Data Analysis for Microsoft Studios

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Overview

Objective: The objective is to examine data on movies, determine why such movies perform they way they do, and recommend the best types of movies MICROSOFT's new studio should produce to increase business returns and profitability.

Data Sets:

I have two datasets obtained from the above sites for this analysis. The data sets are named *bom.movie_gross.csv (obtained from Box Office Mojo website), and tmdb_movies.csv (obtained from TheMovieDB website).

The information helps us to understand movie performance, genres/combinations of genres that perform better in the box office, and whether production costs and release dates influence movie performance.

The datasets are suitable for the analysis as they provide information on the following:

1.Production budgets

2.Best perfoming Studios

3.Gross earnings (both domestic and worldwide)

4.Release Dates

REQUIRMENTS

1. Import Relevant Modules
2. Read the Dataset and its structure
3. Data Wrangling/Cleaning
4. Data Analysis and visualization
5. Recommendation to Microsoft

In [1]:
```
#Import the nessecary tools for analysing data with python

import pandas as pd
import numpy as np
from matplotlib import pyplot as plt
import seaborn as sns
```

Lets Explore the differents Data sets

Dataset 1: 'bom.movie_gross.csv '

In [2]:
```
#Read the files path and data structure
bom_movie_gross = pd.read_csv('bom.movie_gross.csv')
bom_movie_gross.head()
```

Out[2]:

	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 [3]:
```
#Data wrangling
#check for missing values and data in different columns

bom_movie_gross.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 [4]:
```
#removing unnessecary columns
bom_movie_gross = bom_movie_gross[['title', 'studio']]
bom_movie_gross
```

Out[4]:

	title	studio
0	Toy Story 3	BV
1	Alice in Wonderland (2010)	BV
2	Harry Potter and the Deathly Hallows Part 1	WB
3	Inception	WB
4	Shrek Forever After	P/DW
...	...	...
3382	The Quake	Magn.
3383	Edward II (2018 re-release)	FM
3384	El Pacto	Sony
3385	The Swan	Synergetic
3386	An Actor Prepares	Grav.

3387 rows × 2 columns

In [5]:
```
#Checking for duplicate values

if bom_movie_gross.duplicated().any():
    print('There are duplicates in this dataset')
else:
    print('There are no duplicates in this dataset')
```

```
There are no duplicates in this dataset
```

In [6]:
```
#checking for Missing Values in the dataset
bom_missing_values = bom_movie_gross.isna()
bom_missing_values

#checking whether any records return true for missing values
if bom_missing_values.any(axis=None):
    print('There are missing values in this dataset')
else:
    print('There are no missing values in this dataset')
```

```
There are missing values in this dataset
```

There are presence of missing values . better parctice to drop them not skew up the data

In [7]:
```
#dropping records with atleast one missing value
bom_movie_gross = bom_movie_gross.dropna()
bom_movie_gross
```

Out[7]:

	title	studio
0	Toy Story 3	BV
1	Alice in Wonderland (2010)	BV
2	Harry Potter and the Deathly Hallows Part 1	WB
3	Inception	WB
4	Shrek Forever After	P/DW
...	...	...
3382	The Quake	Magn.
3383	Edward II (2018 re-release)	FM
3384	El Pacto	Sony
3385	The Swan	Synergetic
3386	An Actor Prepares	Grav.

3382 rows × 2 columns

In [8]:
```
#setting the title as the index for this dataset
bom_movie_gross.set_index('title', inplace=True)
bom_movie_gross
```

Out[8]:

	studio
title	
Toy Story 3	BV
Alice in Wonderland (2010)	BV
Harry Potter and the Deathly Hallows Part 1	WB
Inception	WB
Shrek Forever After	P/DW
...	...
The Quake	Magn.
Edward II (2018 re-release)	FM
El Pacto	Sony
The Swan	Synergetic
An Actor Prepares	Grav.

3382 rows × 1 columns

Dataset 2: 'tn.movie_budgets.csv'

In [9]:
```
#loading the tn.movie.budget.tsv dataset into a movie_budgets variable
#and reviewing the first 10 rows of data

