Final Project Submission

Please fill out:

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- Student pace: self paced / part time / full time **- PART TIME**
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Box Office Analysis: Identifying Best Performing Movie Genres for Microsoft's New Studio

Overview

This project analyzes the datasets from 3 movie websites namely, Box Office Mojo (https://www.boxofficemojo.com/) , TheMovieDB (https://www.themoviedb.org/) and The Numbers (https://www.the-numbers.com/). The 3 datasets are merged into one pandas DataFrame to enable a more indepth analysis and better findings with regards to the top/best performing movie genres in the Box Office. Microsoft can use the findings from this analysis to help decide what type of films to create so as to stay at par in the movie industry.

Business Understanding

Based on the business problem, which is, Microsoft wants to get in on the fun of creating movies/original video content but they have no knowledge of creating movies, I have formulated 4 business questions whereby I will use my dataset to extract meaningful findings which can be translated into actionable insights for the Head of Microsoft's new movie studio to help him/her decide on what types of films to create. These business questions are:

1. What are the top 4 best performing genres of movies at the box office?

2. What is the relationship between production budget and the success of a movie both domestically and worldwide?

3. What is the competitive landscape of the movie industry in terms of market share?

4. How does the release time of a movie contribute to its success?

Also, to define the idea of a successful movie in the Box Office and to get a comprehensive understanding of the current trends in the movie industry, I will be comparing different metrics such as domestic revenue, worldwide revenue, popularity ratings and vote count of the movies. Then I will compare the top genres across different groupings and look for patterns or similarities that may provide insight into overarching trends.

Data Understanding

The data sources for this analysis are 3 websites namely:

- [Box Office Mojo (https://www.boxofficemojo.com/)](https://www.boxofficemojo.com/)
- [TheMovieDB (https://www.themoviedb.org/)](https://www.themoviedb.org/)
- [The Numbers (https://www.the-numbers.com/)](https://www.the-numbers.com/)

I therefore have 3 separate CSV data files:

- `bom.movie_gross.csv.gz` : each record represents a movie title, with attributes of that movie (eg. `domestic_gross`).
- `tmdb.movies.csv.gz` : each record represents a movie title as well, with attributes such as `release_date` .
- `tn.movie_budgets.csv.gz` : each record represents a movie title as well, with attributes such as `production_budget` .

Also, note that the data may not reflect the most-up-to-date trends and performances in the movie industry since its scope is upto 2020.

Importing necessary libraries

In [1]:

```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import warnings
import calendar
```

Loading the data from [Box Office Mojo (https://www.boxofficemojo.com/)](https://www.boxofficemojo.com/) website with Pandas

In [2]:

```
# Load the data and display the DataFrame to ensure the loading was successful
bom_df = pd.read_csv('zippedData/bom.movie_gross.csv.gz')
bom_df
```

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
...	...	...	...	...	...
3382	The Quake	Magn.	6200.0	NaN	2018
3383	Edward II (2018 re-release)	FM	4800.0	NaN	2018
3384	El Pacto	Sony	2500.0	NaN	2018
3385	The Swan	Synergetic	2400.0	NaN	2018
3386	An Actor Prepares	Grav.	1700.0	NaN	2018

3387 rows × 5 columns

Data Cleaning and Preprocessing

In this section, we take steps to identify and correct or remove incorrect, incomplete, duplicates or incorrectly formatted data within the provided dataset, using techniques such as:

- Removing, replacing or keeping missing values
- Changing column datatypes so as to work with the data accordingly
- Removing duplicates if any

In [3]:

```
# Check for the number of rows and columns
bom_df.shape
```

Out[3]:

```
(3387, 5)
```

In [4]:

```
# Check the columns available in the DataFrame
bom_df.columns
```

Out[4]:

```
Index(['title', 'studio', 'domestic_gross', 'foreign_gross', 'year'], dty
pe='object')
```

In [5]:

```
# Check the metadata of our actual dataset
bom_df.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 [6]:

```
# Check for the column datatypes
bom_df.dtypes
```

Out[6]:

```
title              object
studio             object
domestic_gross    float64
foreign_gross      object
year                int64
dtype: object
```

In [7]:

```
#Check for the total number of missing values per column
bom_df.isna().sum()
```

Out[7]:

```
title                0
studio              5
domestic_gross      28
foreign_gross     1350
year                 0
dtype: int64
```

Let's start with the `studio` column which has only 5 missing values. First we can get the `value_counts()` of the columns to know how the studios are distributed.

In [8]:

```
#Get the value_counts() of the `studio` column
bom_df['studio'].value_counts().head()
```

Out[8]:

```
IFC      166
Uni.     147
WB       140
Magn.    136
Fox      136
Name: studio, dtype: int64
```

From the results above, we can see that the frequencies of the studios are not that far apart. Therefore imputing the missing values with the modal value will be a bit biased, therefore it would probably be best to drop the rows with missing values for studios.

In [9]:

```
# Dropping the rows with missing values based on the `studio` column
bom_df.dropna(subset=['studio'], inplace=True)
```

In [10]:

```
bom_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 3382 entries, 0 to 3386
Data columns (total 5 columns):
 #   Column          Non-Null Count  Dtype  
---  ------          --------------  -----  
 0   title           3382 non-null   object 
 1   studio          3382 non-null   object 
 2   domestic_gross  3356 non-null   float64
 3   foreign_gross   2033 non-null   object 
 4   year            3382 non-null   int64  
dtypes: float64(1), int64(1), object(3)
memory usage: 158.5+ KB
```

Next, we can move on to the `foreign_gross` column which has a significant number of missing values. We'll start with getting the percentage of the missing values by getting the sum of the null values divided by the length of the `foreign_gross` column multiplied by 100%.

In [11]:

```
# Checking for the percentage of missing values in the `foreign_gross` column
missing_percentage = bom_df['foreign_gross'].isnull().sum() / len(bom_df['foreign_gross'
missing_percentage
```

Out[11]:

```
39.8876404494382
```

39.89% of missing values is a big percentage, therefore it would be probably best to drop the entire column, and just work with the `domestic_gross` column.

In [12]:

```
# Dropping the `foreign_gross` column
bom_df.drop('foreign_gross', axis=1, inplace=True)
bom_df.head()
```

Out[12]:

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

In [13]:

```
# Check the number of missing values again
bom_df.isna().sum()
```

Out[13]:

```
title              0
studio             0
domestic_gross    26
year               0
dtype: int64
```

For the `domestic_gross` column, we can handle the missing values by imputing with the median of the column. This is more efficient than imputing with the mean of the column because median is less influenced by outliers/extreme values in the dataset compared to the mean.

In [14]:

```
# Get the median of the `domestic_gross` column
bom_df['domestic_gross'].median()
```

Out[14]:

```
1400000.0
```

In [15]:

```
# Fill the missing values with the median
bom_df['domestic_gross'].fillna(bom_df['domestic_gross'].median(), inplace=True)
```

In the code below, I convert the `year` column into a datetime object in case I would like to perform any datetime operations. I also extract the year and create a new column `release_year` that I will use later on when merging the datasets.

In [16]:

```
# Converting the `year` column to a datetime object
bom_df['year'] = pd.to_datetime(bom_df['year'], format='%Y')

# Creating a new column `release_year` from the `year`
bom_df['release_year'] = bom_df['year'].dt.year

# Confirm the new column has been added
bom_df.head()
```

Out[16]:

	title	studio	domestic_gross	year	release_year
0	Toy Story 3	BV	415000000.0	2010-01-01	2010
1	Alice in Wonderland (2010)	BV	334200000.0	2010-01-01	2010
2	Harry Potter and the Deathly Hallows Part 1	WB	296000000.0	2010-01-01	2010
3	Inception	WB	292600000.0	2010-01-01	2010
4	Shrek Forever After	P/DW	238700000.0	2010-01-01	2010

In [17]:

```
# Confirming one more time if there any more missing values
bom_df.isna().sum()
```

Out[17]:

```
title             0
studio            0
domestic_gross    0
year              0
release_year      0
dtype: int64
```

In [18]:

```
# Checking to see if there are any duplicates
bom_df.duplicated().sum()
```

Out[18]:

```
0
```

Now we can display the **final output** to see how our DataFrame looks like after the cleaning and preprocessing.

In [19]:

```
# Display the final output
bom_df
```

Out[19]:

	title	studio	domestic_gross	year	release_year
0	Toy Story 3	BV	415000000.0	2010-01-01	2010
1	Alice in Wonderland (2010)	BV	334200000.0	2010-01-01	2010
2	Harry Potter and the Deathly Hallows Part 1	WB	296000000.0	2010-01-01	2010
3	Inception	WB	292600000.0	2010-01-01	2010
4	Shrek Forever After	P/DW	238700000.0	2010-01-01	2010
...	...	...	...	...	...
3382	The Quake	Magn.	6200.0	2018-01-01	2018
3383	Edward II (2018 re-release)	FM	4800.0	2018-01-01	2018
3384	El Pacto	Sony	2500.0	2018-01-01	2018
3385	The Swan	Synergetic	2400.0	2018-01-01	2018
3386	An Actor Prepares	Grav.	1700.0	2018-01-01	2018

3382 rows × 5 columns

In [20]:

```
bom_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 3382 entries, 0 to 3386
Data columns (total 5 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   title           3382 non-null   object
 1   studio          3382 non-null   object
 2   domestic_gross  3382 non-null   float64
 3   year            3382 non-null   datetime64[ns]
 4   release_year    3382 non-null   int64
dtypes: datetime64[ns](1), float64(1), int64(1), object(2)
memory usage: 158.5+ KB
```

Next up, loading the next dataset!

Loading the data from [TheMovieDB (https://www.themoviedb.org/)](https://www.themoviedb.org/) website with Pandas

In [21]:

```
# Load and display the DataFrame
tmdb_df = pd.read_csv('zippedData/tmdb.movies.csv.gz', index_col=0)
tmdb_df
```

Out[21]:

	genre_ids	id	original_language	original_title	popularity	release_date	
0	[12, 14, 10751]	12444	en	Harry Potter and the Deathly Hallows: Part 1	33.533	2010-11-19	Ha H
1	[14, 12, 16, 10751]	10191	en	How to Train Your Dragon	28.734	2010-03-26	Hov
2	[12, 28, 878]	10138	en	Iron Man 2	28.515	2010-05-07	
3	[16, 35, 10751]	862	en	Toy Story	28.005	1995-11-22	
4	[28, 878, 12]	27205	en	Inception	27.920	2010-07-16	
...	...	...	...	...	...	...	
26512	[27, 18]	488143	en	Laboratory Conditions	0.600	2018-10-13	
26513	[18, 53]	485975	en	_EXHIBIT_84xxx_	0.600	2018-05-01	_EX
26514	[14, 28, 12]	381231	en	The Last One	0.600	2018-10-01	
26515	[10751, 12, 28]	366854	en	Trailer Made	0.600	2018-06-22	
26516	[53, 27]	309885	en	The Church	0.600	2018-10-05	

26517 rows × 9 columns

I repeat the same steps of **Data Cleaning & Preprocessing** for this dataset as well.

In [22]:

```
# Checking the number of rows and columns
tmdb_df.shape
```

Out[22]:

```
(26517, 9)
```

In [23]:

```
# Checking the columns
tmdb_df.columns
```

Out[23]:

```
Index(['genre_ids', 'id', 'original_language', 'original_title', 'popular
ity',
       'release_date', 'title', 'vote_average', 'vote_count'],
      dtype='object')
```

In [24]:

```
# Checking the column datatypes
tmdb_df.dtypes
```

Out[24]:

```
genre_ids             object
id                     int64
original_language     object
original_title        object
popularity           float64
release_date          object
title                 object
vote_average         float64
vote_count             int64
dtype: object
```

In the code below, I convert the `release_date` column into a datetime object in case I would like to perform any datetime operations. I also extract the year and create a new column `release_year` that I will use later on when merging the datasets.

In [25]:

```
# Convert the `release_date` column to a datetime object
tmdb_df['release_date'] = pd.to_datetime(tmdb_df['release_date'])

# Create a new column `release_year`
tmdb_df['release_year'] = tmdb_df['release_date'].dt.year

# Confirm the new column has been added
tmdb_df.head()
```

Out[25]:

	genre_ids	id	original_language	original_title	popularity	release_date	title	vot
0	[12, 14, 10751]	12444	en	Harry Potter and the Deathly Hallows: Part 1	33.533	2010-11-19	Harry Potter and the Deathly Hallows: Part 1	
1	[14, 12, 16, 10751]	10191	en	How to Train Your Dragon	28.734	2010-03-26	How to Train Your Dragon	
2	[12, 28, 878]	10138	en	Iron Man 2	28.515	2010-05-07	Iron Man 2	
3	[16, 35, 10751]	862	en	Toy Story	28.005	1995-11-22	Toy Story	
4	[28, 878, 12]	27205	en	Inception	27.920	2010-07-16	Inception	

In [26]:

