS             1
PalT            1
Synergetic      1
Name: studio, Length: 257, dtype: int64
```

In [111]:

```
#Let's fill blanks with 'IFC' as it's the most popular
BOM['studio'].fillna('IFC', inplace=True)
```

In [112]:

```
print('Domestic Gross')

print('Mean:',BOM['domestic_gross'].mean().round(3))
print('Median:',BOM['domestic_gross'].median())
```

```
Domestic Gross
Mean: 28754392.638
Median: 1400000.0
```

In [113]:

```
#Filling missing values in the 'domestic_gross' column with the mean value
BOM['domestic_gross'].fillna(BOM['domestic_gross'].mean(),inplace=True)
```

In [114]:

```
#Let's convert the dtype for foreing_gross for further manipulation
BOM['foreign_gross'] = pd.to_numeric(BOM['foreign_gross'],errors = 'coerce')
```

In [115]:

```
print('Foreign Gross')
print('Mean:',BOM['foreign_gross'].mean().round(3))
print('Median:',BOM['foreign_gross'].median())
```

```
Foreign Gross
Mean: 75057041.625
Median: 18900000.0
```

In [116]:

```
#Filling null values with the mean
BOM['foreign_gross'].fillna(BOM['foreign_gross'].mean(),inplace=True)
```

In [117]:

```
#Combining domestic_gross with foreign_gross
BOM['worldwide_gross'] = BOM['domestic_gross'] + BOM['foreign_gross']
```

Data Analysis

The dataframes are ready for further analysis. We'll get to analyze and visualize features and relationships of top movies based on the following:

- Runtimes
- Genre
- Ratings
- Worldwide revenues
- Studios

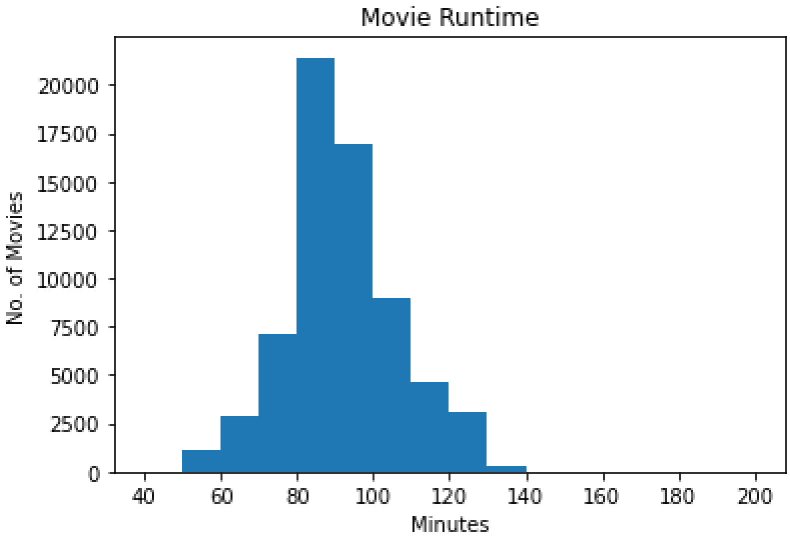
Runtime Analysis

In [118]:

```
df3['runtime_minutes'].plot.hist(range=(40,200),bins = 16)
plt.title('Movie Runtime')
plt.ylabel("No. of Movies")
plt.xlabel('Minutes')
```

Out[118]:

```
Text(0.5, 0, 'Minutes')
```



The above histogram depicts that most movies have a runtimes ranging from 70 minutes to 110 minutes. But we'll have to further analyze this

In [119]:

```
df3.head()
```

Out[119]:

	movie_id	title	release	runtime_minutes	genre	averagerating	numvotes
1	tt0066787	One Day Before the Rainy Season	2019	114.000000	[Biography, Drama]	7.2	43
2	tt0069049	The Other Side of the Wind	2018	122.000000	[Drama]	6.9	4517
3	tt0069204	Sabse Bada Sukh	2018	86.261902	[Comedy, Drama]	6.1	13
4	tt0100275	The Wandering Soap Opera	2017	80.000000	[Comedy, Drama, Fantasy]	6.5	119
5	tt0112502	Bigfoot	2017	86.261902	[Horror, Thriller]	4.1	32

In [120]:

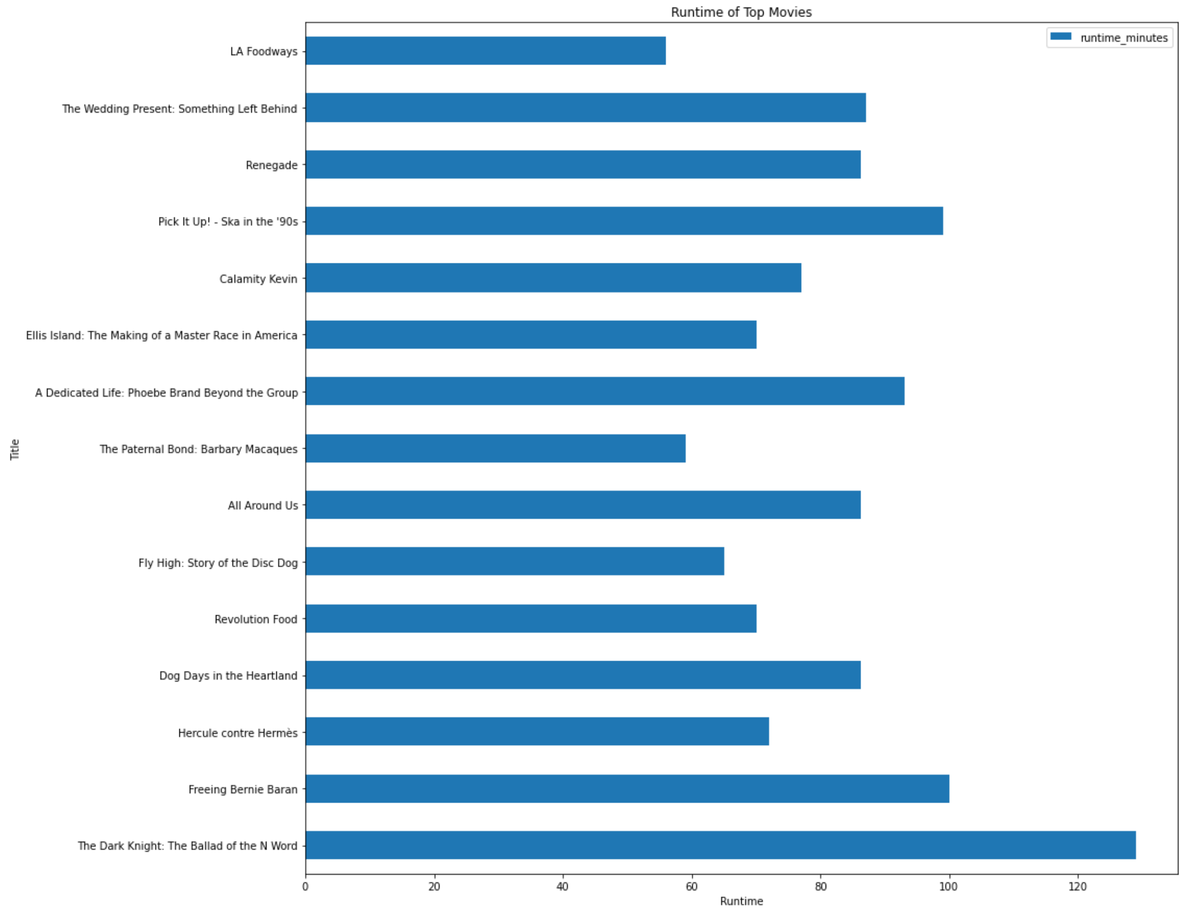
```
top_movies = df3.nlargest(15,'averagerating')[['title','runtime_minutes']]
# top_movies.set_index('title')
```

In [121]:

```
top_movies.plot.barh(x=0,y=1,figsize=(15,15))
plt.title('Runtime of Top Movies')
plt.xlabel('Runtime')
plt.ylabel('Title')
```

Out[121]:

```
Text(0, 0.5, 'Title')
```



Top rated movies seem to have runtimes of about 70 minutes to 130 minutes

Genre Analysis

In [122]:

```
# Overview of some of the genres
df3['genre'].head(10)
```

Out[122]:

```
1                  [Biography, Drama]
2                             [Drama]
3                     [Comedy, Drama]
4            [Comedy, Drama, Fantasy]
5                  [Horror, Thriller]
6      [Adventure, Animation, Comedy]
8                           [History]
10                            [Drama]
11                      [Documentary]
13                            [Drama]
Name: genre, dtype: object
```

In [123]:

```
#Create a list of unique genres
genres = []

for genre in df3['genre']:
    genres.append(genre)

genres
```

Out[123]:

```
[['Biography', 'Drama'],
 ['Drama'],
 ['Comedy', 'Drama'],
 ['Comedy', 'Drama', 'Fantasy'],
 ['Horror', 'Thriller'],
 ['Adventure', 'Animation', 'Comedy'],
 ['History'],
 ['Drama'],
 ['Documentary'],
 ['Drama'],
 ['Drama'],
 ['Drama', 'Mystery'],
 ['Action', 'Animation', 'Comedy'],
 ['Crime', 'Drama'],
 ['Biography', 'Comedy', 'Drama'],
 ['Drama'],
 ['Action', 'Drama'],
 ['Documentary', 'History'],
```

In [124]:

```
#Lets flatten our genres list

flat_list = [x for sublist in genres for x in sublist]
print(flat_list)
```

```
['Biography', 'Drama', 'Drama', 'Comedy', 'Drama', 'Comedy', 'Dram
a', 'Fantasy', 'Horror', 'Thriller', 'Adventure', 'Animation', 'Come
dy', 'History', 'Drama', 'Documentary', 'Drama', 'Drama', 'Drama',
'Mystery', 'Action', 'Animation', 'Comedy', 'Crime', 'Drama', 'Biogr
aphy', 'Comedy', 'Drama', 'Drama', 'Action', 'Drama', 'Documentary',
'History', 'Comedy', 'Documentary', 'Thriller', 'Crime', 'Drama', 'A
ction', 'Crime', 'Drama', 'Drama', 'Horror', 'Drama', 'Mystery', 'Th
riller', 'Drama', 'Family', 'Adventure', 'Comedy', 'Romance', 'Comed
y', 'Drama', 'Adventure', 'Animation', 'Comedy', 'Adventure', 'Dram
a', 'Romance', 'Comedy', 'Crime', 'Drama', 'Biography', 'Horror', 'C
omedy', 'Drama', 'Drama', 'Adventure', 'Comedy', 'Drama', 'Drama',
'Sci-Fi', 'Thriller', 'Comedy', 'Drama', 'Romance', 'Action', 'Crim
e', 'Drama', 'Action', 'Adventure', 'Sci-Fi', 'Action', 'Crime', 'Dr
ama', 'Comedy', 'Drama', 'Crime', 'Drama', 'Adventure', 'Animation',
'Comedy', 'Drama', 'Comedy', 'Family', 'Comedy', 'Drama', 'Romance',
'Adventure', 'Animation', 'Comedy', 'Adventure', 'Comedy', 'Crime',
'Drama', 'Comedy', 'Drama', 'Crime', 'Drama', 'Thriller', 'Action',
'Sci-Fi', 'Thriller', 'Action', 'Crime', 'Drama', 'Fantasy', 'Docume
ntary', 'Drama', 'Mystery', 'Sci-Fi', 'Biography', 'Drama', 'Histor
```

In [125]:

```
 #Function to get unique genres
def unique(myList):
    x = np.array(myList)
    return np.unique(x)

unique_genres = unique(flat_list)
```

In [126]:

```


#Count of unique genres
len(unique_genres)
```

Out[126]:

```
25
```

In [127]:

```
movies_genre = Counter(flat_list)
movies_genre
```

Out[127]:

```
Counter({'Biography': 3417,
         'Drama': 28145,
         'Comedy': 15972,
         'Fantasy': 1948,
         'Horror': 7348,
         'Thriller': 7586,
         'Adventure': 3467,
         'Animation': 1627,
         'History': 2468,
         'Documentary': 15713,
         'Mystery': 2839,
         'Action': 5821,
         'Crime': 4181,
         'Family': 3119,
         'Romance': 5807,
         'Sci-Fi': 2053,
         'Music': 1802,
         'Sport': 1042,
         'Western': 265,
         'Musical': 586,
         'War': 766,
         'News': 519,
         'Reality-TV': 13,
         'Game-Show': 2,
         'Adult': 3})
```

In [128]:

```
# Sort the top genres in Descending order
movies_genre = dict( sorted(movies_genre.items(), key=operator.itemgetter(1),revers
```

In [129]:

```
movies_genre
```

Out[129]:

```
{'Drama': 28145,
 'Comedy': 15972,
 'Documentary': 15713,
 'Thriller': 7586,
 'Horror': 7348,
 'Action': 5821,
 'Romance': 5807,
 'Crime': 4181,
 'Adventure': 3467,
 'Biography': 3417,
 'Family': 3119,
 'Mystery': 2839,
 'History': 2468,
 'Sci-Fi': 2053,
 'Fantasy': 1948,
 'Music': 1802,
 'Animation': 1627,
 'Sport': 1042,
 'War': 766,
 'Musical': 586,
 'News': 519,
 'Western': 265,
 'Reality-TV': 13,
 'Adult': 3,
 'Game-Show': 2}
```

In [130]:

```
top10_genres = dict(itertools.islice(movies_genre.items(), 10))
top10_genres
```

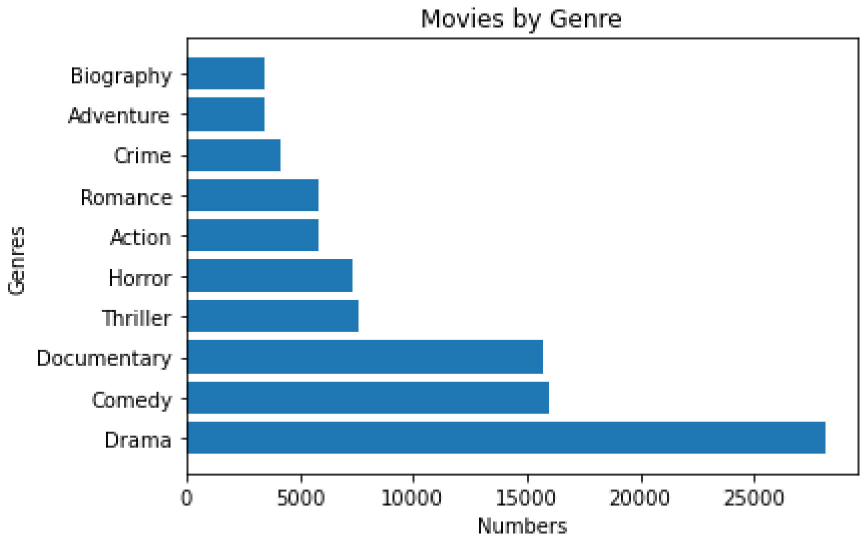
Out[130]:

```
{'Drama': 28145,
 'Comedy': 15972,
 'Documentary': 15713,
 'Thriller': 7586,
 'Horror': 7348,
 'Action': 5821,
 'Romance': 5807,
 'Crime': 4181,
 'Adventure': 3467,
 'Biography': 3417}
```

In [131]:

```
# Ploting the top genres by movie
genre = list(top10_genres.keys())
values = list(top10_genres.values())

plt.barh(range(len(top10_genres)), values, tick_label=genre)
plt.title('Movies by Genre')
plt.ylabel('Genres')
plt.xlabel('Numbers')
plt.show()
```



From the above visualization we get to see that the top genres are Drama, Comedy and Documentaries

Worldwide revenue Analysis

In [132]:

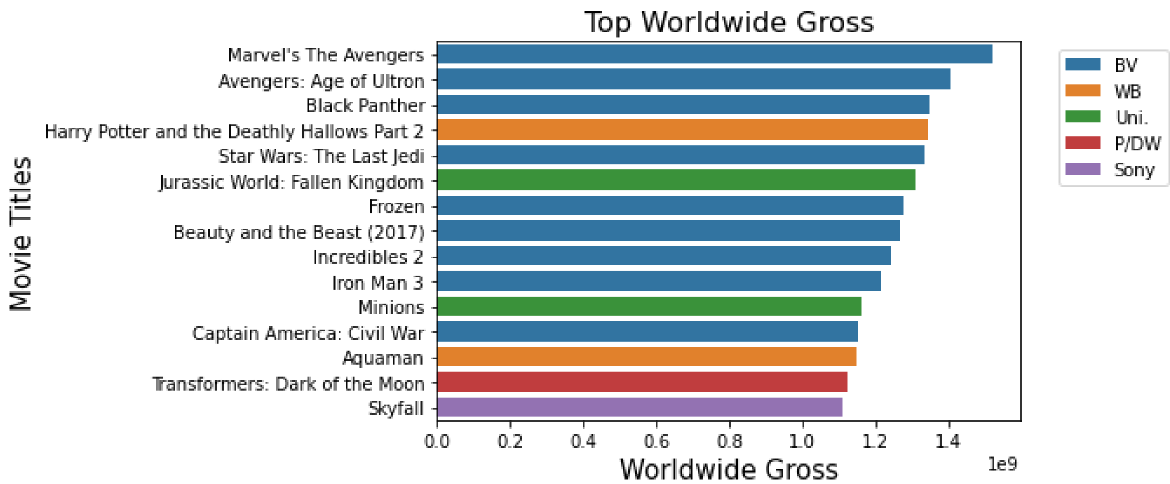
```
#Identify movies that generated the most revenue
top_rev = BOM.nlargest(n=15,columns='worldwide_gross')
top_rev.head()
```

Out[132]:

	title	studio	domestic_gross	foreign_gross	year	worldwide_gross
727	Marvel's The Avengers	BV	623400000.0	895500000.0	2012	1.518900e+09
1875	Avengers: Age of Ultron	BV	459000000.0	946400000.0	2015	1.405400e+09
3080	Black Panther	BV	700100000.0	646900000.0	2018	1.347000e+09
328	Harry Potter and the Deathly Hallows Part 2	WB	381000000.0	960500000.0	2011	1.341500e+09
2758	Star Wars: The Last Jedi	BV	620200000.0	712400000.0	2017	1.332600e+09

In [133]:

```
# Graph the results
sns.barplot(data = top_rev, x = 'worldwide_gross', y ='title', hue = 'studio', dodg
plt.title('Top Worldwide Gross', fontsize = 16)
plt.xlabel('Worldwide Gross', fontsize = 15)
plt.ylabel('Movie Titles', fontsize = 15)
plt.legend(bbox_to_anchor = (1.05,1), loc = 2)
plt.show();
```



BV studio has produced a significant number of top movies based on Worlwide gross(domestic + foreign). Microsoft should therefore research on BV studio's best practices.

Conclusion

From the analysis performed, I propose:

- A movie with a runtime of 60 minutes and slightly over the 2 hr mark seem to be popular
- Most of the produced movies have an aspect of Drama and Comedy. However this metric doesn't provide an actionable insight. But for sure movies with multiple genres will receive greater attention.
- Top studios seem to have an edge in the movie business. Further analysis of their work will provide more insight on movie plots.