movie_budgets = pd.read_csv('tn.movie_budgets.csv')
movie_budgets.head()
```

Out[9]:

	id	release_date	movie	production_budget	domestic_gross	worldwide_gross
0	1	Dec 18, 2009	Avatar	$425,000,000	$760,507,625	$2,776,345,279
1	2	May 20, 2011	Pirates of the Caribbean: On Stranger Tides	$410,600,000	$241,063,875	$1,045,663,875
2	3	Jun 7, 2019	Dark Phoenix	$350,000,000	$42,762,350	$149,762,350
3	4	May 1, 2015	Avengers: Age of Ultron	$330,600,000	$459,005,868	$1,403,013,963
4	5	Dec 15, 2017	Star Wars Ep. VIII: The Last Jedi	$317,000,000	$620,181,382	$1,316,721,747

We need to rename the movie column to match the other datasets. The new column name will be title as used in the other data set bom.movie

In [10]:
```
#Reaname movie to tittle
movie_budgets = movie_budgets.rename(columns={'movie': 'title'})
movie_budgets
```

Out[10]:

	id	release_date	title	production_budget	domestic_gross	worldwide_gross
0	1	Dec 18, 2009	Avatar	$425,000,000	$760,507,625	$2,776,345,279
1	2	May 20, 2011	Pirates of the Caribbean: On Stranger Tides	$410,600,000	$241,063,875	$1,045,663,875
2	3	Jun 7, 2019	Dark Phoenix	$350,000,000	$42,762,350	$149,762,350
3	4	May 1, 2015	Avengers: Age of Ultron	$330,600,000	$459,005,868	$1,403,013,963
4	5	Dec 15, 2017	Star Wars Ep. VIII: The Last Jedi	$317,000,000	$620,181,382	$1,316,721,747
...	...	...	...	...	...	...
5777	78	Dec 31, 2018	Red 11	$7,000	$0	$0
5778	79	Apr 2, 1999	Following	$6,000	$48,482	$240,495
5779	80	Jul 13, 2005	Return to the Land of Wonders	$5,000	$1,338	$1,338
5780	81	Sep 29, 2015	A Plague So Pleasant	$1,400	$0	$0
5781	82	Aug 5, 2005	My Date With Drew	$1,100	$181,041	$181,041

5782 rows × 6 columns

In [11]:
```
#Data cleaning
#check any missing values?
#What data types are we dealing with?

movie_budgets.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5782 entries, 0 to 5781
Data columns (total 6 columns):
 #   Column             Non-Null Count  Dtype 
---  ------             --------------  ----- 
 0   id                 5782 non-null   int64 
 1   release_date       5782 non-null   object
 2   title              5782 non-null   object
 3   production_budget  5782 non-null   object
 4   domestic_gross     5782 non-null   object
 5   worldwide_gross    5782 non-null   object
dtypes: int64(1), object(5)
memory usage: 271.2+ KB
```

In [12]:
```
#Placeholders
#Removing the '$' and ',' from the values in the production_budget column and
#coverting it to int

movie_budgets['production_budget'] = movie_budgets['production_budget'].str.re

#Removing the '$' and ',' from the values in the production_budget column and
#coverting it to int

movie_budgets['domestic_gross'] = movie_budgets['domestic_gross'].str.replace

#Removing the '$' and ',' from the values in the production_budget column and
#coverting it to int

movie_budgets['worldwide_gross'] = movie_budgets['worldwide_gross'].str.repla

movie_budgets.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5782 entries, 0 to 5781
Data columns (total 6 columns):
 #   Column             Non-Null Count  Dtype 
---  ------             --------------  ----- 
 0   id                 5782 non-null   int64 
 1   release_date       5782 non-null   object
 2   title              5782 non-null   object
 3   production_budget  5782 non-null   int64 
 4   domestic_gross     5782 non-null   int64 
 5   worldwide_gross    5782 non-null   int64 
dtypes: int64(4), object(2)
memory usage: 271.2+ KB
```

In [13]:
```
#Checking for duplicates
if movie_budgets.duplicated().any():
    print('There are duplicates in this dataset')
else:
    print('There are no duplicates in this dataset')
```

```
There are no duplicates in this dataset
```

We need to set the title as the index, essentially making the movie titles the primary way to reference and organize the data in the DataFrame.

In [14]:

```
#setting the movie column to be the index

movie_budgets.set_index('title', inplace=True)
movie_budgets
```

Out[14]:

	id	release_date	production_budget	domestic_gross	worldwide_gross
title					
Avatar	1	Dec 18, 2009	425000000	760507625	2776345279
Pirates of the Caribbean: On Stranger Tides	2	May 20, 2011	410600000	241063875	1045663875
Dark Phoenix	3	Jun 7, 2019	350000000	42762350	149762350
Avengers: Age of Ultron	4	May 1, 2015	330600000	459005868	1403013963
Star Wars Ep. VIII: The Last Jedi	5	Dec 15, 2017	317000000	620181382	1316721747
...	...	...	...	...	...
Red 11	78	Dec 31, 2018	7000	0	0
Following	79	Apr 2, 1999	6000	48482	240495
Return to the Land of Wonders	80	Jul 13, 2005	5000	1338	1338
A Plague So Pleasant	81	Sep 29, 2015	1400	0	0
My Date With Drew	82	Aug 5, 2005	1100	181041	181041

5782 rows × 5 columns

COMBINING THE TWO DATA SETS

'bom.movie_gross.csv ' AND 'tn.movie_budgets.csv'

This new dataset will be assigned to the variable combined_movie_data for further cleaning and analysis. The combined_movie_data will return only records with matching title.

In [15]:
```
#joining movie_budgets and movie_data datasets
combined_movie_data= movie_budgets .join(bom_movie_gross , how='inner')
combined_movie_data.head()
```

Out[15]:

	id	release_date	production_budget	domestic_gross	worldwide_gross	studio
title						
10 Cloverfield Lane	54	Mar 11, 2016	5000000	72082999	108286422	Par.
12 Strong	64	Jan 19, 2018	35000000	45819713	71118378	WB
12 Years a Slave	18	Oct 18, 2013	20000000	56671993	181025343	FoxS
127 Hours	6	Nov 5, 2010	18000000	18335230	60217171	FoxS
13 Hours: The Secret Soldiers of Benghazi	30	Jan 15, 2016	50000000	52853219	69411370	Par.

In [16]:
```
#reviewing the columns for this data
combined_movie_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 1246 entries, 10 Cloverfield Lane to mother!
Data columns (total 6 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   id                 1246 non-null   int64
 1   release_date       1246 non-null   object
 2   production_budget  1246 non-null   int64
 3   domestic_gross     1246 non-null   int64
 4   worldwide_gross    1246 non-null   int64
 5   studio             1246 non-null   object
dtypes: int64(4), object(2)
memory usage: 68.1+ KB
```

In [17]:
```
#sorting the dataset based on worldwide_gross column
combined_movie_data = combined_movie_data.sort_values('worldwide_gross', ascen
combined_movie_data
```

Out[17]:

title	id	release_date	production_budget	domestic_gross	worldwide_gross	studio
Avengers: Infinity War	7	Apr 27, 2018	300000000	678815482	2048134200	BV
Jurassic World	34	Jun 12, 2015	215000000	652270625	1648854864	Uni.
Furious 7	67	Apr 3, 2015	190000000	353007020	1518722794	Uni.
Avengers: Age of Ultron	4	May 1, 2015	330600000	459005868	1403013963	BV
Black Panther	42	Feb 16, 2018	200000000	700059566	1348258224	BV
...	...	...	...	...	...	...
Skin Trade	19	May 8, 2015	9000000	1242	1242	Magn.
Snitch	52	Dec 31, 2012	850000	0	0	LG/S
Eden	66	Jan 19, 2016	2300000	0	0	BG
Trance	31	Dec 31, 2012	950000	0	0	FoxS
Point Blank	69	Sep 18, 1967	3000000	0	0	Magn.

1246 rows × 6 columns

Next is restructure combined data further, by replacing the genre_ids values with the respective genre names and separating the release_date column to year and month columns. We will also remove the id column from the dataset because it is unnesseary for the analysis.

First, we need to drop the id column from the dataset

In [18]:
```
#removing the id column from the dataset
combined_movie_data.drop('id', axis=1, inplace=True)
combined_movie_data
```

Out[18]:

	release_date	production_budget	domestic_gross	worldwide_gross	studio
title					
Avengers: Infinity War	Apr 27, 2018	300000000	678815482	2048134200	BV
Jurassic World	Jun 12, 2015	215000000	652270625	1648854864	Uni.
Furious 7	Apr 3, 2015	190000000	353007020	1518722794	Uni.
Avengers: Age of Ultron	May 1, 2015	330600000	459005868	1403013963	BV
Black Panther	Feb 16, 2018	200000000	700059566	1348258224	BV
...	...	...	...	...	...
Skin Trade	May 8, 2015	9000000	1242	1242	Magn.
Snitch	Dec 31, 2012	850000	0	0	LG/S
Eden	Jan 19, 2016	2300000	0	0	BG
Trance	Dec 31, 2012	950000	0	0	FoxS
Point Blank	Sep 18, 1967	3000000	0	0	Magn.

1246 rows × 5 columns

In [19]:
```
# Creating new columns for month and year
combined_movie_data['year'] = combined_movie_data['release_date'].str[-4:].as
combined_movie_data['month'] = combined_movie_data['release_date'].str[:3]