```
# Get the metadata of our data
tmdb_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 26517 entries, 0 to 26516
Data columns (total 10 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   genre_ids          26517 non-null  object
 1   id                 26517 non-null  int64
 2   original_language  26517 non-null  object
 3   original_title     26517 non-null  object
 4   popularity         26517 non-null  float64
 5   release_date       26517 non-null  datetime64[ns]
 6   title              26517 non-null  object
 7   vote_average       26517 non-null  float64
 8   vote_count         26517 non-null  int64
 9   release_year       26517 non-null  int64
dtypes: datetime64[ns](1), float64(2), int64(3), object(4)
memory usage: 2.2+ MB
```

In [27]:

```
# Confirming that our dataset has no missing values
tmdb_df.isna().sum()
```

Out[27]:

```
genre_ids            0
id                   0
original_language    0
original_title       0
popularity           0
release_date         0
title                0
vote_average         0
vote_count           0
release_year         0
dtype: int64
```

In [28]:

```
# Checking to see if there are any duplicates
tmdb_df.duplicated().sum()
```

Out[28]:

```
1020
```

Below I sort and display the duplicates next to each other to inspect how the various rows are duplicated, which will aid in decision-making, as to either drop the duplicates or keep them. I will use the `id` column since each movie has its own unique id.

In [29]:

```
# Sort the DataFrame by the 'id' column
df_sorted = tmdb_df.sort_values(by='id')

# Create a subset dataframe indicating which rows are duplicates
duplicated = df_sorted.duplicated(subset=['id'], keep=False)

# Display only the duplicated rows
duplicated_rows = df_sorted[duplicated]

# Display the result
duplicated_rows.head(10)
```

Out[29]:

	genre_ids	id	original_language	original_title	popularity	release_date	title
14173	[16, 10751, 14]	129	ja	千と千尋の神隠し	32.043	2002-09-20	Spirited Away
20626	[16, 10751, 14]	129	ja	千と千尋の神隠し	32.043	2002-09-20	Spirited Away
24000	[35, 10749]	239	en	Some Like It Hot	14.200	1959-03-18	Some Like It Hot
43	[35, 10749]	239	en	Some Like It Hot	14.200	1959-03-18	Some Like It Hot
17395	[28, 53, 878]	280	en	Terminator 2: Judgment Day	24.604	1991-07-03	Terminator 2: Judgment Day
20639	[28, 53, 878]	280	en	Terminator 2: Judgment Day	24.604	1991-07-03	Terminator 2: Judgment Day
14222	[18, 36, 10752]	387	de	Das Boot	16.554	1982-02-10	Das Boot
2494	[18, 36, 10752]	387	de	Das Boot	16.554	1982-02-10	Das Boot
2473	[16, 35, 10751]	862	en	Toy Story	28.005	1995-11-22	Toy Story
3	[16, 35, 10751]	862	en	Toy Story	28.005	1995-11-22	Toy Story

As displayed above, we have duplicated records which have the potential of making the analysis biased. Therefore, I will drop the duplicates permanently from the `tmdb_df` DataFrame.

In [30]:

```
# Drop the duplicates
tmdb_df = tmdb_df.drop_duplicates()

# Confirm they've been dropped
tmdb_df.duplicated().sum()
```

Out[30]:

```
0
```

Now that the duplicates have been dealt, I'll go ahead and check the unique `genre_ids` and do a `value_counts()` .

In [31]:

```
# Check the unique `genre_ids`
tmdb_df['genre_ids'].unique()
```

Out[31]:

```
array(['[12, 14, 10751]', '[14, 12, 16, 10751]', '[12, 28, 878]', ...,
       '[18, 14, 27, 878, 10749, 53]', '[16, 27, 9648]',
       '[10751, 12, 28]'], dtype=object)
```

In [32]:

```
# Get the value_counts
tmdb_df['genre_ids'].value_counts().head(10)
```

Out[32]:

```
[99]           3565
[]             2461
[18]           2119
[35]           1622
[27]           1125
[53]            466
[35, 18]        423
[10402]         398
[27, 53]        353
[18, 10749]     333
Name: genre_ids, dtype: int64
```

Above, I noted something interesting. There are **2,461** movies with no specified genres. This could be an instance of missing values denoted with a placeholder.

Therefore, I will replace the `[]` with `NaN` , get the percentage by getting the sum of the null values divided by the length of the `genre_ids` column multiplied by 100%. Then finally find a way to deal with the missing genres.

In [33]:

```
warnings.filterwarnings('ignore')

# Replace the `[]` with `NaN`
tmdb_df['genre_ids'] = tmdb_df['genre_ids'].replace('[]', np.nan)
```

In [34]:

```
# Get the missing percentage
missing_percentage2 = tmdb_df['genre_ids'].isnull().sum() / len(tmdb_df['genre_ids']) *
missing_percentage2
```

Out[34]:

```
9.652115935208064
```

9.6% is not a big percentage of missing values, but I will go ahead and drop the rows with the missing genre ids because these rows will not be of benefit since a major part of my analysis will be centered on the `genre_ids` column.

In [35]:

```
# Dropping the rows with missing genre ids
tmdb_df.dropna(subset=['genre_ids'], inplace=True)
```

In [36]:

```
# Get the value_counts again
tmdb_df['genre_ids'].value_counts().head(10)
```

Out[36]:

```
[99]           3565
[18]           2119
[35]           1622
[27]           1125
[53]            466
[35, 18]        423
[10402]         398
[27, 53]        353
[18, 10749]     333
[18, 35]        274
Name: genre_ids, dtype: int64
```

Below, I define a mapping dictionary for genre_ids. Then apply the mapping dictionary to the `genre_ids` column and create a new column `genres` with genre names that will be easier to interpret especially in the visualizations.

In addition, you can get the definitions of the various `genre_ids` values at [TheMovieDB `genre_ids` definitions (https://www.themoviedb.org/talk/5daf6eb0ae36680011d7e6ee)](https://www.themoviedb.org/talk/5daf6eb0ae36680011d7e6ee)

In [37]:

```
# Define a mapping dictionary for genre ids to genre names
genre_map = {28: 'Action', 12: 'Adventure', 16: 'Animation', 35: 'Comedy',
             80: 'Crime', 99: 'Documentary', 18: 'Drama', 10751: 'Family',
             14: 'Fantasy', 36: 'History', 27: 'Horror', 10402: 'Music',
             9648: 'Mystery', 10749: 'Romance', 878: 'Science Fiction',
             10770: 'TV Movie', 53: 'Thriller', 10752: 'War', 37: 'Western'}

# Apply the mapping dictionary to the `genre_ids` column and create a new column with ge
tmdb_df['genres'] = tmdb_df['genre_ids'].apply(lambda x: [genre_map[int(i.strip('[]'))]
                                               if isinstance(x, str) and len(x) > 0 else

# Convert the `genres` datatype from list to tuple to make them hashable
tmdb_df['genres'] = tmdb_df['genres'].apply(lambda x: tuple(x))

#Display to confirm it has worked
tmdb_df.head()
```

Out[37]:

	genre_ids	id	original_language	original_title	popularity	release_date	title	vot
0	[12, 14, 10751]	12444	en	Harry Potter and the Deathly Hallows: Part 1	33.533	2010-11-19	Harry Potter and the Deathly Hallows: Part 1	
1	[14, 12, 16, 10751]	10191	en	How to Train Your Dragon	28.734	2010-03-26	How to Train Your Dragon	
2	[12, 28, 878]	10138	en	Iron Man 2	28.515	2010-05-07	Iron Man 2	
3	[16, 35, 10751]	862	en	Toy Story	28.005	1995-11-22	Toy Story	
4	[28, 878, 12]	27205	en	Inception	27.920	2010-07-16	Inception	

Now we can display the **final output** to see how our DataFrame looks like after the cleaning and preprocessing.

In [38]:

```
tmdb_df
```

Out[38]:

	genre_ids	id	original_language	original_title	popularity	release_date	
0	[12, 14, 10751]	12444	en	Harry Potter and the Deathly Hallows: Part 1	33.533	2010-11-19	Ha H
1	[14, 12, 16, 10751]	10191	en	How to Train Your Dragon	28.734	2010-03-26	Hov
2	[12, 28, 878]	10138	en	Iron Man 2	28.515	2010-05-07	
3	[16, 35, 10751]	862	en	Toy Story	28.005	1995-11-22	
4	[28, 878, 12]	27205	en	Inception	27.920	2010-07-16	
...	...	...	...	...	...	...	
26512	[27, 18]	488143	en	Laboratory Conditions	0.600	2018-10-13	
26513	[18, 53]	485975	en	_EXHIBIT_84xxx_	0.600	2018-05-01	_EX
26514	[14, 28, 12]	381231	en	The Last One	0.600	2018-10-01	
26515	[10751, 12, 28]	366854	en	Trailer Made	0.600	2018-06-22	
26516	[53, 27]	309885	en	The Church	0.600	2018-10-05	

23036 rows × 11 columns

In [39]:

```
tmdb_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 23036 entries, 0 to 26516
Data columns (total 11 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   genre_ids          23036 non-null  object
 1   id                 23036 non-null  int64
 2   original_language  23036 non-null  object
 3   original_title     23036 non-null  object
 4   popularity         23036 non-null  float64
 5   release_date       23036 non-null  datetime64[ns]
 6   title              23036 non-null  object
 7   vote_average       23036 non-null  float64
 8   vote_count         23036 non-null  int64
 9   release_year       23036 non-null  int64
 10  genres             23036 non-null  object
dtypes: datetime64[ns](1), float64(2), int64(3), object(5)
memory usage: 2.1+ MB
```

Next, after cleaning and pre-processing, I **merge** the dataset from [TheMovieDB (https://www.themoviedb.org/)](https://www.themoviedb.org/) with the dataset from [Box Office Mojo (https://www.boxofficemojo.com/)](https://www.boxofficemojo.com/).

In [40]:

```
# Merge the two datasets on the `title` and `release_year` columns
merged_df = pd.merge(bom_df, tmdb_df, on=['title','release_year'], how='inner')
merged_df
```

Out[40]:

	title	studio	domestic_gross	year	release_year	genre_ids	id	original_lan
0	Toy Story 3	BV	415000000.0	2010-01-01	2010	[16, 10751, 35]	10193	
1	Inception	WB	292600000.0	2010-01-01	2010	[28, 878, 12]	27205	
2	Shrek Forever After	P/DW	238700000.0	2010-01-01	2010	[35, 12, 14, 16, 10751]	10192	
3	The Twilight Saga: Eclipse	Sum.	300500000.0	2010-01-01	2010	[12, 14, 18, 10749]	24021	
4	Iron Man 2	Par.	312400000.0	2010-01-01	2010	[12, 28, 878]	10138	
...	...	...	...	...	...	...	...	
2092	I Am Not a Witch	FM	50900.0	2018-01-01	2018	[18]	449757	
2093	Elliot: The Littlest Reindeer	Scre.	24300.0	2018-01-01	2018	[16, 10751, 12]	455842	
2094	Loving Pablo	Uni.	22000.0	2018-01-01	2018	[80, 18]	425336	
2095	The Quake	Magn.	6200.0	2018-01-01	2018	[12]	416194	
2096	An Actor Prepares	Grav.	1700.0	2018-01-01	2018	[35, 18]	434596	

2097 rows × 14 columns

In the process of merging, we lose data in terms of the number of records(rows) but I have more features(columns) to analyze. Sometimes the number of records in a dataset is not always an indication of its quality or usefulness. What matters most is whether the data is relevant to your analysis and can help you make informed decisions or take action. That's why I did an **inner** join operation as opposed to the other types of joins since they would have resulted in a lot of missing data for records with no matching values.

Next up, loading the third and final dataset!

Loading the data from [The Numbers (https://www.the-numbers.com/)](https://www.the-numbers.com/) website with Pandas

In [41]:

```
tn_df = pd.read_csv('zippedData/tn.movie_budgets.csv.gz')
tn_df
```

Out[41]:

	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
...	...	...	...	...	...	...
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

I repeat the same steps of **Data Cleaning & Preprocessing** for this dataset as well.

In [42]:

```
# Checking the number of rows and columns
tn_df.shape
```

Out[42]:

```
(5782, 6)
```

In [43]:

```
# Checking the columns
tn_df.columns
```

Out[43]:

```
Index(['id', 'release_date', 'movie', 'production_budget', 'domestic_gros
s',
       'worldwide_gross'],
      dtype='object')
```

In [44]:

```
# Checking the column datatypes
tn_df.dtypes
```

Out[44]:

```
id                    int64
release_date         object
movie                object
production_budget    object
domestic_gross       object
worldwide_gross      object
dtype: object
```

In the code below, I convert the `release_date` column into a datetime object in case I would like to perform any datetime operations. I also extract the year and create a new column `release_year` that I will use later on when merging the datasets. Additionally, I will rename the column name `movie` to `title` to also enable a successful merging of DataFrames.

In [45]:

```
# Convert the `release_date` column to a datetime object
tn_df['release_date'] = pd.to_datetime(tn_df['release_date'])
tn_df.dtypes

# Create a new column `release_year` to enable merging the DataFrame
tn_df['release_year'] = tn_df['release_date'].dt.year

# Change the `movie` column name to `title` to also enable merging
tn_df.rename(columns={'movie':'title'}, inplace=True)

# Display the DataFrame
tn_df.head()
```

Out[45]:

	id	release_date	title	production_budget	domestic_gross	worldwide_gross	releas
0	1	2009-12-18	Avatar	$425,000,000	$760,507,625	$2,776,345,279	
1	2	2011-05-20	Pirates of the Caribbean: On Stranger Tides	$410,600,000	$241,063,875	$1,045,663,875	
2	3	2019-06-07	Dark Phoenix	$350,000,000	$42,762,350	$149,762,350	
3	4	2015-05-01	Avengers: Age of Ultron	$330,600,000	$459,005,868	$1,403,013,963	
4	5	2017-12-15	Star Wars Ep. VIII: The Last Jedi	$317,000,000	$620,181,382	$1,316,721,747	

Below, define a function for fixing some structural issues with the way the currency column values are stored, that is, removing the **currency notation($)** and the **commas**, then I convert the datatype into integers which will enable me to perform mathematical operations.

In [46]:

```
# Define a function to convert currency strings to integers
def currency_to_int(currency_string):
    cleaned_string = currency_string.replace('$', '').replace(',', '') # remove dollar s
    return int(cleaned_string)

# Convert currency columns to integers
currency_columns = ['production_budget', 'domestic_gross', 'worldwide_gross']
for column in currency_columns:
    tn_df[column] = tn_df[column].apply(currency_to_int)
```

In [47]:

```
# Checking the metadata of our dataset
tn_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5782 entries, 0 to 5781
Data columns (total 7 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   id                 5782 non-null   int64
 1   release_date       5782 non-null   datetime64[ns]
 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
 6   release_year       5782 non-null   int64
dtypes: datetime64[ns](1), int64(5), object(1)
memory usage: 316.3+ KB
```

In [48]:

```
# Confirming if there are missing values
tn_df.isna().sum()
```

Out[48]:

```
id                   0
release_date         0
title                0
production_budget    0
domestic_gross       0
worldwide_gross      0
release_year         0
dtype: int64
```

In [49]:

```
# Checking for duplicates
tn_df.duplicated().sum()
```

Out[49]:

```
0
```

Now we can display the **final output** to see how our DataFrame looks like after the cleaning and preprocessing.

In [50]:

```
tn_df
```

Out[50]:

	id	release_date	title	production_budget	domestic_gross	worldwide_gross	re
0	1	2009-12-18	Avatar	425000000	760507625	2776345279	
1	2	2011-05-20	Pirates of the Caribbean: On Stranger Tides	410600000	241063875	1045663875	
2	3	2019-06-07	Dark Phoenix	350000000	42762350	149762350	
3	4	2015-05-01	Avengers: Age of Ultron	330600000	459005868	1403013963	
4	5	2017-12-15	Star Wars Ep. VIII: The Last Jedi	317000000	620181382	1316721747	
...	...	...	...	...	...	...	
5777	78	2018-12-31	Red 11	7000	0	0	
5778	79	1999-04-02	Following	6000	48482	240495	
5779	80	2005-07-13	Return to the Land of Wonders	5000	1338	1338	
5780	81	2015-09-29	A Plague So Pleasant	1400	0	0	
5781	82	2005-08-05	My Date With Drew	1100	181041	181041	

5782 rows × 7 columns

In [51]:

```
tn_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5782 entries, 0 to 5781
Data columns (total 7 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   id                 5782 non-null   int64
 1   release_date       5782 non-null   datetime64[ns]
 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
 6   release_year       5782 non-null   int64
dtypes: datetime64[ns](1), int64(5), object(1)
memory usage: 316.3+ KB
```

Merging the 3 datasets into one DataFrame with a variable name `merged_df2`

Next, after cleaning and pre-processing, I merge the `merged_df` DataFrame with the dataset from [The Numbers (https://www.the-numbers.com/)](https://www.the-numbers.com/) website, specifying the `how` parameter to an `inner` join, and passing in the `suffixes` parameter to avoid a naming collusion between columns with similar names.

This will enable me to perform a comprehensive Bivariate analysis of the numerical columns for better insights.

In [52]:

```
# Merge the `merged_df` with the `tn_df`
merged_df2 = pd.merge(merged_df, tn_df, on=['title','release_year'], how='inner', suffix
merged_df2.head(10)
```

Out[52]:

	title	studio	domestic_gross_1	year	release_year	genre_ids	id_1	original_lan
0	Toy Story 3	BV	415000000.0	2010-01-01	2010	[16, 10751, 35]	10193	
1	Inception	WB	292600000.0	2010-01-01	2010	[28, 878, 12]	27205	
2	Shrek Forever After	P/DW	238700000.0	2010-01-01	2010	[35, 12, 14, 16, 10751]	10192	
3	The Twilight Saga: Eclipse	Sum.	300500000.0	2010-01-01	2010	[12, 14, 18, 10749]	24021	
4	Iron Man 2	Par.	312400000.0	2010-01-01	2010	[12, 28, 878]	10138	
5	Tangled	BV	200800000.0	2010-01-01	2010	[16, 10751]	38757	
6	Despicable Me	Uni.	251500000.0	2010-01-01	2010	[16, 10751, 35]	20352	
7	How to Train Your Dragon	P/DW	217600000.0	2010-01-01	2010	[14, 12, 16, 10751]	10191	
8	The Chronicles of Narnia: The Voyage of the Da...	Fox	104400000.0	2010-01-01	2010	[12, 10751, 14]	10140	
9	The Karate Kid	Sony	176600000.0	2010-01-01	2010	[28, 12, 18, 10751]	38575	

Note again the number of records(rows) has reduced since I used an `inner` join whereby only the records with matching values from the DataFrames are returned. I will go ahead and investigate if the remaining data will be sufficient to answer the business questions provided. I start by first exploring the structure of the final `merged_df2` .

In [53]:

```
# Check the rows and columns
merged_df2.shape
```

Out[53]:

```
(1117, 19)
```

In [54]:

```
# Check the columns
merged_df2.columns
```

Out[54]:

```
Index(['title', 'studio', 'domestic_gross_1', 'year', 'release_year',
       'genre_ids', 'id_1', 'original_language', 'original_title',
       'popularity', 'release_date_1', 'vote_average', 'vote_count', 'gen
res',
       'id_2', 'release_date_2', 'production_budget', 'domestic_gross_2',
       'worldwide_gross'],
      dtype='object')
```

In [55]:

```
# Check the column datatypes
merged_df2.dtypes
```

Out[55]:

```
title                        object
studio                       object
domestic_gross_1            float64
year                 datetime64[ns]
release_year                  int64
genre_ids                    object
id_1                          int64
original_language            object
original_title               object
popularity                  float64
release_date_1       datetime64[ns]
vote_average                float64
vote_count                    int64
genres                       object
id_2                          int64
release_date_2       datetime64[ns]
production_budget             int64
domestic_gross_2              int64
worldwide_gross               int64
dtype: object
```

In [56]:

```
# Confirm there are no missing values
merged_df2.isna().sum()
```

Out[56]:

```
title                0
studio               0
domestic_gross_1     0
year                 0
release_year         0
genre_ids            0
id_1                 0
original_language    0
original_title       0
popularity           0
release_date_1       0
vote_average         0
vote_count           0
genres               0
id_2                 0
release_date_2       0
production_budget    0
domestic_gross_2     0
worldwide_gross      0
dtype: int64
```

In [57]:

```
# Confirming there are no duplicates
merged_df2.duplicated().sum()
```

Out[57]:

```
0
```

In [58]:

```
merged_df2.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1117 entries, 0 to 1116
Data columns (total 19 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   title              1117 non-null   object
 1   studio             1117 non-null   object
 2   domestic_gross_1   1117 non-null   float64
 3   year               1117 non-null   datetime64[ns]
 4   release_year       1117 non-null   int64
 5   genre_ids          1117 non-null   object
 6   id_1               1117 non-null   int64
 7   original_language  1117 non-null   object
 8   original_title     1117 non-null   object
 9   popularity         1117 non-null   float64
 10  release_date_1     1117 non-null   datetime64[ns]
 11  vote_average       1117 non-null   float64
 12  vote_count         1117 non-null   int64
 13  genres             1117 non-null   object
 14  id_2               1117 non-null   int64
 15  release_date_2     1117 non-null   datetime64[ns]
 16  production_budget  1117 non-null   int64
 17  domestic_gross_2   1117 non-null   int64
 18  worldwide_gross    1117 non-null   int64
dtypes: datetime64[ns](3), float64(3), int64(7), object(6)
memory usage: 174.5+ KB
```

Now we can finally start the next step which is Exploratory Data Analysis.

Data Exploration and Analysis

In this section we perform basic descriptive statistics and create visualizations to get a feel of our dataset's characteristics. Descriptive statistics include:

- Measures of central tendency
- Measures of dispersion
- Correlation

Visualizations will include:

- Boxplots
- Histograms
- Scatter plots, etc.

In [59]:

```
# Check the descriptive statistics for the numerical columns
merged_df2.drop(['id_1','id_2','release_year'], axis=1)
merged_df2.describe()
```

Out[59]:

	domestic_gross_1	release_year	id_1	popularity	vote_average	vote_cc
count	1.117000e+03	1117.000000	1117.000000	1117.000000	1117.000000	1117.000
mean	6.520066e+07	2013.654432	181247.752014	13.867436	6.396867	2436.211
std	8.762581e+07	2.531984	134788.934011	7.810460	0.778139	2990.050
min	1.000000e+03	2010.000000	1771.000000	0.600000	4.000000	2.000
25%	1.150000e+07	2011.000000	59108.000000	8.965000	5.900000	515.000
50%	3.630000e+07	2014.000000	138832.000000	12.083000	6.400000	1317.000
75%	8.010000e+07	2016.000000	296098.000000	16.356000	6.900000	3133.000
max	7.001000e+08	2018.000000	505058.000000	80.773000	8.400000	22186.000

Univariate Analysis

For categorical columns:

1. Involves getting frequency tables and plotting value counts. It's important to choose appropriate visualizations eg. barplots or pie charts
2. Stating observations and interpreting the findings

For numerical columns:

1. Involves calculating the measures of central tendency, dispersion and other statistics such as correlation.
2. Plotting appropriate distributions.
3. ingInterpret the findings.

Our sepecific columns of interest are going to be

- `title`
- `genres`
- `genre_ids`
- `studio`
- `popularity`
- `production_budget`
- `worldwide_gross`
- `domestic_gross_2`
- `vote_average`
- `vote_count`
- `release_date_2`

In [60]:

```
# Get the relevant columns
relevant_columns = ['genre_ids','genres','title','studio','release_date_2','popularity',
                    'vote_average','production_budget','domestic_gross_2','worldwide_gro
```

In [61]:

```
# Create a subset DataFrame with the relevant columns
merged_df3 = merged_df2.loc[:, relevant_columns]
merged_df3.head()
```

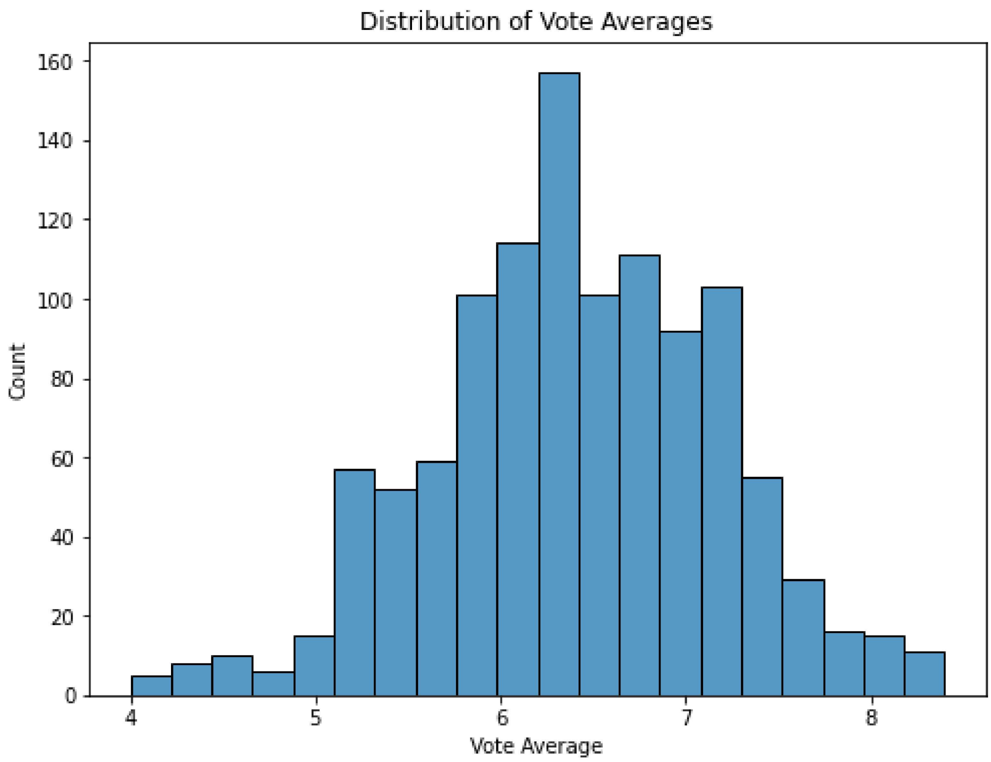
Out[61]:

	genre_ids	genres	title	studio	release_date_2	popularity	vote_count	vote_ave
0	[16, 10751, 35]	(Animation, Family, Comedy)	Toy Story 3	BV	2010-06-18	24.445	8340	
1	[28, 878, 12]	(Action, Science Fiction, Adventure)	Inception	WB	2010-07-16	27.920	22186	
2	[35, 12, 14, 16, 10751]	(Comedy, Adventure, Fantasy, Animation, Family)	Shrek Forever After	P/DW	2010-05-21	15.041	3843	
3	[12, 14, 18, 10749]	(Adventure, Fantasy, Drama, Romance)	The Twilight Saga: Eclipse	Sum.	2010-06-30	20.340	4909	
4	[12, 28, 878]	(Adventure, Action, Science Fiction)	Iron Man 2	Par.	2010-05-07	28.515	12368	

i) A histogram to show distribution of vote averages

In [62]:

```
# Create a histogram to show the distribution of vote averages
plt.figure(figsize=(8, 6))
sns.histplot(x='vote_average', data=merged_df3, bins=20)
plt.xlabel('Vote Average')
plt.ylabel('Count')
plt.title('Distribution of Vote Averages')
plt.savefig('visualization11.png')
```

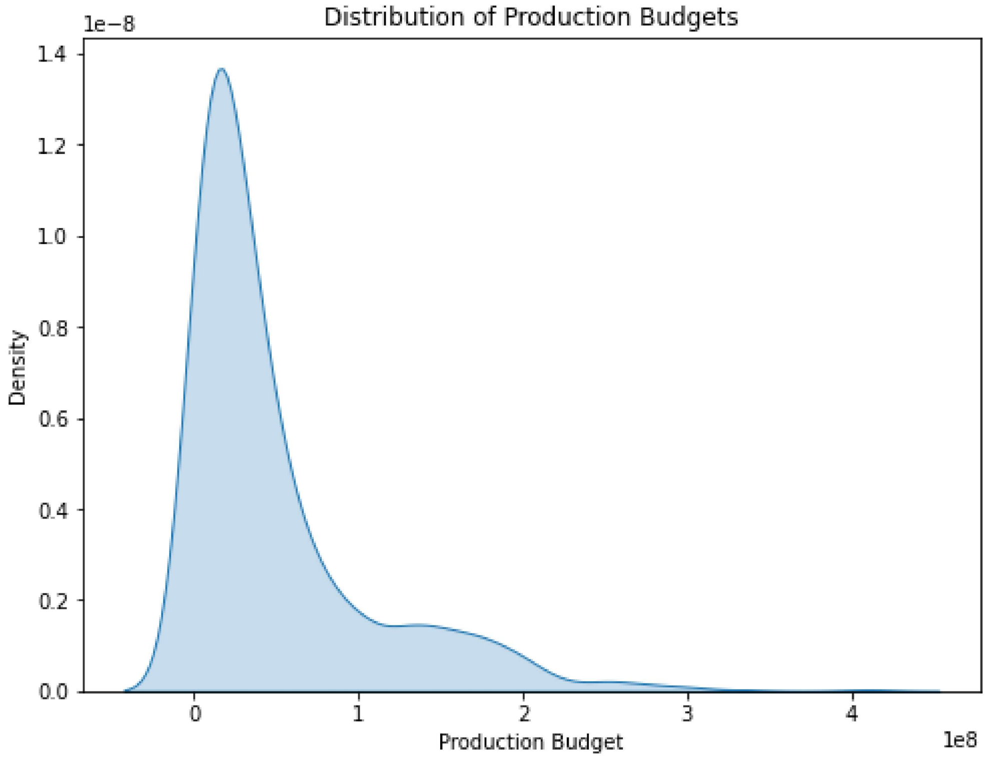


From the histogram above, I can observe that a majority of movies received a vote average of 6 to 6.5.

ii) A kernel density plot to show the distribution of production budgets

In [63]:

```
# Create a kernel density plot to show the distribution of production budgets
plt.figure(figsize=(8, 6))
sns.kdeplot(x='production_budget', data=merged_df3, shade=True)
plt.xlabel('Production Budget')
plt.title('Distribution of Production Budgets')
plt.savefig('visualization12.png')
```

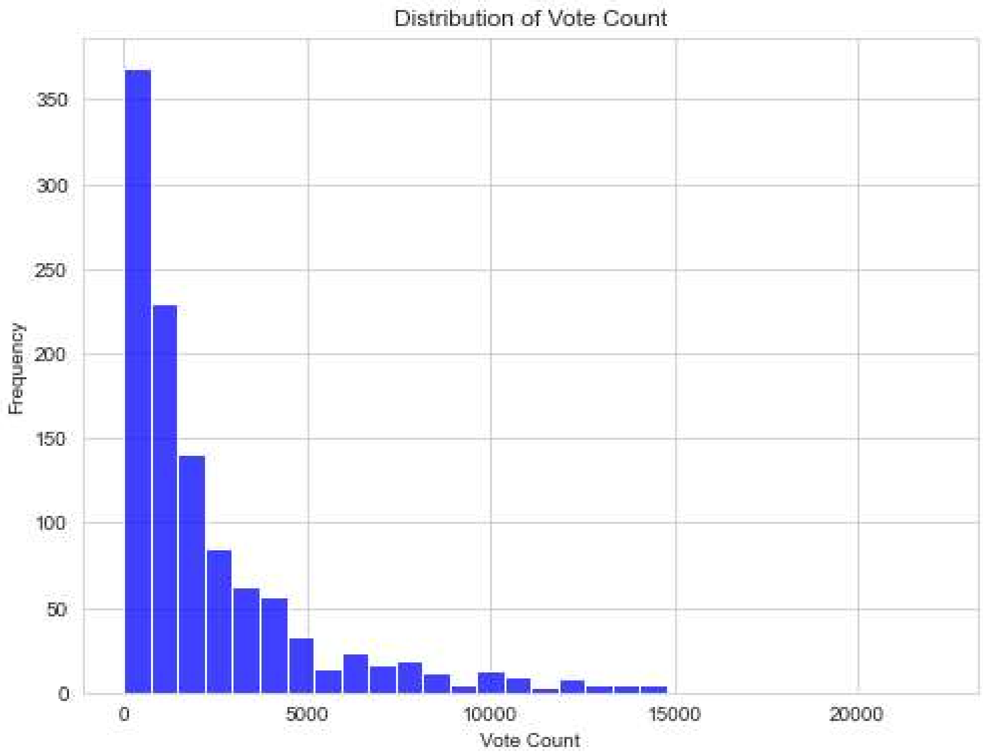


From the above kernel density, the peak denotes the value of the production budget that is most frequently observed among the movies. I can observe that the peak of the distribution is skewed to the right, this suggests that a majority of movies have lower production budgets, with fewer movies having higher production budgets.

iii) A histogram to show the distribution of vote count

In [64]:

```
# Create a histogram to show distribution of vote count
sns.set_style('whitegrid')
plt.figure(figsize=(8,6))
sns.histplot(x=merged_df3['vote_count'], bins=30, kde=False, color='blue')
plt.title('Distribution of Vote Count')
plt.xlabel('Vote Count')
plt.ylabel('Frequency')
plt.savefig('visualization13.png')
```



From the above histogram, I can observe that a majority of the movies have low vote counts since the peak of the histogram is skewed to the right.

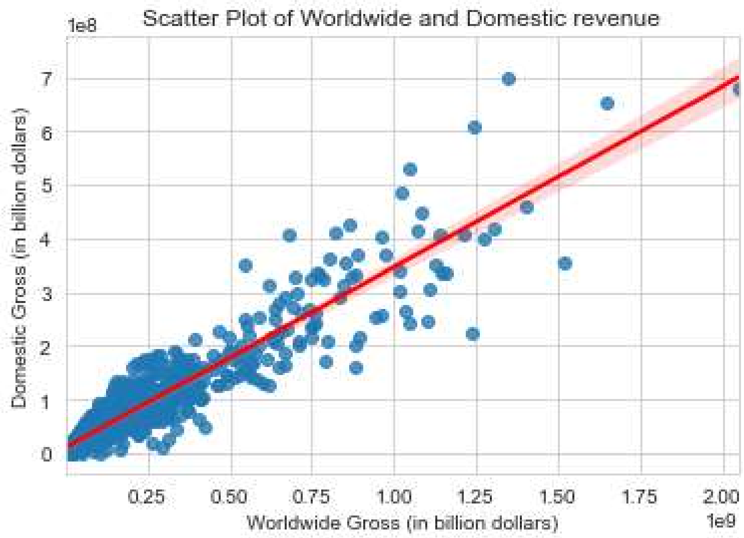
Bivariate Analysis

Here I will be generating plots to describe the relationships between different features/variables.

i) A scatter plot showing the relationship between `worldwide_gross` and `domestic_gross`

In [65]:

```
# Creating a scatter plot
sns.regplot(x='worldwide_gross', y='domestic_gross_2', data=merged_df3, line_kws={'color
plt.xlabel('Worldwide Gross (in billion dollars)')
plt.ylabel('Domestic Gross (in billion dollars)')
plt.title('Scatter Plot of Worldwide and Domestic revenue')
plt.savefig('visualization14.png')
```

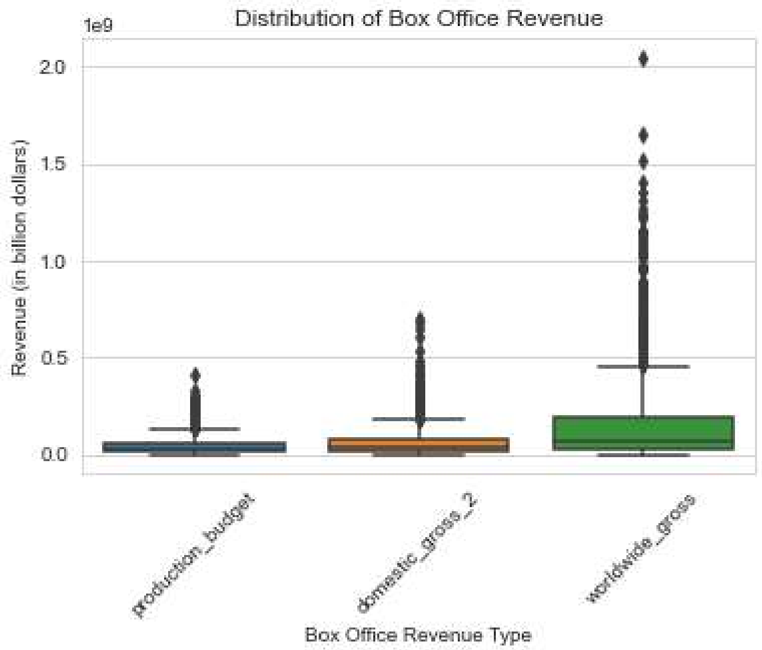


Using the line of best fit from the above scatter plot, I can observe and conclude that there is a positive correlation between `worldwide_gross` and `domestic_gross_2` variables. This means that as the domestic revenue from a movie increases, its worldwide revenue increases too.

ii) A box plot showing the distribution of `production_budget` , `domestic_gross_2` and `worldwide_gross` revenues.

In [66]:

```
# Checking for distribution of revenues using a boxplot
sns.boxplot(data=merged_df2[['production_budget', 'domestic_gross_2', 'worldwide_gross']
plt.title('Distribution of Box Office Revenue')
plt.xticks(rotation=45)
plt.xlabel('Box Office Revenue Type')
plt.ylabel('Revenue (in billion dollars)')
plt.savefig('visualization15.png')
```

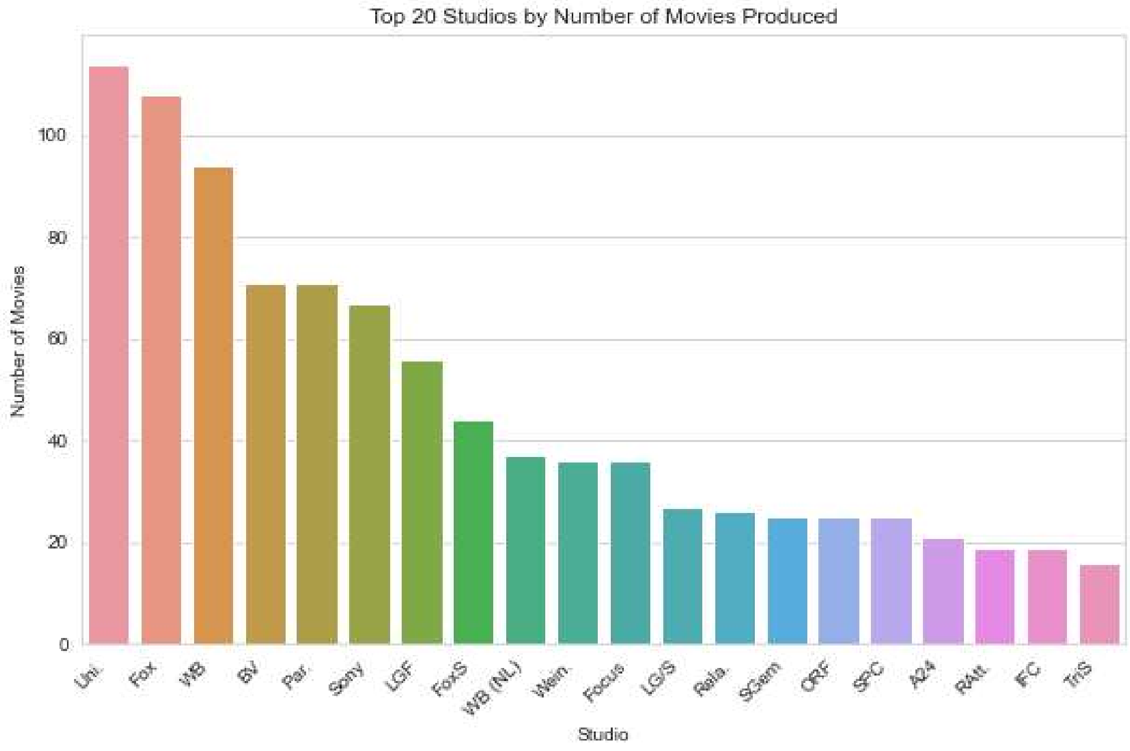


The boxplot above shows the distribution of `production_budget` , `domestic_gross_2` and `worldwide_gross` variables. There's quite a vast number of outliers in all the three variables. But given that this is a Movies dataset, I will keep the outliers, since they are representative of the real world data whereby we can have some Box Office movies performing exceptionally well in the market.

iii) A bar plot showing the Top 20 Studios by the number of movies produced

In [67]:

```
# Group the data by studio and count the number of movies for each studio
grouped_by_studio = merged_df3.groupby('studio')['title'].count().reset_index()
grouped_by_studio = grouped_by_studio.rename(columns={'title': 'count'})

# Sort the data by count in descending order and keep only the top 20 studios
grouped_by_studio = grouped_by_studio.sort_values('count', ascending=False).head(20)

# Create a bar plot to show the number of movies produced by each studio
plt.figure(figsize=(10, 6))
ax = sns.barplot(x='studio', y='count', data=grouped_by_studio)
ax.set(xlabel='Studio', ylabel='Number of Movies', title='Top 20 Studios by Number of Mo
plt.xticks(rotation=45, ha='right')
plt.savefig('visualization16.png')
```



The bar plot above shows the distribution of number of movies produced by studios. From the bar plot, it is clear that Uni. Studio takes the lead in movie production followed by Fox and WB. But it is important to note that producing more movies doesn't necessarily mean that it is the best performing studio. Other factors such as return on investment must be considered too.

Performing Aggregations to answer Business Question no.1

The business question:

- What are the top 4 best performing genres of movies at the box office?

Here I use the `groupby()` built-in method and group the dataset by the `genres` column to answer the question.

Also of importance to note is that some movies are a mixture of different genres. So it begs the question, to either treat each genre ID individually or as a whole? The answer to this question depends on the analysis being performed. If one is analyzing the popularity of each individual genre separately, then they would treat each ID individually. However, if one is analyzing the popularity of movies with a specific combination of genres, then they would treat the list of IDs as a whole.

That said, I will be treating the list of genres IDs as a whole, since a movie can be of one genre or also a combination of different genres.

In addition, you can get the definitions of the various `genre_ids` values at [TheMovieDB `genre_ids`]

To gain a better understanding of the current trends in the movie industry, it may be useful to explore multiple perspectives and consider how they relate to one another. I will compare the top genres across different groupings and look for patterns or similarities that may provide insight into overarching trends.

It's also important to keep in mind that the top genres by one metric may not necessarily be the same as the top genres by another metric. For example, a genre may be highly profitable but not very popular among audiences, or it may receive high ratings but not generate a lot of revenue. Therefore, it's important to consider multiple metrics when analyzing the data to get a more comprehensive understanding of the current trends in the movie industry.

To come up with a final top 4, I will consider the top genres across multiple metrics and determine which genres are consistently ranking high across the board. For instance, I will create plots that show the rankings for each genre by `domestic_gross_2`, `worldwide_gross`, `popularity`, `vote_count`, and `vote_average`, and then compare the results.

i) Group the DataFrame by `genre_ids` and sum `domestic_gross_2`

In [68]:

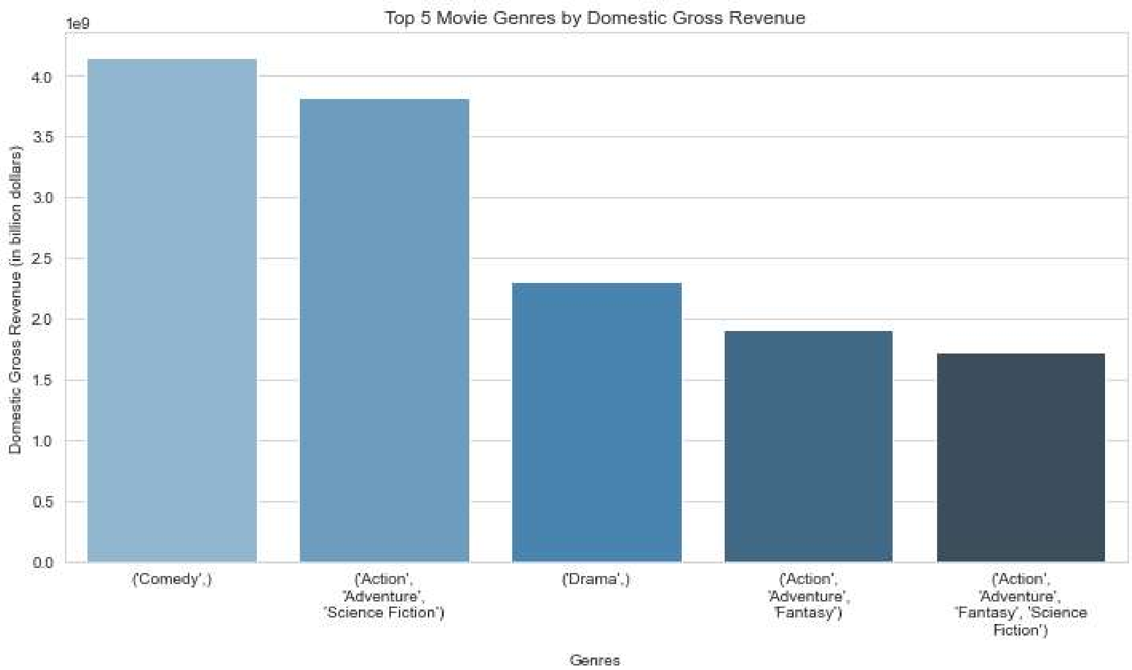
```
# Group the DataFrame by `genre_ids`
# Then sort in Descending order by `domestic_gross_2`
grouped_genre = merged_df3.groupby('genres')['domestic_gross_2'].sum().sort_values(ascer
grouped_genre.head()
```

Out[68]:

```
genres
(Comedy,)                                       4146421980
(Action, Adventure, Science Fiction)            3814586155
(Drama,)                                        2297463879
(Action, Adventure, Fantasy)                    1910474900
(Action, Adventure, Fantasy, Science Fiction)   1717846297
Name: domestic_gross_2, dtype: int64
```

In [69]:

```
# get the top 5 genres
top_genres = grouped_genre.head(5)

# plot the domestic gross revenue for each of the top 5 genres using Seaborn
import textwrap

plt.figure(figsize=(10, 6))
sns.barplot(x=top_genres.index, y=top_genres.values, palette='Blues_d')
plt.title('Top 5 Movie Genres by Domestic Gross Revenue')
plt.xlabel('Genres', labelpad=10)
plt.ylabel('Domestic Gross Revenue (in billion dollars)')
labels = [textwrap.fill(str(label), 20) for label in top_genres.index]
plt.xticks(ha='center', ticks=range(len(labels)), labels=labels)
plt.tight_layout()
plt.savefig('visualization1.png')
```



Using the definitions of the various `genre_ids` values at [TheMovieDB `genre_ids` definitions (https://www.themoviedb.org/talk/5daf6eb0ae36680011d7e6ee)](https://www.themoviedb.org/talk/5daf6eb0ae36680011d7e6ee);

From the above results, the top 5 `genres` sorted by `domestic_gross_2` are:

1. **Comedy**
2. **Action, Adventure & Science Fiction**
3. **Drama**
4. **Action, Adventure & Fantasy**
5. **Action, Adventure, Fantasy & Science Fiction**

ii) Group the DataFrame by `genre_ids` and sum `worldwide_gross`

In [70]:

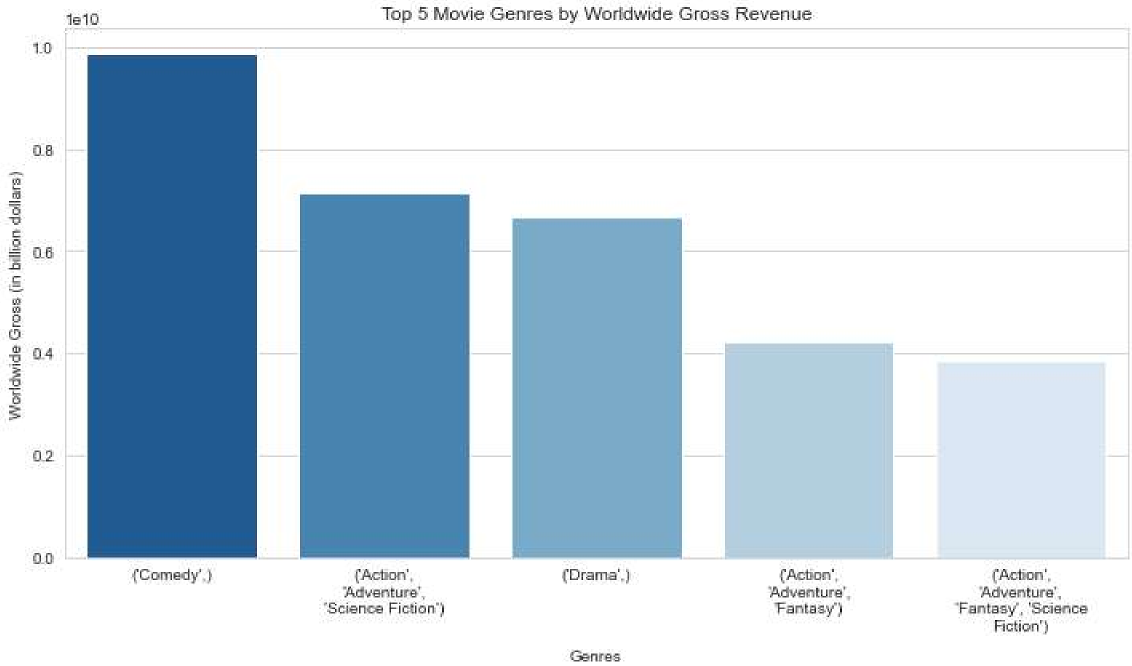
```
# Group the DataFrame by `genre_ids`
# Then sort in Descending order by `worldwide_gross`
grouped_genre2 = merged_df3.groupby('genres')['worldwide_gross'].sum().sort_values(ascer
grouped_genre2.head()
```

Out[70]:

```
genres
(Action, Adventure, Science Fiction)            9871431305
(Comedy,)                                       7158659968
(Action, Adventure, Fantasy)                    6666020354
(Action, Adventure, Fantasy, Science Fiction)   4235307048
(Drama,)                                        3856186439
Name: worldwide_gross, dtype: int64
```

In [71]:

```
# Select the top 5 movie genres with the highest worldwide gross
top_genres2 = grouped_genre2.head(5)

# Plot the worldwide gross for each of the top 5 genres using Seaborn
plt.figure(figsize=(10, 6))
sns.barplot(x=top_genres2.index, y=top_genres2.values, palette='Blues_r')
plt.title('Top 5 Movie Genres by Worldwide Gross Revenue')
plt.xlabel('Genres', labelpad=10)
plt.ylabel("Worldwide Gross (in billion dollars)")
labels = [textwrap.fill(str(label), 20) for label in top_genres.index]
plt.xticks(ha='center', ticks=range(len(labels)), labels=labels)
plt.tight_layout()
plt.savefig('visualization2.png')
```



Using the definitions of the various `genre_ids` values provided at [TheMovieDB `genre_ids` definitions (https://www.themoviedb.org/talk/5daf6eb0ae36680011d7e6ee)](https://www.themoviedb.org/talk/5daf6eb0ae36680011d7e6ee);

From the above results, the top 5 `genres` sorted by `worldwide_gross` are:

1. **Action, Adventure & Science Fiction**
2. **Comedy**
3. **Action, Adventure & Fantasy**
4. **Action, Adventure, Fantasy & Science Fiction**
5. **Drama**

iii) Group the DataFrame by `genre_ids` and mean of `popularity`

In [72]:

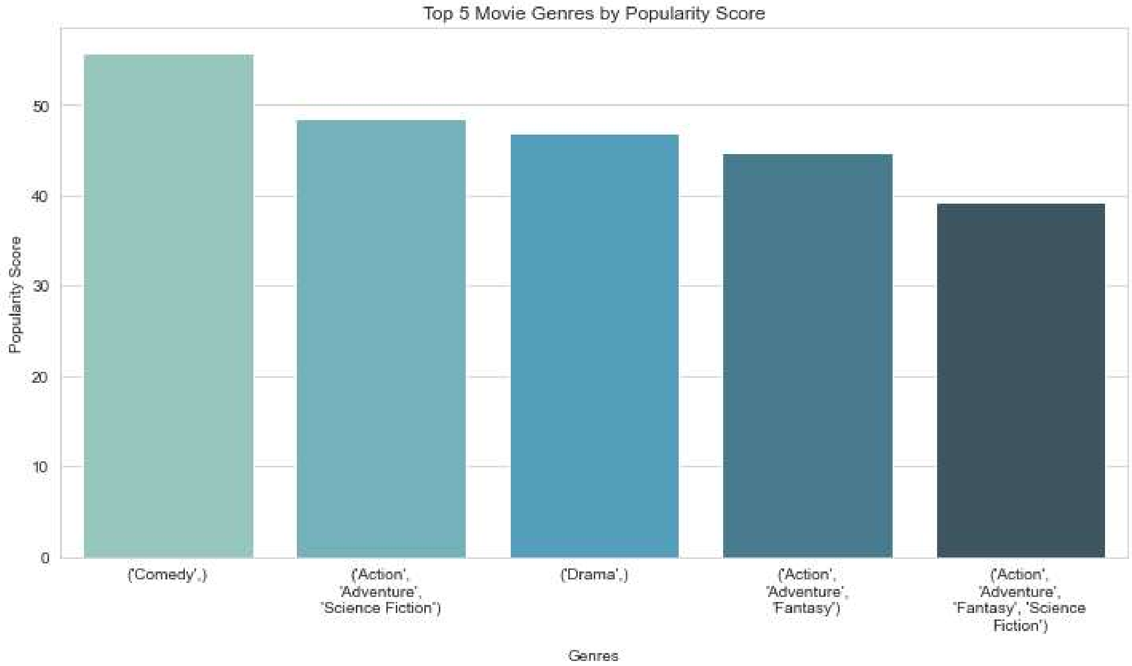
```
# Group the DataFrame by `genre_ids`
# Then sort in Descending order by `popularity`
grouped_genre3 = merged_df3.groupby('genres')['popularity'].mean().sort_values(ascending
grouped_genre3.head()
```

Out[72]:

```
genres
(Adventure, Action, Fantasy)                      55.676
(Adventure,)                                      48.508
(Action, Adventure, Science Fiction, Drama)       46.775
(Action, Adventure, Science Fiction, Comedy)      44.729
(Action, Adventure, Science Fiction, Fantasy)     39.293
Name: popularity, dtype: float64
```

In [73]:

```
# Select the top 5 movie genres with the highest popularity score
top_genres3 = grouped_genre3.head(5)

# Plot the popularity score for each of the top 5 genres using Seaborn
plt.figure(figsize=(10, 6))
sns.barplot(x=top_genres3.index, y=top_genres3.values, palette='GnBu_d')
plt.title('Top 5 Movie Genres by Popularity Score')
plt.xlabel('Genres', labelpad=10)
plt.ylabel('Popularity Score')
labels = [textwrap.fill(str(label), 20) for label in top_genres.index]
plt.xticks(ha='center', ticks=range(len(labels)), labels=labels)
plt.tight_layout()
plt.savefig('visualization3.png')
```



Using the definitions of the various `genre_ids` values provided at [TheMovieDB `genre_ids` definitions (https://www.themoviedb.org/talk/5daf6eb0ae36680011d7e6ee)](https://www.themoviedb.org/talk/5daf6eb0ae36680011d7e6ee);

From the above results, the top 5 `genres` sorted by `popularity` are:

1. **Adventure, Action & Fantasy**
2. **Adventure**
3. **Action, Adventure, Science Fiction & Drama**
4. **Action, Adventure, Science Fiction & Comedy**
5. **Action, Adventure, Science Fiction & Fantasy**

iv) Group the DataFrame by `genre_ids` and sum `vote_count`

In [74]:

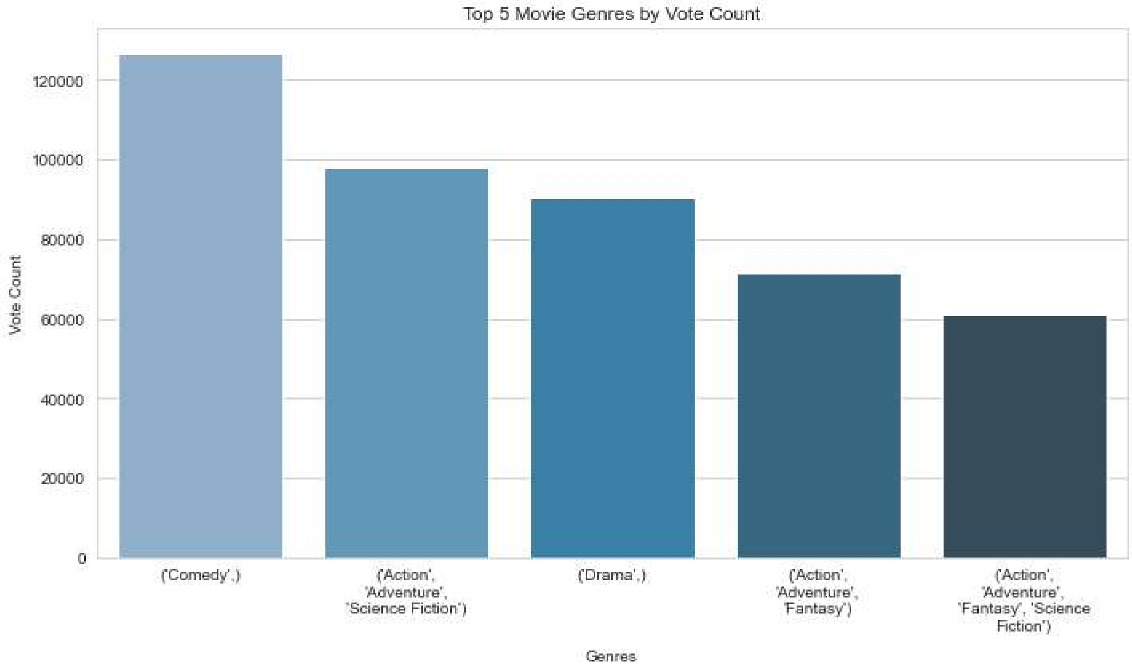
```
# Group the DataFrame by `genre_ids`
# Then sort in Descending order by `vote_count`
grouped_genre4 = merged_df3.groupby('genres')['vote_count'].sum().sort_values(ascending=
grouped_genre4.head()
```

Out[74]:

```
genres
(Action, Adventure, Science Fiction)    126572
(Comedy,)                                98219
(Drama,)                                 90573
(Action, Adventure, Fantasy)             71550
(Action, Science Fiction, Adventure)     60948
Name: vote_count, dtype: int64
```

In [75]:

```
# Select the top 5 movie genres with the highest vote count
top_genres4 = grouped_genre4.head(5)

# Plot the vote count for each of the top 5 genres using Seaborn
plt.figure(figsize=(10, 6))
sns.barplot(x=top_genres4.index, y=top_genres4.values, palette='PuBu_d')
plt.title('Top 5 Movie Genres by Vote Count')
plt.xlabel('Genres', labelpad=10)
plt.ylabel('Vote Count')
labels = [textwrap.fill(str(label), 20) for label in top_genres.index]
plt.xticks(ha='center', ticks=range(len(labels)), labels=labels)
plt.tight_layout()
plt.savefig('visualization4.png')
```



Using the definitions of the various `genre_ids` values provided at [TheMovieDB `genre_ids` definitions (https://www.themoviedb.org/talk/5daf6eb0ae36680011d7e6ee)](https://www.themoviedb.org/talk/5daf6eb0ae36680011d7e6ee);

From the above results, the top 5 `genres` sorted by `vote_count` are:

1. **Action, Adventure & Science Fiction**
2. **Comedy**
3. **Drama**
4. **Action, Adventure & Fantasy**
5. **Action, Science Fiction & Adventure**

v) Group the DataFrame by `genre_ids` mean of `vote_average`

In [76]:

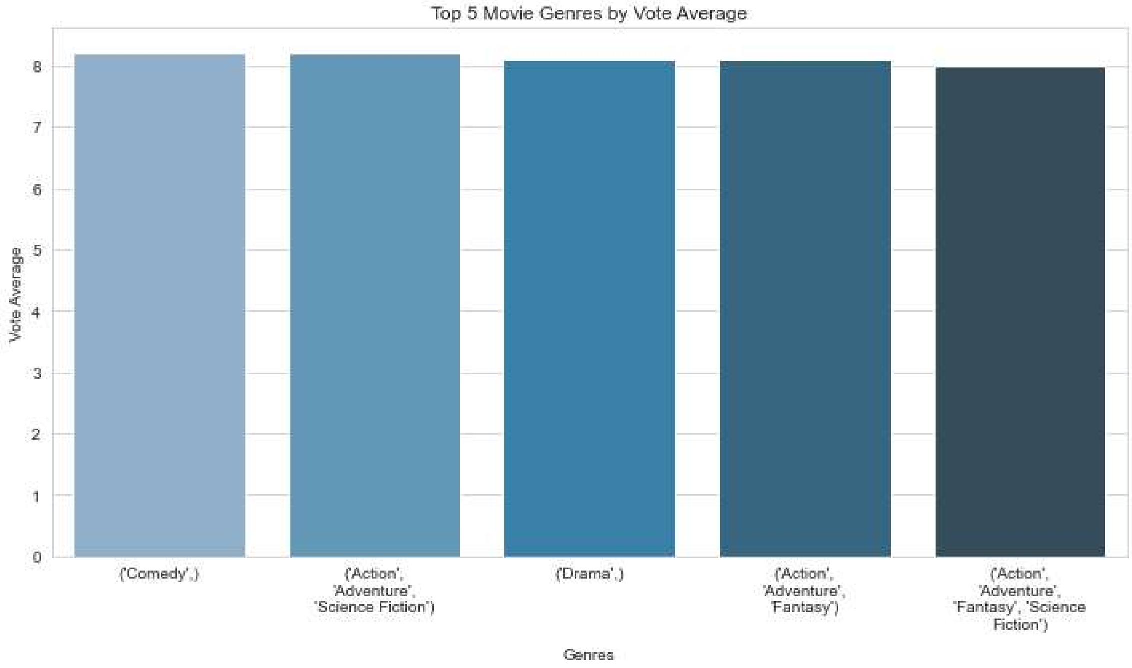
```
# Group the DataFrame by `genre_ids`
# Then sort in Descending order by `vote_average`
grouped_genre5 = merged_df3.groupby('genres')['vote_average'].mean().sort_values(ascendi
grouped_genre5.head()
```

Out[76]:

```
genres
(Drama, Documentary)                                8.2
(Animation, Family, Comedy, Adventure, Fantasy)     8.2
(Drama, History, War)                               8.1
(History, Drama, Thriller, War)                     8.1
(Drama, Comedy, Animation, Family)                  8.0
Name: vote_average, dtype: float64
```

In [77]:

```
# Select the top 5 movie genres with the highest vote count
top_genres5 = grouped_genre5.head(5)

# Plot the vote count for each of the top 5 genres using Seaborn
plt.figure(figsize=(10, 6))
sns.barplot(x=top_genres5.index, y=top_genres5.values, palette='PuBu_d')
plt.title('Top 5 Movie Genres by Vote Average')
plt.xlabel('Genres', labelpad=10)
plt.ylabel('Vote Average')
labels = [textwrap.fill(str(label), 20) for label in top_genres.index]
plt.xticks(ha='center', ticks=range(len(labels)), labels=labels)
plt.tight_layout()
plt.savefig('visualization5.png')
```



Using the definitions of the various `genre_ids` values provided at [TheMovieDB `genre_ids` definitions (https://www.themoviedb.org/talk/5daf6eb0ae36680011d7e6ee)](https://www.themoviedb.org/talk/5daf6eb0ae36680011d7e6ee);

From the above results, the top 5 `genres` sorted by `vote_average` are:

1. **Drama & Documentary**
2. **Animation, Family, Comedy, Adventure & Fantasy**
3. **Drama, History & War**
4. **History, Drama, Thriller & War**
5. **Drama, Comedy, Animation & Family**

Therefore, from these 5 sets of analyses I can conclude that the top 4 best performing types of movies are a combination of:

- **Action, Adventure & Science Fiction** genres
- **Action, Adventure & Fantasy** genres
- **Comedy** genres
- **Drama** genres

Creating a correlation matrix to answer Business Question no.2

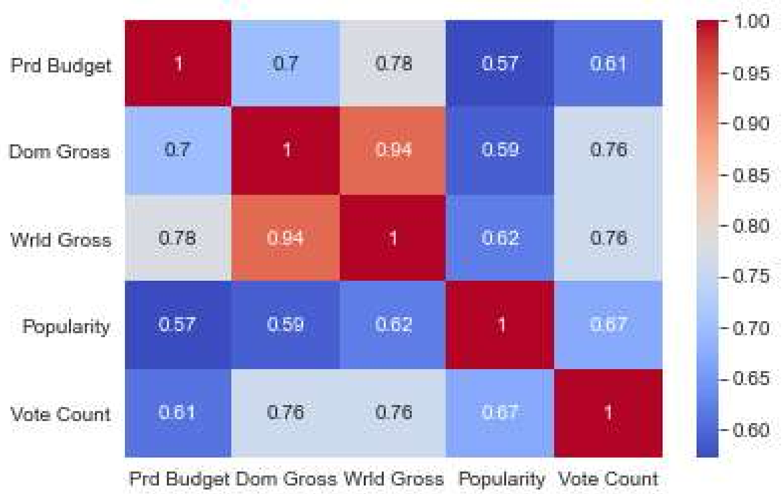
The business question:

- What is the relationship between production budget and the success of a movie both domestically and worldwide?

Below I create a correlation matrix for the features which are indicators of a successful movie in the Box Office.

In [78]:

```
# Performing correlations using seaborn
correlations = merged_df3[['production_budget', 'domestic_gross_2', 'worldwide_gross', '
correlations.columns = ['Prd Budget', 'Dom Gross', 'Wrld Gross', 'Popularity', 'Vote Cou
correlations.index = ['Prd Budget', 'Dom Gross', 'Wrld Gross', 'Popularity', 'Vote Count
sns.heatmap(correlations, annot=True, cmap='coolwarm')

plt.savefig('visualization6.png')
```



- The correlation coefficient between `production_budget` and `worldwide_gross` is **0.78**; and between `production_budget` and `domestic_gross_2` is **0.7**. Both figures indicate a strong positive correlation between the variables. This means that as `production_budget` increases, `worldwide_gross` and `domestic_gross_2` tend to increase as well. Therefore, the production budget allocated to a movie production may be a good indicator of its success or failure in the Box Office.

- The correlation coefficient between `domestic_gross_2` and `vote_count` is **0.76**; and between `domestic_gross_2` and `worldwide_gross` is **0.94**. Both figures indicate a strong positive correlation between the variables. This means that as a movie that is successful locally is highly likely to be successful internationally/worldwide as the relationship between the two variables is relatively strong.

- The correlation between `worldwide_gross` and `popularity` is **0.62**. This indicates a moderate positive correlation. This also suggests that as a movie becomes more successful internationally, so does its popularity among the audiences.

- The correlation coefficient between `popularity` and `vote_count` is **0.67**, which indicates a moderate positive correlation between the two variables. This suggests that as a movie becomes more popular, it tends to have a higher number of votes.

- The correlation coefficient between `vote_count` and `worldwide_gross` is **0.76**, which indicates a strong positive correlation between these two variables. This also suggests that as a movie becomes more successful internationally, it tends to have a higher number of votes

Therefore, based on these correlation coefficients, I can conclude that the production budget allocated to a movie is a good indicator of its success or lack thereof, both domestically and internationally.

Performing Aggregations and Engineering a new feature `market_share` to answer Business Question no.3

The business question:

- What is the competitive landscape of the movie industry in terms of market share?

In this section I introduce a new feature in my dataset, that is, `market_share` (based on the studios' domestic revenues). I find this to be an important aspect because as Microsoft dives into the movie industry, it's imperative they understand who they are going to be competing against in terms of capturing the audience's attention. The `market_share` is calculated as the sum of a studio's domestic revenue divided by the total domestic revenue of all the studios multiplied by 100%. Finally, I will create a bar plot using Seaborn to illustrate the findings.

In [79]:

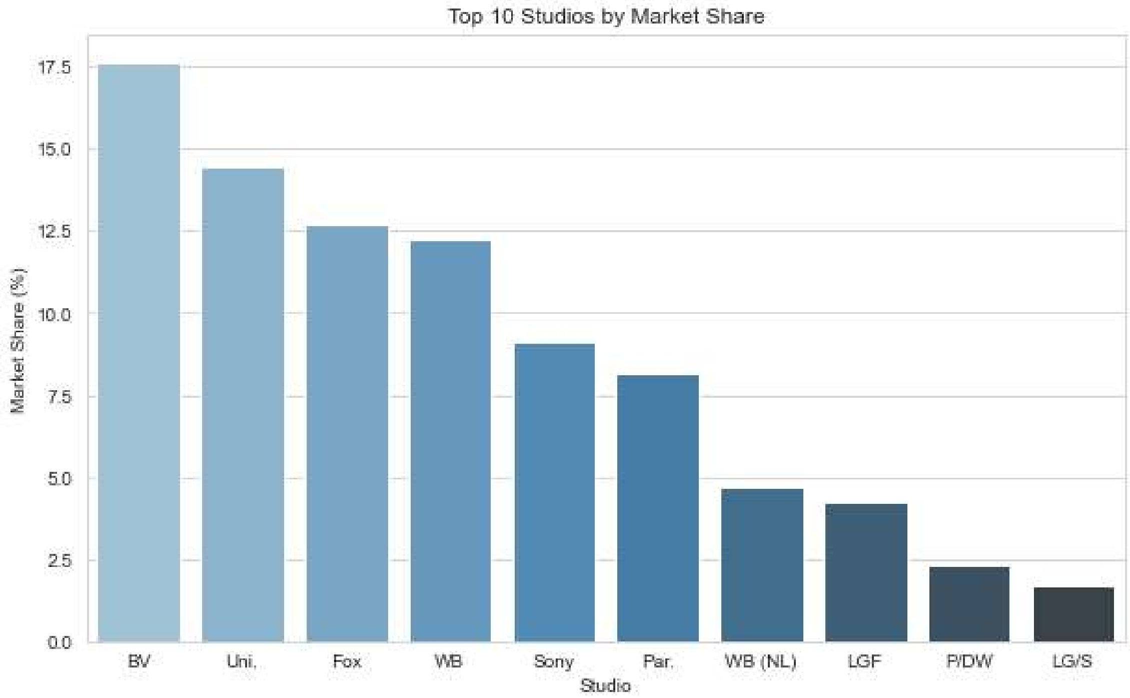
```
# Group by studio and calculate various metrics
grouped = merged_df3.groupby('studio').agg({
    'domestic_gross_2': ['sum', 'count', 'mean'],
    'worldwide_gross': ['sum', 'count', 'mean'],
    'vote_average': 'mean',
    'popularity': 'mean',
    'vote_count': 'sum'})

# Flatten column names
grouped.columns = ['_'.join(col).strip() for col in grouped.columns.values]

# Sort by `domestic_gross_2_sum`
sorted_grouped = grouped.sort_values(by='domestic_gross_2_sum', ascending=False)

# Calculate market share
sorted_grouped['market_share'] = (sorted_grouped['domestic_gross_2_sum'] / sorted_groupe

# Display the top 10 studios by `domestic_gross_2_sum`
top_10 = sorted_grouped[['domestic_gross_2_sum', 'worldwide_gross_sum', 'vote_count_sum'
                         'popularity_mean', 'market_share']].reset_index().head(10)
top_10
```

Out[79]:

	studio	domestic_gross_2_sum	worldwide_gross_sum	vote_count_sum	vote_average_mea
0	BV	12826174501	33092279960	367266	6.8845
1	Uni.	10522372515	26942069716	310000	6.1938
2	Fox	9223170866	26359964257	348085	6.3592
3	WB	8907412947	21807122002	332751	6.4180
4	Sony	6654419301	16834675820	194687	6.1417
5	Par.	5953142188	14277819179	228511	6.3014
6	WB (NL)	3417630150	8540864247	111818	6.3243
7	LGF	3103430608	6643134795	138665	6.3571
8	P/DW	1682914686	5078027601	33781	6.5200
9	LG/S	1211412751	3177476448	85477	6.4111

In [80]:

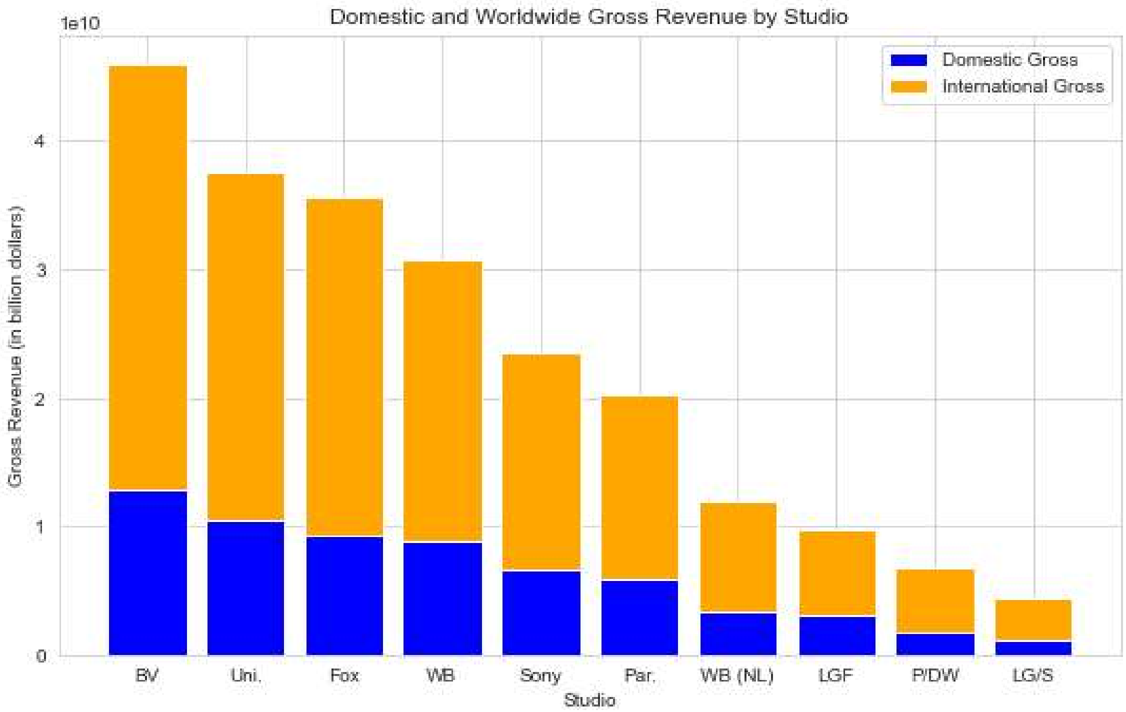
```
# Creating a barplot using Seaborn to visualize the above findings
top_10 = sorted_grouped[['domestic_gross_2_sum', 'worldwide_gross_sum', 'vote_count_sum'
                         'popularity_mean', 'market_share']].reset_index().head(10)

sns.set_style('whitegrid')
fig, ax = plt.subplots(figsize=(10, 6))
sns.barplot(x='studio', y='market_share', data=top_10, ax=ax, palette='Blues_d')
ax.set_xlabel('Studio')
ax.set_ylabel('Market Share (%)')
ax.set_title('Top 10 Studios by Market Share')
plt.savefig('visualization7.png')
```



Based on the above analysis, BV Studio has the highest domestic and worldwide gross revenue, the highest total vote count, and the highest mean popularity. BV Studio has a market share of 17.6%, followed by Uni. with 14.5% and Fox with 12.7%. This suggests that BV Studio is the clear leader in many metrics. This provides insight into the competitive landscape of the movie industry based on the chosen metrics.

In [81]:

```
# Create a stacked bar chart of domestic and worldwide gross for each studio
# Subset the data to only include the top 10 studios by market share
top_10_ = sorted_grouped.sort_values('market_share', ascending=False).reset_index().head

fig, ax = plt.subplots(figsize=(10, 6))
ax.bar(top_10_['studio'], top_10_['domestic_gross_2_sum'], label='Domestic Gross', color
ax.bar(top_10_['studio'], top_10_['worldwide_gross_sum'], bottom=top_10_['domestic_gross
       label='International Gross', color='orange')
ax.set_xlabel('Studio')
ax.set_ylabel('Gross Revenue (in billion dollars)')
ax.set_title('Domestic and Worldwide Gross Revenue by Studio')
ax.legend()
plt.savefig('visualization8.png')
```



The stacked bar plot shows the domestic and worldwide gross revenue of the top 10 movie studios, broken down by region,i.e.Domestic revenue and Worldwide revenue. Each bar represents a studio, and is divided into two sections: blue for domestic gross revenue, and orange for worldwide gross revenue.

The height of each bar represents the total gross revenue for that studio, and the width of each section represents the proportion of that revenue coming from the domestic or worldwide market. For example, the tallest bar represents BV Studio, and we can see that the majority of its revenue comes from the international market.

Overall, this plot helps us visualize the revenue breakdown of the top movie studios, and can provide insights into the relative importance of different regions for these studios. This is also an indicator to Microsoft's new movie studio, in that they can anticipate more of their revenue generated from the international market, as compared to the domestic market.

Performing Aggregations to answer Business Question no.4

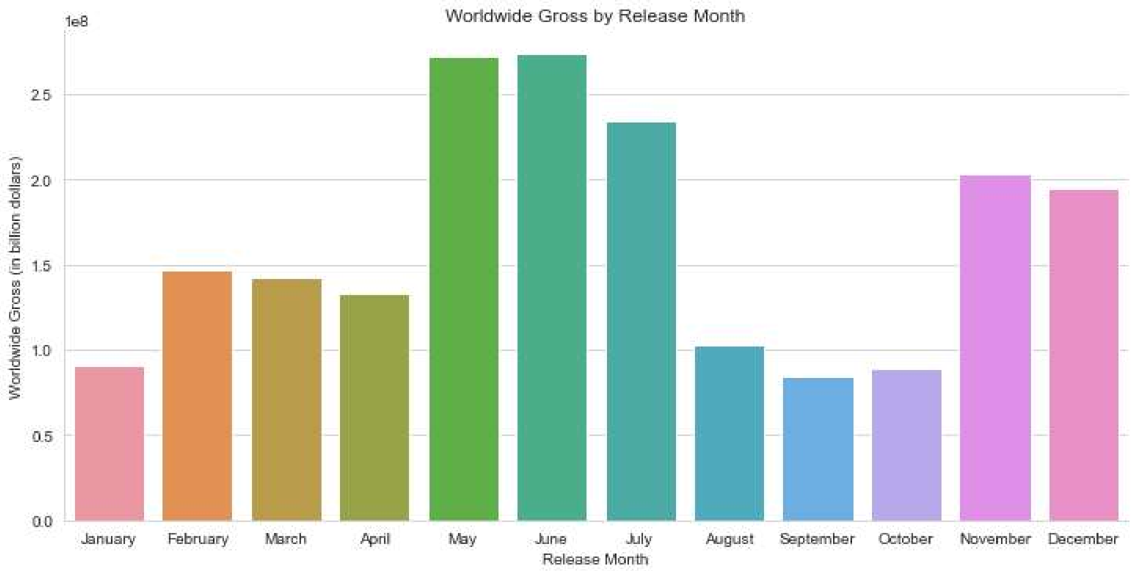
The business question:

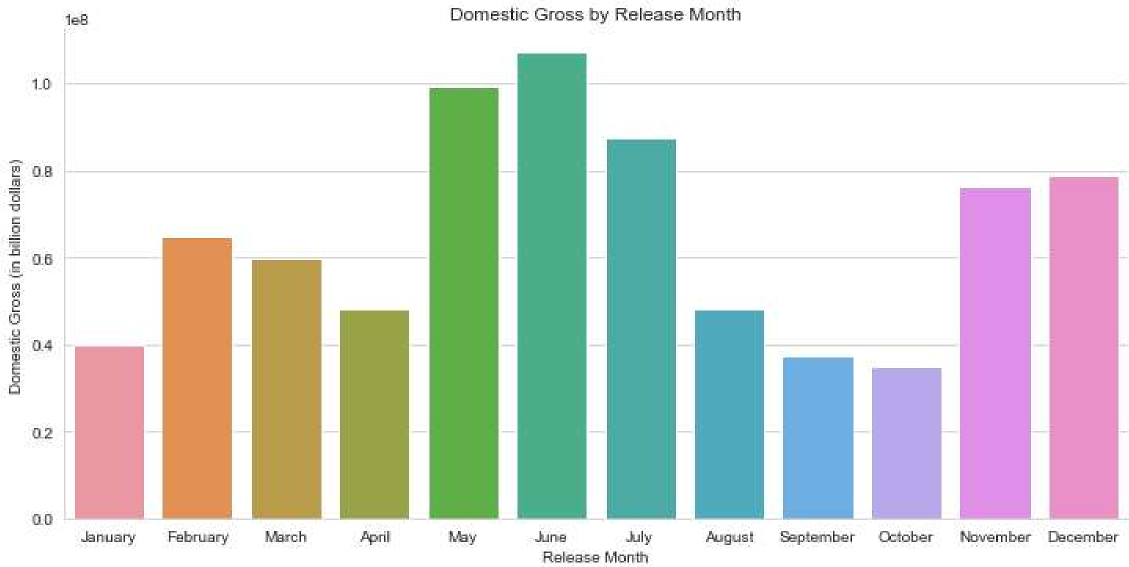
- How does the release time of a movie contribute to its success?

Here I will be using the `worldwide_gross` and `domestic_gross_2` variables as my units of measurement to depict the revenues generated in the different months and hence determine when it is suitable to release a movie, thereby increasing its chances of success.

In [82]:

```
# Convert the 'release_date_2' column to datetime format
merged_df3['release_date_2'] = pd.to_datetime(merged_df3['release_date_2'])

# Extract the release month from the release date
merged_df3['release_month'] = merged_df3['release_date_2'].dt.month

# Calculate the average worldwide gross by release month
avg_world_gross = merged_df3.groupby('release_month')['worldwide_gross'].mean().reset_ir

# Calculate the average domestic gross by release month
avg_dom_gross = merged_df3.groupby('release_month')['domestic_gross_2'].mean().reset_inc

# Convert month numbers to month names
month_names = [calendar.month_name[i] for i in range(1, 13)]

# Worldwide gross plot
worldwide_plot = sns.catplot(x='release_month', y='worldwide_gross', kind='bar', data=av
worldwide_plot.set(title='Worldwide Gross by Release Month', xlabel='Release Month',
                   ylabel='Worldwide Gross (in billion dollars)')
# Setting xticks with month names and align them with the center of the bars
plt.xticks(horizontalalignment='center', fontsize=10)
worldwide_plot.set_xticklabels(month_names)
plt.savefig('visualization9.png')

# Domestic gross plot
domestic_plot = sns.catplot(x='release_month', y='domestic_gross_2', kind='bar', data=av
domestic_plot.set(title='Domestic Gross by Release Month', xlabel='Release Month',
                  ylabel='Domestic Gross (in billion dollars)')
# Setting xticks with month names and align them with the center of the bars
plt.xticks(horizontalalignment='center', fontsize=10)
domestic_plot.set_xticklabels(month_names)
plt.savefig('visualization10.png')

# Adjust the position of the plots to prevent overlapping xtick labels
plt.subplots_adjust(wspace=0.5)
```





r the movies in

The x-axis shows the months of the year, and the y-axis shows the average gross in billion dollars. Each bar represents the average gross for a particular month.

The "Worldwide Gross by Release Month" plot shows that the months of May, June and July have the highest average worldwide gross, while the months of September and October have the lowest.

The "Domestic Gross by Release Month" plot show a similar trend, with May, June and July having the highest average domestic gross, and September and October having the lowest.

Overall, these plots suggest that releasing a movie in May, June or July may lead to higher gross revenue, both domestically and worldwide, while releasing a movie in September or October may result in lower gross revenue.

Conclusion

This analysis leads to four **recommendations** that will enable Microsoft get into the movie industry with a resounding success for the movies that will be produced/created.

1. Based on the findings of the top 4 best performing types of movies in the Box Office, Microsoft should consider producing movies around the genre combinations of:

   - **Action, Adventure & Science Fiction**
   - **Action, Adventure & Fantasy**
   - **Comedy**
   - **Drama**

   Also, they can play around the genres creatively and come up with something a bit unique, for example, a combination of **Action, Comedy & Drama** or even **Science Fiction, Adventure & Comedy** to see the response and reaction from the movie lovers.

2. Based on the findings of strong positive correlation between production budget and domestic gross, and production budget and worldwide gross, for the genres stated above in the first recommendation, the Head of Microsoft's new movie studio should liaise with the finance department and ensure that sufficient budgetary allocation is made to film production. This would enable the several aspects involved in film production to be taken care of sufficiently, for instance;

   - Production equipment: Getting the latest equipment and editing tools is key to producing high quality video content.

- Visuals and Sound: The visual elements of a movie are critical in creating an immersive and engaging experience for viewers. This includes everything from the cinematography and special effects to the costumes and set design. A good soundtrack can help set the tone of a film and enhance the emotional impact of key scenes.
- Marketing: Finally, filmmakers will need to consider the marketing and distribution of the new movie. They will need to think about how they will promote the movie and ensure that it is being distributed in a way that will reach their intended audience. Effective marketing will certainly increase the movie's popularity, which in turn may mean success for the new movie.

Therefore, the investment in a movie's production really influences its success in the Box Office.

3. Based on the findings of how competitive the movie industry is in terms of market share, Microsoft will need to differentiate itself in order to stand out, for example;
    - Microsoft's new movie studio could focus on producing high-quality movies with unique and compelling storylines with diverse and inclusive casts.
    - Partnering with well-known and respected directors and actors.
    - Leveraging innovative marketing and distribution strategies to reach wider audiences.
    - Additionally, they could explore new combinations of the popular genres as stated in the first recommendation.

4. Based on the findings of the best months to release a movie being May, June and July, the Microsoft new movie studio should consider releasing movies around this time. There could be various factors that contribute to the high revenues in May, June and July. One possibility is that these months fall within the summer blockbuster season, which typically runs from May to August, where studios release highly anticipated movies that are expected to perform well at the box office, as well as audience availability. Therefore, if Microsoft takes advantage of this period, the movies released are likely to yield higher gross revenues.

Next Steps

Further analyses could yield additional insights to further improve decision-making for the movie genres to produce in the new Microsoft studio:

- A further analysis into the directors/actors in the film industry. This analysis could provide insights on whom to hire during production of movies. Involving highly rated/successful directors & actors in production increases the probability of success for a movie.

- A further analysis into the reviews made my the public by conducting sentiment analysis on social media and other online platforms to gauge the public's reaction to movie trailers, posters, and other promotional materials.This analysis can help Microsoft studio identify potential issues with marketing campaigns or aspects of the movie that may not be well-received by the audience and hence make adjustments to its marketing and production strategies in real-time, potentially increasing the chances of success for its movies.