# Dropping the release_date column
combined_movie_data.drop('release_date', axis=1, inplace=True)

combined_movie_data
```

Out[19]:

title	production_budget	domestic_gross	worldwide_gross	studio	year	month
Avengers: Infinity War	300000000	678815482	2048134200	BV	2018	Apr
Jurassic World	215000000	652270625	1648854864	Uni.	2015	Jun
Furious 7	190000000	353007020	1518722794	Uni.	2015	Apr
Avengers: Age of Ultron	330600000	459005868	1403013963	BV	2015	May
Black Panther	200000000	700059566	1348258224	BV	2018	Feb
...	...	...	...	...	...	...
Skin Trade	9000000	1242	1242	Magn.	2015	May
Snitch	850000	0	0	LG/S	2012	Dec
Eden	2300000	0	0	BG	2016	Jan
Trance	950000	0	0	FoxS	2012	Dec
Point Blank	3000000	0	0	Magn.	1967	Sep

1246 rows × 6 columns

In [20]:
```
#removing domestic gross
combined_movie_data.drop('domestic_gross', axis=1, inplace=True)
combined_movie_data.head()
```

Out[20]:

title	production_budget	worldwide_gross	studio	year	month
Avengers: Infinity War	300000000	2048134200	BV	2018	Apr
Jurassic World	215000000	1648854864	Uni.	2015	Jun
Furious 7	190000000	1518722794	Uni.	2015	Apr
Avengers: Age of Ultron	330600000	1403013963	BV	2015	May
Black Panther	200000000	1348258224	BV	2018	Feb

Combined Data is clean and now we proceed to analysing.

EXPLAROTARY DATA ANALYSIS

Visualization

1. Focus will be on comparisons between top movies and bottom movies in terms of genres, release month, studio, popularity, vote_count, and vote_average.

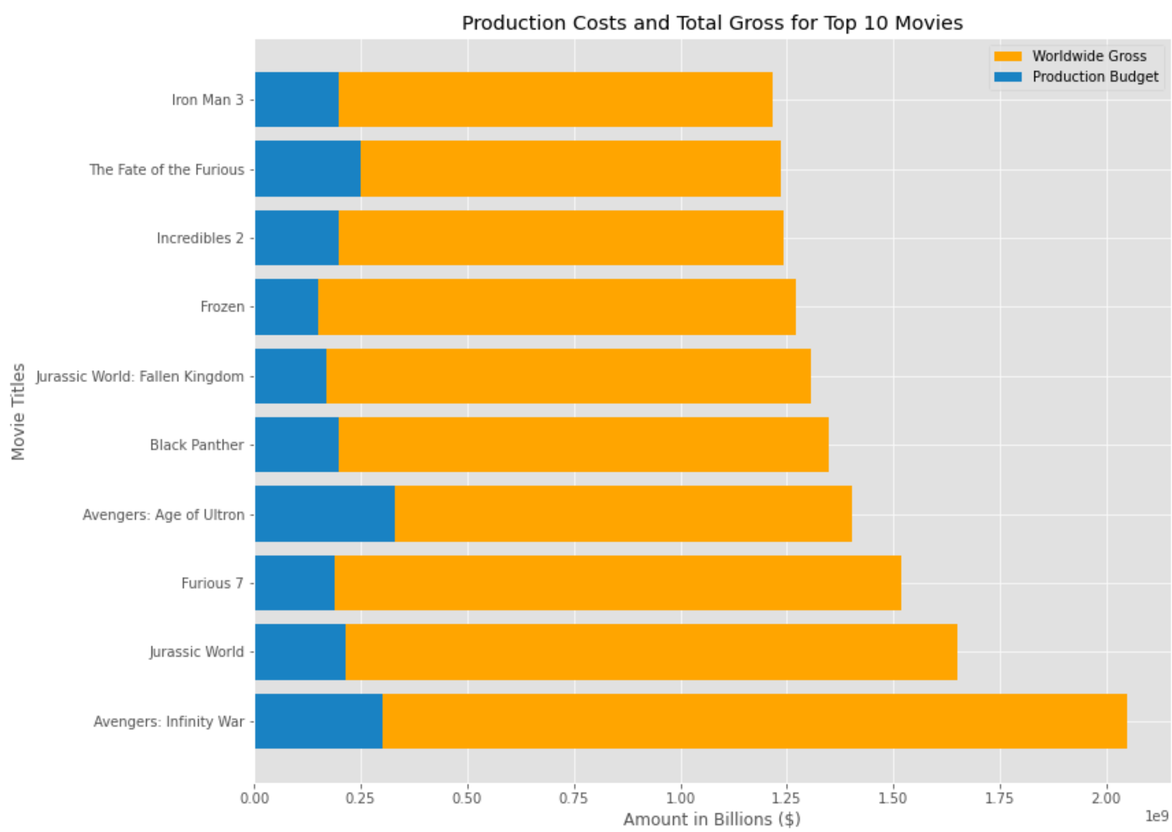
Visualizations will help identify some of these relationships and what they mean to Microsoft's production studio. For example, is there a correlation between popularity and box office? Other questions would be, does the release month affect the popularity and movies' box office? And are there any relationships between production costs, popularity, and worldwide grossing.

We are trying to answer below questions

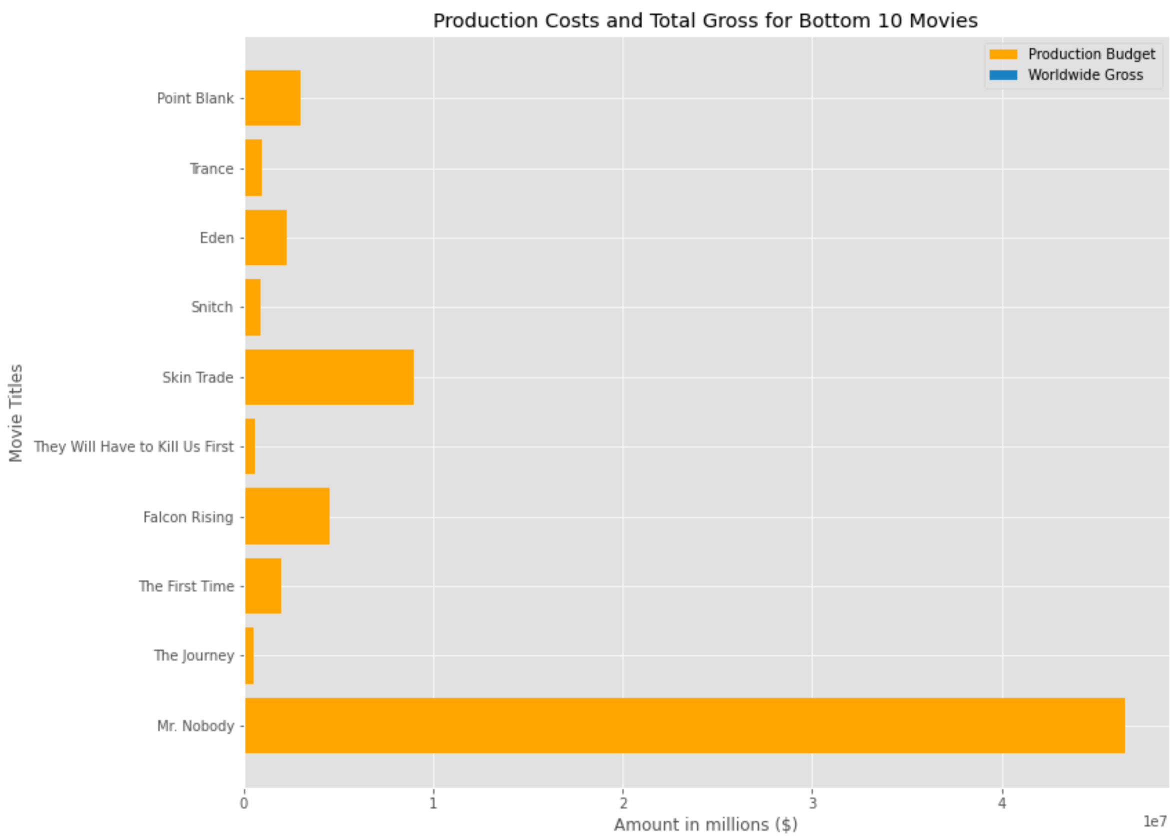
1.Production Budget vs Box Office figures 2.Understanding the relationship between production budgets and worldwide gross can help predict, to some level, whether investing more in movie production will result in high grosses.

As a result, an horizontal bar chart that compares costs vs revenues for the top 30 and bottom 20 movies will be appropriate for this analysis

In [21]:
```
# Getting the top 10 movies
top_20_movies = combined_movie_data.sort_values('worldwide_gross', ascending=

#reset the index for top_30_movies
top_20_movies.reset_index(drop=False, inplace=True)

# Setting the style
plt.style.use('ggplot')

# Create the figure and axes objects
fig, ax = plt.subplots(figsize=(12, 10))

# Plot the data
ax.barh(top_20_movies['title'], top_20_movies['worldwide_gross'], label='Worl
ax.barh(top_20_movies['title'], top_20_movies['production_budget'], label='Pr

# Set the axis labels and title
ax.set_xlabel('Amount in Billions ($)')
ax.set_ylabel('Movie Titles')
ax.set_title('Production Costs and Total Gross for Top 10 Movies')

# Add a legend
ax.legend()

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



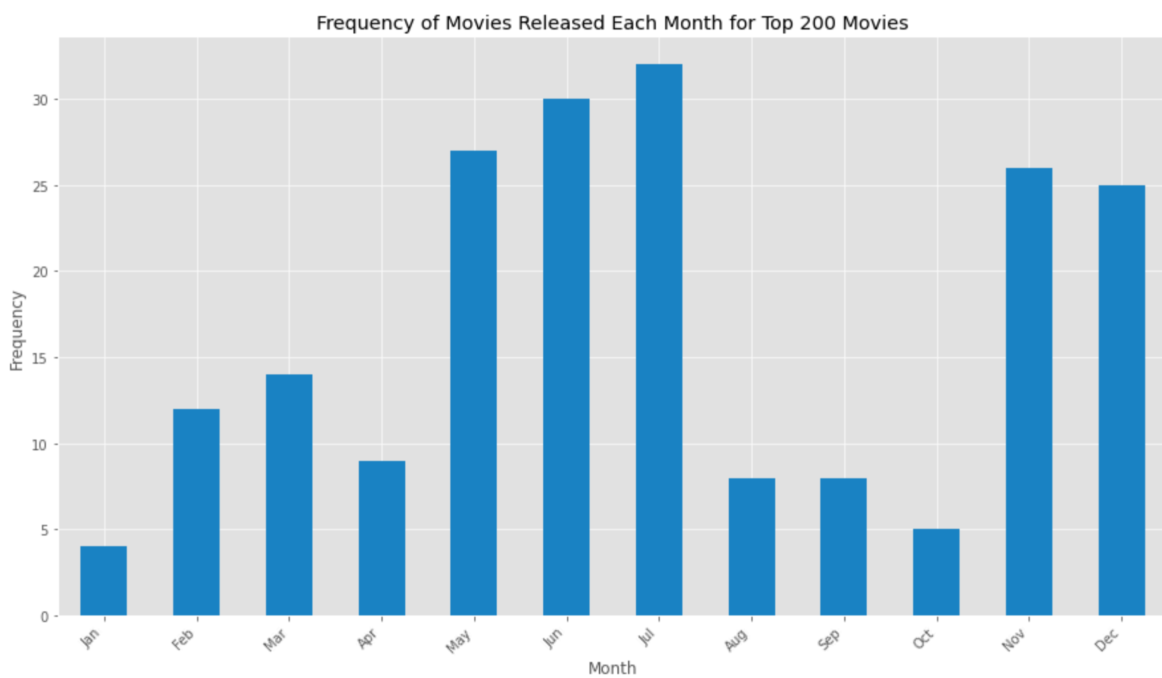
In [22]:
```
# Getting the top 10 movies
bottom_10_movies = combined_movie_data.sort_values('worldwide_gross', ascendi

#reset the index for top_30_movies
bottom_10_movies.reset_index(drop=False, inplace=True)

# Setting the style
plt.style.use('ggplot')

# Create the figure and axes objects
fig, ax = plt.subplots(figsize=(12, 10))

# Plot the data
ax.barh(bottom_10_movies['title'], bottom_10_movies['production_budget'], labe
ax.barh(bottom_10_movies['title'], bottom_10_movies['worldwide_gross'], label=

# Set the axis labels and title
ax.set_xlabel('Amount in millions ($)')
ax.set_ylabel('Movie Titles')
ax.set_title('Production Costs and Total Gross for Bottom 10 Movies')

# Add a legend
ax.legend()

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



Monthly Release Dates for the top 100 Movies

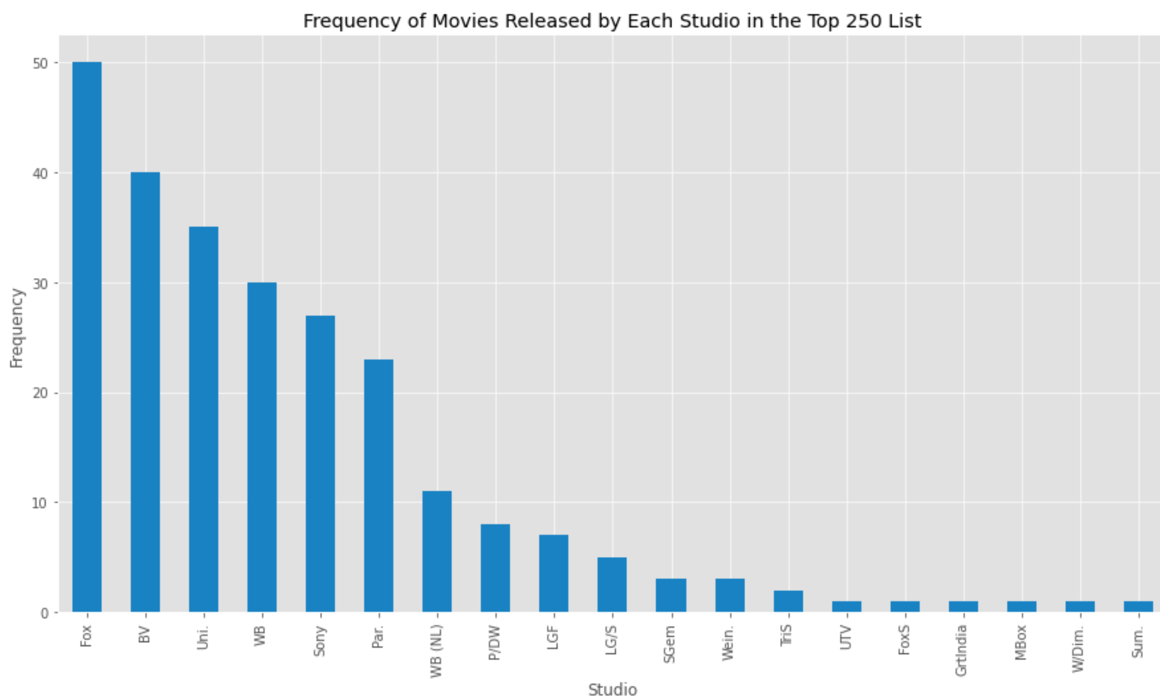
Here, we need to understand which month saw the release of the most movies from the top 200 list. This will help in comparing whether the release month plays any role on a movie's

In [23]:
```
# Get the top 500 movies
top_200_movies = combined_movie_data.sort_values('worldwide_gross', ascending=

# Reset the index for this dataframe
top_200_movies.reset_index(drop=True, inplace=True)

# Group the movies by month and count the number of movies in each month
movies_by_month = top_200_movies['month'].value_counts().reindex(['Jan', 'Feb

# Create the figure and axes objects
fig, ax = plt.subplots(figsize=(15, 8))

# Plot the data as a bar chart
movies_by_month.plot(kind='bar', color='#1984c5', ax=ax)

# Set the x-axis tick locations and labels
ax.set_xticklabels(movies_by_month.index, rotation=45, ha='right')

# Set the axis labels and title
ax.set_xlabel('Month')
ax.set_ylabel('Frequency')
ax.set_title('Frequency of Movies Released Each Month for Top 200 Movies')

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



Studios with the Highest number of Movies in Top 250 List

In [24]:
```
# Getting the top 250 movies
top_250_movies = combined_movie_data.sort_values('worldwide_gross', ascending=

# Reset the index for this dataframe
top_250_movies.reset_index(drop=True, inplace=True)

# Group the movies by studio and count the number of movies by each studio
movies_by_studio = top_250_movies['studio'].value_counts()

# Create the figure and axes objects
fig, ax = plt.subplots(figsize=(15, 8))

# Plot the data as a bar chart
movies_by_studio.plot(kind='bar', color='#1984c5', ax=ax)

# Set the axis labels and title
ax.set_xlabel('Studio')
ax.set_ylabel('Frequency')
ax.set_title('Frequency of Movies Released by Each Studio in the Top 250 List

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



In [25]:
```
top_250_movies = combined_movie_data.sort_values('worldwide_gross', ascending

# Reset the index for this dataframe
top_250_movies.reset_index(drop=True, inplace=True)

# Get the unique studio names
studio_names = top_250_movies['studio'].unique()

# Print the studio names
print("Studio Names:")
for studio in studio_names:
    print(studio)
```

```
Studio Names:
BV
Uni.
WB
P/DW
Sony
Par.
WB (NL)
Fox
LGF
Sum.
Wein.
LG/S
FoxS
SGem
UTV
TriS
GrtIndia
W/Dim.
MBox
```

Recommendations based on Analysis

Analysis reveals significant correlations between various factors, indicating opportunities for Microsoft's new studio to thrive in the film industry.

The examination aimed to uncover relationships between production costs and box office performance, release month and box office performance, as well as production studio and box office performance. Results and visualizations suggest a strong association between production studio and performance. However, correlations are notably weaker regarding production budget and release month.

Based on these findings, I propose four strategic actions for Microsoft's movie development process, listed in order of priority:

1.Forge Partnerships: Collaborate with established production studios. Fox emerges as the frontrunner, boasting approximately 49 movies in the top 250, closely trailed by (BV) Pictures—a subsidiary of Walt Disney Studios—with 44 movies. Following suit are Uni studios with 39 movies, (WB) Pictures with 28 movies, alongside Sony and Par Pictures with 25 and 23 respectively. These studios represent key players that have effectively dominated the market, consistently delivering highest-grossing films. Their success translates to substantial profits for parent companies and shareholders. Consequently, they offer valuable opportunities for Microsoft Studios to glean insights from or potentially collaborate with.

2.Consider Production Costs: While of lower priority, Microsoft's new studio should factor in production costs. Avoiding movies with budgets below $100 million is advisable, as they often yield minimal or negative returns.

3.Optimize Release Timing: Explore releasing movies during peak months for box office success, such as May, June, July, and November and December. These months typically witness the release of highest-grossing films, indicating increased audience engagement. Collaborating with seasoned studios can provide valuable insights into the factors driving audience behavior during these periods.

4.Evaluate Additional Factors: Explore additional factors beyond the scope of this analysis that may influence box office performance, such as marketing strategies, audience demographics, and critical reception. Incorporating these considerations into the movie development process

In [ ]: