Final Project Submission

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* Student pace: full time

* Scheduled project review date/time:

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* Blog post URL:

Project Overview

Following the creation of movie studio, we have been tasked by Microsoft, who have no idea about making films, to identify what makes a film perform well at the box office. After identifying return on investment (RoI) as the primary metric of success, we narrowed down the datasets provided to the top 200 most grossing movies worldwide then calculated the RoI for each. After plotting several scatter and bar plots comparing runtime, production budget, gross revenue, release date, genre, directors,

Business Problem

Microsoft sees all the big companies creating original video content and they want to get in on the fun. They have decided to create a new movie studio, but they don't know anything about creating movies. You are charged with exploring what types of films are currently doing the best at the box office. You must then translate those findings into actionable

In [72]:
```
#importing pandas for data analysis.
import pandas as pd
#importing numpy for numerical analysis.
import numpy as np
#importing seaborn and matplotlib for data visualization.
import seaborn as sns
import matplotlib.pyplot as plt
#importing sqlite3 for basement management.
import sqlite3
```

THE IMDB DATA SET.

DATA UNDERSTANDING.

In [73]:
```
imdb = pd.read_sql("""SELECT * FROM movie_basics; """, conn)
imdb.head(10)
```

Out[73]:

	movie_id	primary_title	original_title	start_year	runtime_minutes	genres
0	tt0063540	Sunghursh	Sunghursh	2013	175.0	Action,Crime,Drama
1	tt0066787	One Day Before the Rainy Season	Ashad Ka Ek Din	2019	114.0	Biography,Drama
2	tt0069049	The Other Side of the Wind	The Other Side of the Wind	2018	122.0	Drama
3	tt0069204	Sabse Bada Sukh	Sabse Bada Sukh	2018	NaN	Comedy,Drama
4	tt0100275	The Wandering Soap Opera	La Telenovela Errante	2017	80.0	Comedy,Drama,Fantasy
5	tt0111414	A Thin Life	A Thin Life	2018	75.0	Comedy
6	tt0112502	Bigfoot	Bigfoot	2017	NaN	Horror,Thriller
7	tt0137204	Joe Finds Grace	Joe Finds Grace	2017	83.0	Adventure,Animation,Comedy
8	tt0139613	O Silêncio	O Silêncio	2012	NaN	Documentary,History
9	tt0144449	Nema aviona za Zagreb	Nema aviona za Zagreb	2012	82.0	Biography

In [74]:
```
#Importing the data set and previewing.
imdb = pd.read_sql("""SELECT * FROM movie_ratings; """, conn)
imdb.head(10)
```

Out[74]:

	movie_id	averagerating	numvotes
0	tt10356526	8.3	31
1	tt10384606	8.9	559
2	tt1042974	6.4	20
3	tt1043726	4.2	50352
4	tt1060240	6.5	21
5	tt1069246	6.2	326
6	tt1094666	7.0	1613
7	tt1130982	6.4	571
8	tt1156528	7.2	265
9	tt1161457	4.2	148

In [75]:
```
imdb = pd.read_sql(""" SELECT *
FROM movie_basics
JOIN movie_ratings
USING(movie_id);
""",conn).head(10)
```

In [76]:
```
#getting data summary
imdb.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10 entries, 0 to 9
Data columns (total 8 columns):
 #   Column           Non-Null Count  Dtype  
---  ------           --------------  -----  
 0   movie_id         10 non-null     object 
 1   primary_title    10 non-null     object 
 2   original_title   10 non-null     object 
 3   start_year       10 non-null     int64  
 4   runtime_minutes  8 non-null      float64
 5   genres           10 non-null     object 
 6   averagerating    10 non-null     float64
 7   numvotes         10 non-null     int64  
dtypes: float64(2), int64(2), object(4)
memory usage: 768.0+ bytes
```

This is a pandas DataFrame object that has 73856 rows and 3 columns. There are no missing values in any of the columns, as indicated by the non-null count. The memory usage of this DataFrame is 1.7+ MB.

In [77]:
```
#getting statistical summary
imdb.describe()
```

Out[77]:

	start_year	runtime_minutes	averagerating	numvotes
count	10.000000	8.000000	10.000000	10.000000
mean	2015.200000	123.750000	6.490000	563.200000
std	3.392803	38.130415	1.260026	1395.785466
min	2010.000000	80.000000	4.100000	13.000000
25%	2013.000000	95.750000	6.200000	45.500000
50%	2017.000000	118.000000	6.850000	70.500000
75%	2017.750000	145.750000	7.150000	227.000000
max	2019.000000	180.000000	8.100000	4517.000000

The summary statistics provide information about the distribution of four columns - start_year, runtime_minutes, averagerating, and numvotes in a DataFrame.

For the start_year column, we can see that there are 10 entries and the earliest start year is 2010, while the latest is 2019. This tells us the range of years when the movies were released.

The runtime_minutes column has only 8 entries, indicating that two movies have missing values. The average runtime across all movies is 123.75 minutes, with a standard deviation of 38.13 minutes. The minimum and maximum values of the runtime column show the shortest and longest movies in the dataset.

For the averagerating column, we can see that there are 10 entries and the average rating across all movies is 6.49, with a standard deviation of 1.26. The minimum and maximum values of the column show the lowest and highest ratings in the dataset.

For the numvotes column, we can see that there are 10 entries, and the average number of votes across all movies is 563.2, with a standard deviation of 1395.79. The minimum and maximum values of the column show the least and most voted movies in the dataset.

DATA CLEANING

In [78]:
```
#checking for missing values
imdb.isnull().sum()
```

Out[78]:
```
movie_id           0
primary_title      0
original_title     0
start_year         0
runtime_minutes    2
genres             0
averagerating      0
numvotes           0
dtype: int64
```

The runtime_minutes column contains two null values. All the other columns do not have any null values.

In [79]:
```
#finding dublicates
imdb.duplicated().sum()
```

Out[79]:
```
0
```

This data does not contain any dupkicated values.

In [80]:
```
#replacing genres missing values with the mode since this is a categorical data
imdb['genres'].mode()[0]
imdb['genres'].value_counts()
```

Out[80]:
```
Drama                        2
Action,Crime,Drama           1
Biography,Drama              1
Comedy,Drama                 1
Comedy,Drama,Fantasy         1
Horror,Thriller              1
Adventure,Animation,Comedy   1
History                      1
Documentary                  1
Name: genres, dtype: int64
```

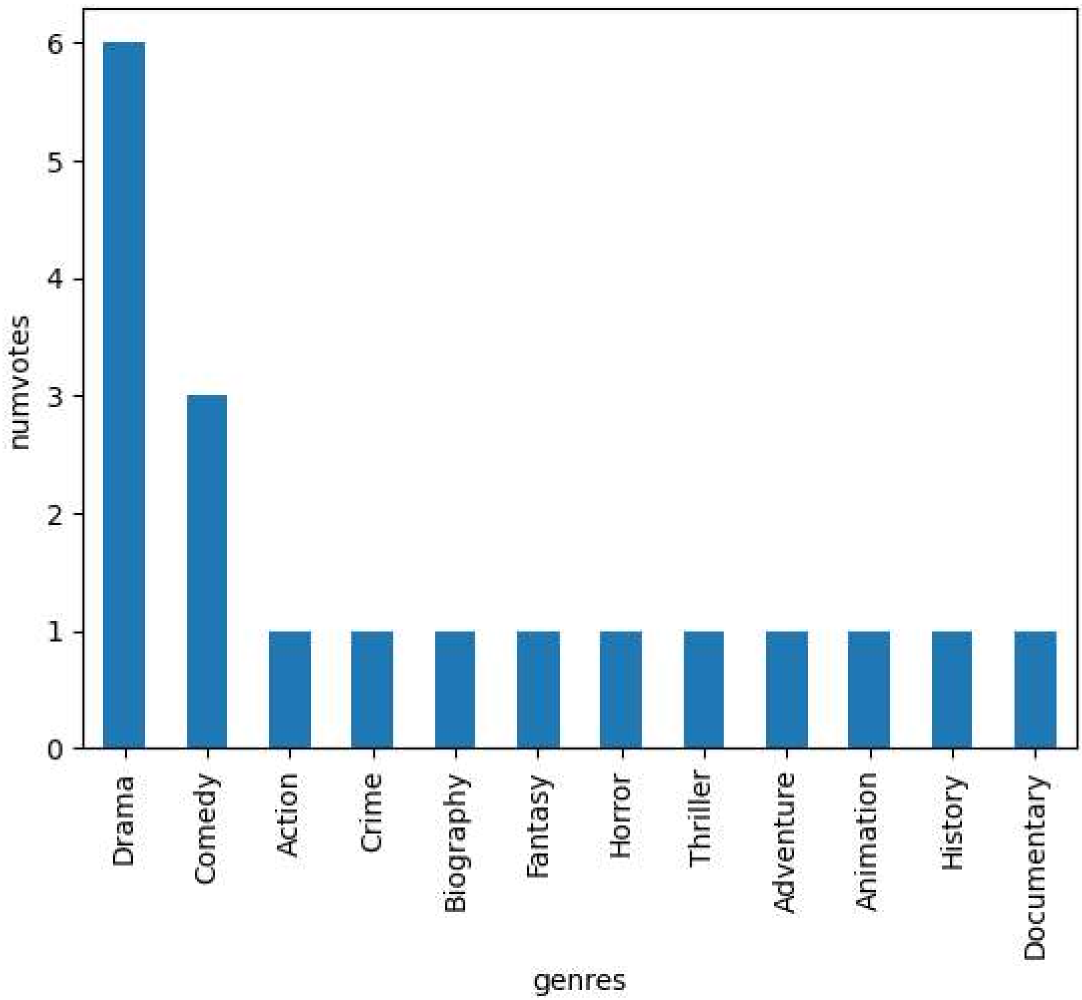
In [81]:
```
#filling runtime_minutes null values with mode

imdb_mode = imdb['runtime_minutes'].mode()[0]
imdb['runtime_minutes'].fillna('imdb_mode', inplace = True)

imdb.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10 entries, 0 to 9
Data columns (total 8 columns):
 #   Column           Non-Null Count  Dtype  
---  ------           --------------  -----  
 0   movie_id         10 non-null     object 
 1   primary_title    10 non-null     object 
 2   original_title   10 non-null     object 
 3   start_year       10 non-null     int64  
 4   runtime_minutes  10 non-null     object 
 5   genres           10 non-null     object 
 6   averagerating    10 non-null     float64
 7   numvotes         10 non-null     int64  
dtypes: float64(1), int64(2), object(5)
memory usage: 768.0+ bytes
```

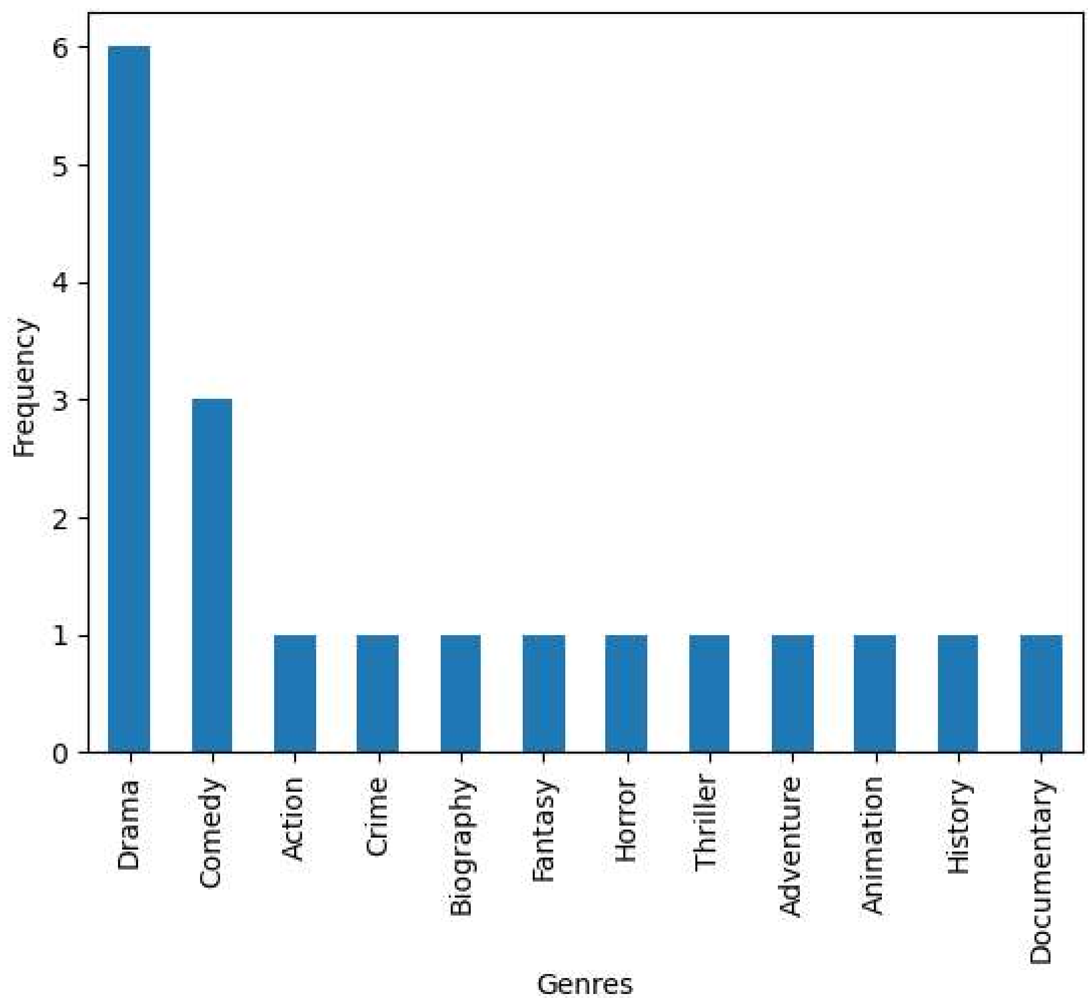
In [82]:
```
#cheking now if the data is clean

imdb.isnull().sum()
```

Out[82]:
```
movie_id           0
primary_title      0
original_title     0
start_year         0
runtime_minutes    0
genres             0
averagerating      0
numvotes           0
dtype: int64
```

In [89]:
```
#Creating a histogram showing the frequency of each genre in the genres column

genres = imdb.genres.str.split(',', expand=True).stack().reset_index(drop=True
genres.value_counts().plot(kind='bar')
plt.ylabel('numvotes')
plt.xlabel('genres')
plt.show()
```

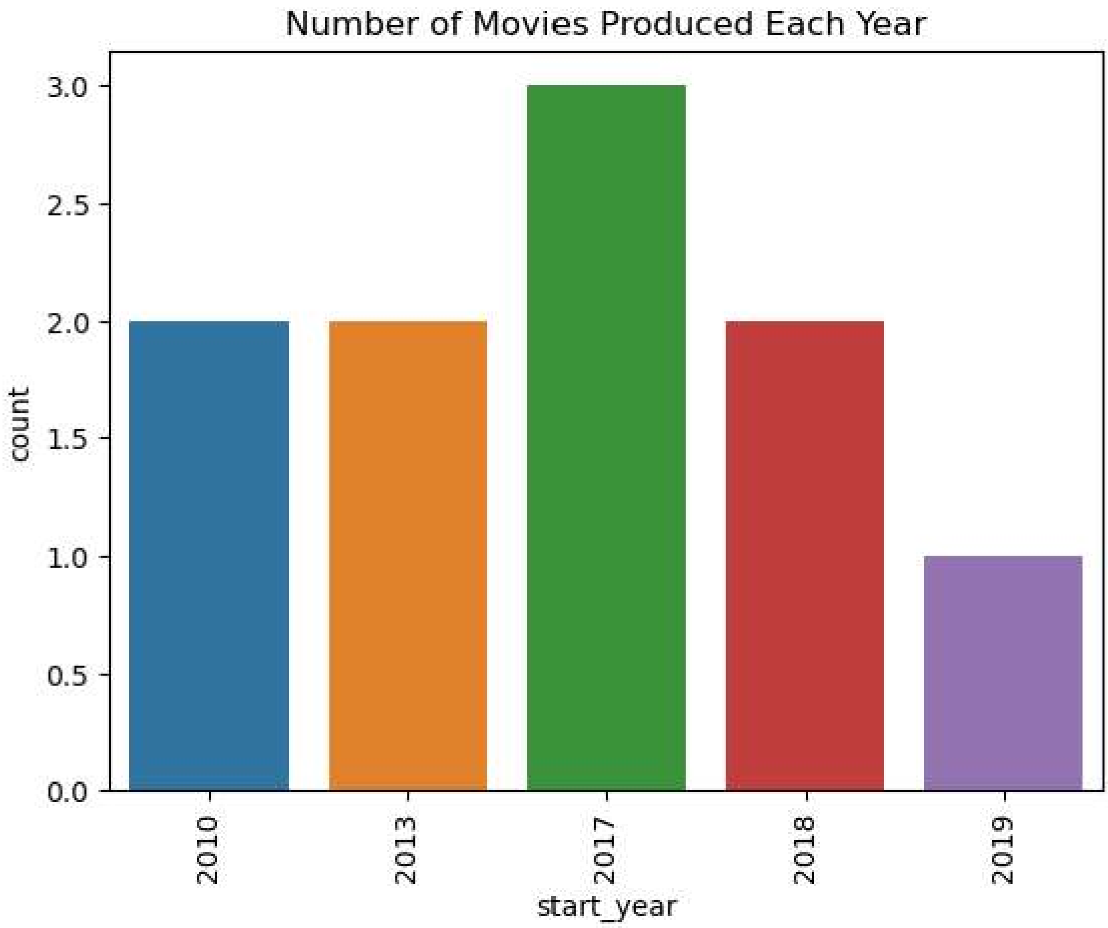


In [87]:
```
# Create a histogram showing the frequency of each genre in the genres column (

genres = imdb.genres.str.split(',', expand=True).stack().reset_index(drop=True
genres.value_counts().plot(kind='bar')
plt.xlabel('Genres')
plt.ylabel('Frequency')
plt.show()
```



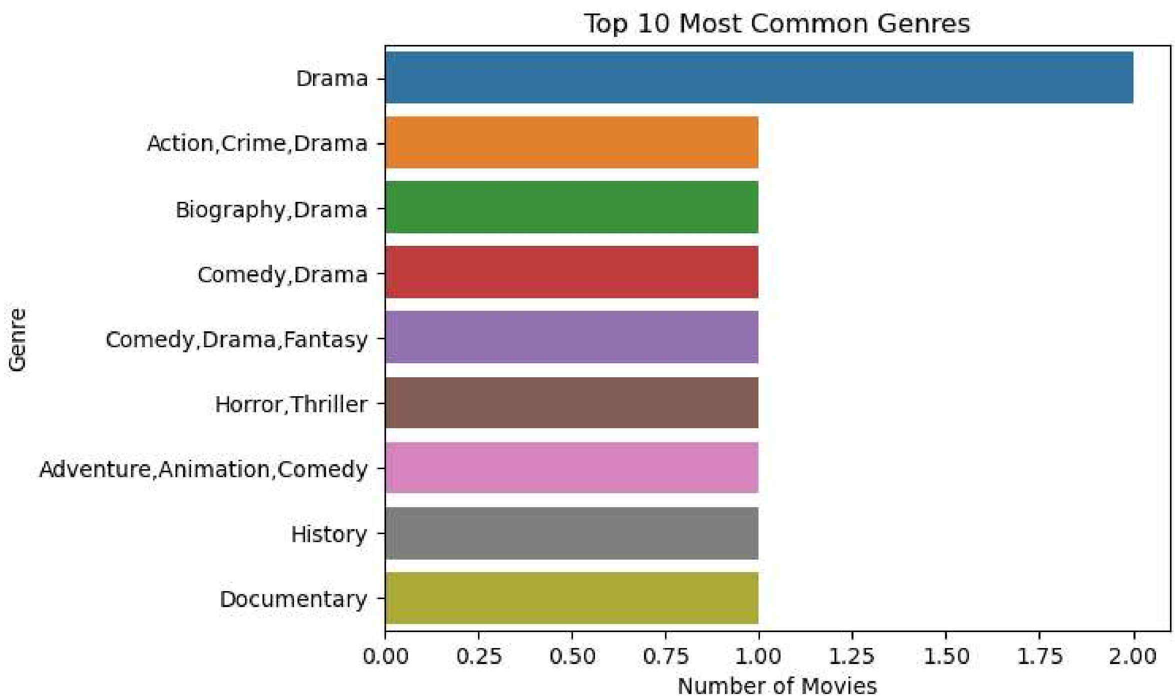
Drama movies had the highest frequency followed by comedy and action at third.

In [86]:
```
#Plotting number of movies produced per year.
sns.countplot(data=imdb, x='start_year')
plt.xticks(rotation=90)
plt.title('Number of Movies Produced Each Year')
plt.show()
```



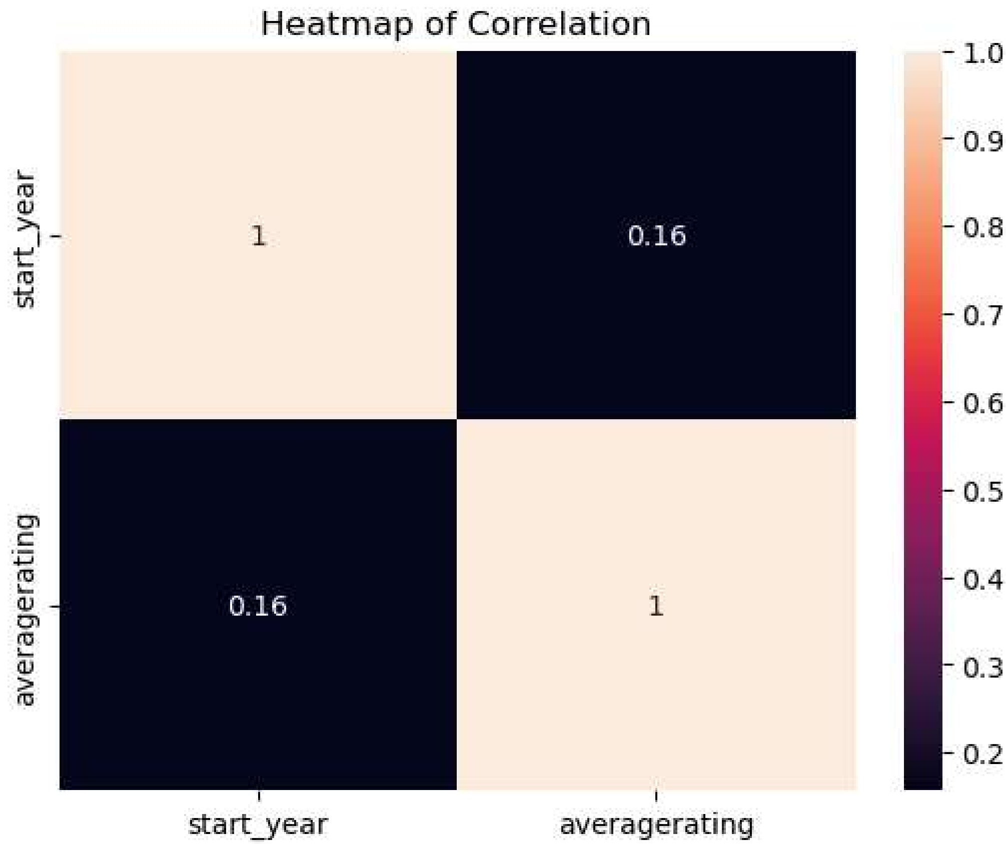
2017 had the highest number of movie productions.

In [85]:
```
#Plotting top ten most common genres.
top_genres = imdb['genres'].value_counts().head(10)

sns.barplot(x=top_genres.values, y=top_genres.index)
plt.xlabel('Number of Movies')
plt.ylabel('Genre')
plt.title('Top 10 Most Common Genres')
plt.show()
```



The above graph ndicates that drama was th most common genre.

In [84]:
```
#Plotting a heat map of correlation
corr_matrix = imdb[['start_year', 'runtime_minutes', 'averagerating']].corr()
sns.heatmap(corr_matrix, annot=True)
plt.title('Heatmap of Correlation')
plt.show()
```



FINDINGS.

Drama got the highest number of voters followed by Documentary, Comedy, Thriller, Horror, Action, Romance, Crime, Adventure, Biography, Family, Mystery, History, Sci-Fi, Fantacy, Music, Animation, Sport, War, Musical, News, Western, Reality-TV, Adult, Game-Show and Short in that order.

RECOMMENDATIONS.

Highly recommend Microsoft to produce a lot of Drama genres, Documentary and Comedy since these three, in the order, recored highest number of voters.

In [ ]:

THE TMDB MOVIES DATA CSV DATA SET.

DATA UNDERSTANDING .

In [152]:
```
# Importing and reading the data.
df = pd.read_csv("tmdb.movies.csv.gz", index_col = 0)
df.head()
```

Out[152]:

	genre_ids	id	original_language	original_title	popularity	release_date	title	vote_ave
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 [153]:
```
# Check the data types and number of rows and columns
print(df.info())
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 26517 entries, 0 to 26516
Data columns (total 9 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  object 
 6   title              26517 non-null  object 
 7   vote_average       26517 non-null  float64
 8   vote_count         26517 non-null  int64  
dtypes: float64(2), int64(2), object(5)
memory usage: 2.0+ MB
None
```

This data conists of float, integer and object as data types.

In [154]:
```
#finding the shape of the data
df.shape
```

Out[154]:
```
(26517, 9)
```

This data consists of 26517 rows and 9 columns.

In [155]:
```
# Check the summary statistics of each column
print(df.describe())
```

```
                  id    popularity  vote_average    vote_count
count   26517.000000  26517.000000  26517.000000  26517.000000
mean   295050.153260      3.130912      5.991281    194.224837
std    153661.615648      4.355229      1.852946    960.961095
min        27.000000      0.600000      0.000000      1.000000
25%    157851.000000      0.600000      5.000000      2.000000
50%    309581.000000      1.374000      6.000000      5.000000
75%    419542.000000      3.694000      7.000000     28.000000
max    608444.000000     80.773000     10.000000  22186.000000
```

The table shows summary statistics for four variables - id, popularity, vote_average, and vote_count - with a sample size of 26,517.

count: The count column shows the number of non-missing values for each variable. In this case, there are 26,517 non-missing values for each variable.

mean: The mean column shows the average value for each variable. For example, the mean value for the "popularity" variable is 3.130912. This means that, on average, the movies in the dataset have a popularity score of 3.130912.

std: The std column shows the standard deviation of the values for each variable. For example, the standard deviation of the "popularity" variable is 4.355229. This means that the popularity scores for movies in the dataset vary widely, with some movies having very high popularity scores and others having very low popularity scores.

min: The min column shows the minimum value for each variable. For example, the minimum value for the "vote_average" variable is 0. This means that there are movies in the dataset with a vote average score of 0.

25%, 50%, 75%: These columns show the quartiles of the distribution of values for each variable. For example, the 25th percentile of the "vote_count" variable is 2, which means that 25% of the movies in the dataset have a vote count of 2 or less. Similarly, the 50th percentile (median) of the "popularity" variable is 1.374, which means that 50% of the movies in the dataset have a popularity score of 1.374 or less.

max: The max column shows the maximum value for each variable. For example, the maximum value for the "vote_count" variable is 22,186. This means that there is at least one movie in the dataset with a very high vote count.

DATA CLEANING.

In [156]:
```
#checking for null values in the data.
print(df.isnull().sum())
```

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

The data does not contain any null values.

In [157]:
```
# Check for duplicates
print(df.duplicated().value_counts())
```

```
False    25497
True      1020
dtype: int64
```

The table shows the count of two categories - False and True - for a variable. There are 25,497 values of False and 1,020 values of True for the variable in the dataset. The data has 1020 duplicated values.

In [158]:
```
#viewing the duplicated values by title.
df[df.duplicated(keep = False)].sort_values(by = 'title')
```

Out[158]:

	genre_ids	id	original_language	original_title	popularity	release_date	title	vot
9191	[99]	95383	en	$ellebrity	1.420	2013-01-11	$ellebrity	
6315	[99]	95383	en	$ellebrity	1.420	2013-01-11	$ellebrity	
20070	[99, 36, 10770]	430364	en	'85: The Greatest Team in Pro Football History	0.600	2018-01-29	'85: The Greatest Team in Pro Football History	
26340	[99, 36, 10770]	430364	en	'85: The Greatest Team in Pro Football History	0.600	2018-01-29	'85: The Greatest Team in Pro Football History	
18016	[18, 10749]	416691	en	1 Night	5.409	2017-02-10	1 Night	
...	...	...	...	...	...	...	...	
21273	[18]	326382	es	Zama	5.671	2017-09-30	Zama	
15061	[10751, 16]	94196	fr	Zarafa	2.705	2012-11-11	Zarafa	
5888	[10751, 16]	94196	fr	Zarafa	2.705	2012-11-11	Zarafa	
25188	[10752, 10751, 36]	472553	en	Zoo	2.550	2018-06-08	Zoo	
21676	[10752, 10751, 36]	472553	en	Zoo	2.550	2018-06-08	Zoo	

2016 rows × 9 columns

In [159]:
```
#viewing the duplicated values by id.
duplicates = df[df.duplicated(subset=['id'], keep=False)]
duplicates
```

Out[159]:

	genre_ids	id	original_language	original_title	popularity	release_date	title
3	[16, 35, 10751]	862	en	Toy Story	28.005	1995-11-22	Toy Story
10	[16, 35, 10751]	863	en	Toy Story 2	22.698	1999-11-24	Toy Story 2
43	[35, 10749]	239	en	Some Like It Hot	14.200	1959-03-18	Some Like It Hot
54	[12, 28, 878]	20526	en	TRON: Legacy	13.459	2010-12-10	TRON: Legacy
56	[35, 16, 10751]	9994	en	The Great Mouse Detective	13.348	1986-07-02	The Great Mouse Detective
...	...	...	...	...	...	...	...
26481	[35, 18]	270805	en	Summer League	0.600	2013-03-18	Summer League
26485	[27, 53]	453259	en	Devils in the Darkness	0.600	2013-05-15	Devils in the Darkness
26504	[27, 35, 27]	534282	en	Head	0.600	2015-03-28	Head
26510	[99]	495045	en	Fail State	0.600	2018-10-19	Fail State
26511	[99]	492837	en	Making Filmmakers	0.600	2018-04-07	Making Filmmakers

2016 rows × 9 columns

In [160]:
```
#sorting the duplicated values by id.
duplicates_sorted = duplicates.sort_values(['id'])
duplicates_sorted
```

Out[160]:

	genre_ids	id	original_language	original_title	popularity	release_date	title	v
20626	[16, 10751, 14]	129	ja	千と千尋の神隠し	32.043	2002-09-20	Spirited Away	
14173	[16, 10751, 14]	129	ja	千と千尋の神隠し	32.043	2002-09-20	Spirited Away	
43	[35, 10749]	239	en	Some Like It Hot	14.200	1959-03-18	Some Like It Hot	
24000	[35, 10749]	239	en	Some Like It Hot	14.200	1959-03-18	Some Like It Hot	
20639	[28, 53, 878]	280	en	Terminator 2: Judgment Day	24.604	1991-07-03	Terminator 2: Judgment Day	
...	...	...	...	...	...	...	...	
17071	[27]	560717	en	Requiem	0.600	2015-01-01	Requiem	
23685	[35]	564441	en	Adopting Trouble	0.600	2016-04-08	Adopting Trouble	
20461	[35]	564441	en	Adopting Trouble	0.600	2016-04-08	Adopting Trouble	
23785	[99]	572012	en	Harvested Alive - 10 Years of Investigations	0.600	2016-11-28	Harvested Alive	
20569	[99]	572012	en	Harvested Alive - 10 Years of Investigations	0.600	2016-11-28	Harvested Alive	

2016 rows × 9 columns

In [161]:
```
#dropping the duplicates.
df.drop_duplicates(keep = "first", inplace = True)
```

In [162]:
```
#checking to see if we have any remaining duplicates.
print(df.duplicated().value_counts())
```

```
False    25497
dtype: int64
```

This data set no longer contains any duplicated values.

In [163]:
```
# Get information about the data types and non-null values in each column
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 25497 entries, 0 to 26516
Data columns (total 9 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   genre_ids          25497 non-null  object 
 1   id                 25497 non-null  int64  
 2   original_language  25497 non-null  object 
 3   original_title     25497 non-null  object 
 4   popularity         25497 non-null  float64
 5   release_date       25497 non-null  object 
 6   title              25497 non-null  object 
 7   vote_average       25497 non-null  float64
 8   vote_count         25497 non-null  int64  
dtypes: float64(2), int64(2), object(5)
memory usage: 1.9+ MB
```

In [164]:
```
#dropping the original_language and original_title columns from the data frame
df= df.drop(['original_language','original_title'], axis=1)
```

In [165]:
```
df.shape
```

Out[165]:
```
(25497, 7)
```

The data frame now has fewer columns = 7.

In [166]:
```
df['release_date'] = pd.to_datetime(df['release_date'])
df['year'] = df['release_date'].dt.year
df['month'] = df['release_date'].dt.month
df['day'] = df['release_date'].dt.day
```

In [167]:
```
df.dtypes
```

Out[167]:
```
genre_ids                 object
id                         int64
popularity               float64
release_date      datetime64[ns]
title                     object
vote_average             float64
vote_count                 int64
year                       int64
month                      int64
day                        int64
dtype: object
```

In [168]:
```
df.head()
```

Out[168]:

	genre_ids	id	popularity	release_date	title	vote_average	vote_count	year	month
0	[12, 14, 10751]	12444	33.533	2010-11-19	Harry Potter and the Deathly Hallows: Part 1	7.7	10788	2010	11
1	[14, 12, 16, 10751]	10191	28.734	2010-03-26	How to Train Your Dragon	7.7	7610	2010	3
2	[12, 28, 878]	10138	28.515	2010-05-07	Iron Man 2	6.8	12368	2010	5
3	[16, 35, 10751]	862	28.005	1995-11-22	Toy Story	7.9	10174	1995	11
4	[28, 878, 12]	27205	27.920	2010-07-16	Inception	8.3	22186	2010	7

In [169]:
```
import warnings

warnings.filterwarnings("ignore")

# Code that generates a DeprecationWarning will be ignored.
```

In [170]:
```
#Viewing the data.
df.head()
```

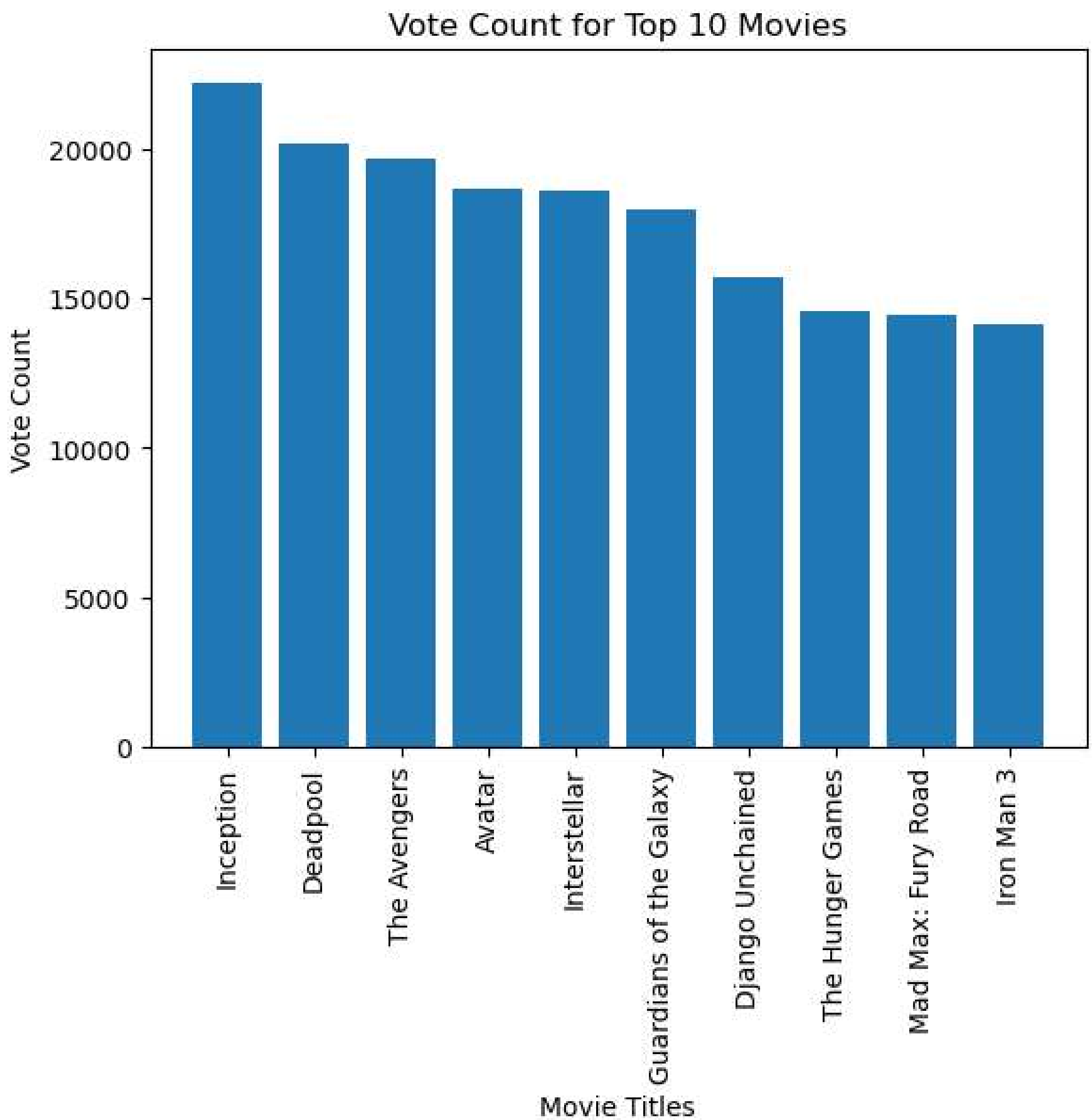
Out[170]:

	genre_ids	id	popularity	release_date	title	vote_average	vote_count	year	month
0	[12, 14, 10751]	12444	33.533	2010-11-19	Harry Potter and the Deathly Hallows: Part 1	7.7	10788	2010	11
1	[14, 12, 16, 10751]	10191	28.734	2010-03-26	How to Train Your Dragon	7.7	7610	2010	3
2	[12, 28, 878]	10138	28.515	2010-05-07	Iron Man 2	6.8	12368	2010	5
3	[16, 35, 10751]	862	28.005	1995-11-22	Toy Story	7.9	10174	1995	11
4	[28, 878, 12]	27205	27.920	2010-07-16	Inception	8.3	22186	2010	7

DATA ANALYSIS AND VISUALIZATION.

Top Ten Movies as per the Vote Count.

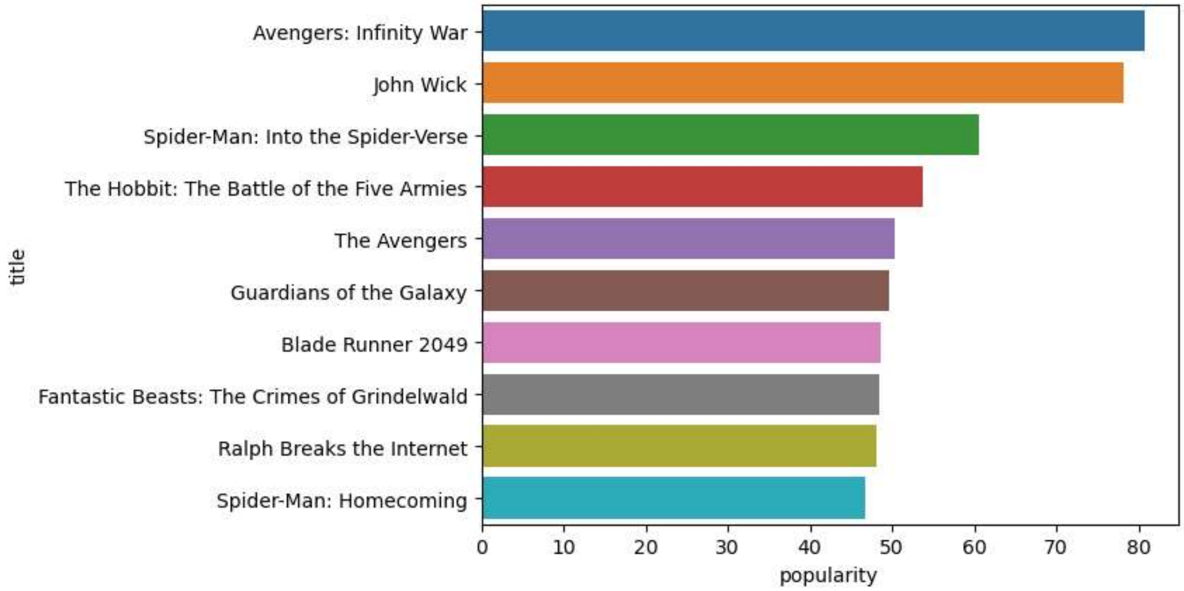
In [171]:
```
# Sort the DataFrame by vote count and select the top 10 movies
top_movies = df.sort_values(by='vote_count', ascending=False).head(10)

# Create a histogram of the vote count for the top 10 movies
plt.bar(top_movies['title'], top_movies['vote_count'])
plt.xticks(rotation=90)
plt.xlabel('Movie Titles')
plt.ylabel('Vote Count')
plt.title('Vote Count for Top 10 Movies')
plt.show()
```



The bar graph diplays the most popular movies as per the vote count. The most popular movie was Inception followed by Deadpool, The Avengers, Avatar, Interstellar, guardians of the Galaxy,Django Unchained, The hunger Games, Mad Max: Fury Road and Iron Man 3 in that order.

Top ten Movies as per Popularity.

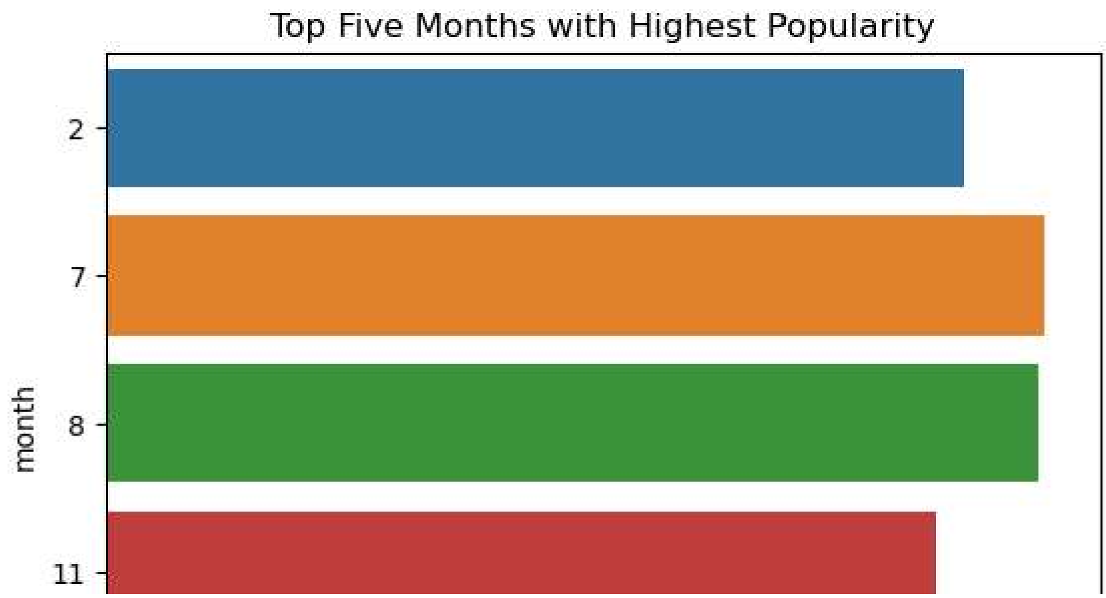
In [172]:
```
#plotting bargraph using seaborn of movies vs popularity.
top_movies2 = df.sort_values(by='popularity', ascending=False).head(10)
sns.barplot(y='title', x='popularity', data=top_movies2, orient='h');
```



The bar graph diplays the most popular movies as per the popularity index.. The most popular movie was the AVengers: infinity War followed by john Wick, Spider_Man: Into the Spider-Verse, The Hobbit: The battle of the Five Armies, Th Avengers, Guardians of the Galaxy, Blade Runner 2049, Fantastic Beasts: The crimes of Grindelwald, Ralph Breaks the Internet and Spider-Man:Homecoming in that order.

In [173]:
```
#plotting bar graph displaying top ten month with the highest popularity of mov
top_months = df.groupby('month')['popularity'].mean().reset_index().sort_value:
sns.barplot(y='month', x='popularity', data=top_months, orient='h')
plt.title('Top Five Months with Highest Popularity')
```

Out[173]:
```
Text(0.5, 1.0, 'Top Five Months with Highest Popularity')
```



This plot displays the top five months with the highest popularity. Movies released in december were the most popular followed by movies released in July, August, february and November in that order.

FINDINGS.

1. December is the most appropriate time to release new movies as shown by the popularity of movies released in december.
2. The top three most popular movies are:

> AVengers: infinity War.

> john Wick.

> Spider_Man: Into the Spider-Verse.

3. The most voted for movies as per the vote count include the Inception, Deadpool and The Avengers.

RECOMMENDATIONS.

1. Microsoft should major in producing movies in December.
2. Microsoft should produce the following movies:

> Avengers: Infinity War.

> John Wick.

BOM.MOVIE_GROSS.CSV.gz

DATA UNDERSTANDING.

In [174]:
```
# Importing and reading the data.
bom_movies_gross_df = pd.read_csv("bom.movie_gross.csv.gz", index_col = 0)
bom_movies_gross_df.head()
```

Out[174]:

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

In [175]:
```
#Previewing the data shape
bom_movies_gross_df.shape
```

Out[175]:
```
(3387, 4)
```

The data conisdts of 3387 rows and 4 columns.

In [176]:
```
#Getting information about the bom_movies_gross
bom_movies_gross_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 3387 entries, Toy Story 3 to An Actor Prepares
Data columns (total 4 columns):
 #   Column          Non-Null Count  Dtype  
---  ------          --------------  -----  
 0   studio          3382 non-null   object 
 1   domestic_gross  3359 non-null   float64
 2   foreign_gross   2037 non-null   object 
 3   year            3387 non-null   int64  
dtypes: float64(1), int64(1), object(2)
memory usage: 132.3+ KB
```

The data consists of object , float and integer data types.

In [177]:
```
#checking the summary statistics of each column.
bom_movies_gross_df.describe()
```

Out[177]:

	domestic_gross	year
count	3.359000e+03	3387.000000
mean	2.874585e+07	2013.958075
std	6.698250e+07	2.478141
min	1.000000e+02	2010.000000
25%	1.200000e+05	2012.000000
50%	1.400000e+06	2014.000000
75%	2.790000e+07	2016.000000
max	9.367000e+08	2018.000000

This is a summary of a dataset with two columns: domestic_gross and year.

The domestic_gross column represents the total gross earnings of a movie in the domestic (US) market, and the year column represents the year in which the movie was released.

Here are some observations about the summary statistics:

There are 3,359 movies in the dataset. The average domestic gross earnings for a movie in the dataset is approximately $28.7 million.

The standard deviation of the domestic gross earnings is approximately $67 million, indicating that the earnings are spread out over a wide range.

The minimum domestic gross earnings for a movie in the dataset is $100, indicating that there are some very low-grossing movies in the dataset.

The 25th percentile of the domestic gross earnings is $120,000, indicating that 25% of the movies in the dataset earned less than this amount.

The median (50th percentile) of the domestic gross earnings is $1.4 million, indicating that half of the movies in the dataset earned less than this amount and half earned more.

The 75th percentile of the domestic gross earnings is $27.9 million, indicating that 75% of the movies in the dataset earned less than this amount.

The maximum domestic gross earnings for a movie in the dataset is $936.7 million, indicating that there are some very high-grossing movies in the dataset.

The dataset covers the years 2010 through 2018, with most of the movies released in 2013 and 2014.

DATA CLEANING.

In [178]:
```
#Finding missing values.
bom_movies_gross_df.isnull().sum()
```

Out[178]:
```
studio               5
domestic_gross      28
foreign_gross     1350
year                 0
dtype: int64
```

The studio column has non-null values for 5 rows.

The domestic_gross column has non-null values for 28 rows.

The foreign_gross column has non-null values for 1350 rows.

The year column has non-null values for 0 rows, which may indicate that the column is empty or missing.

In [179]:
```
#filling missing values.
bom_movies_gross_df['domestic_gross'].fillna(bom_movies_gross_df['domestic_gro
bom_movies_gross_df['studio'].fillna('Missing', inplace = True)

bom_movies_gross_df.isna().sum()
```

Out[179]:
```
studio               0
domestic_gross       0
foreign_gross     1350
year                 0
dtype: int64
```

In [180]:
```
#dropping foreign gross row
bom_movies_gross_df.drop('foreign_gross', axis=1, inplace=True)
```

In [181]:
```
#previewing null values.
bom_movies_gross_df.isna().sum()
```

Out[181]:
```
studio            0
domestic_gross    0
year              0
dtype: int64
```

In [182]:
```
#checking for the range of values and outliers.
bom_movies_gross_df['domestic_gross'].unique()
```

Out[182]:
```
array([4.150e+08, 3.342e+08, 2.960e+08, ..., 2.070e+04, 1.290e+04,
       2.400e+03])
```

In [183]:
```
#checking for the range of values and outliers.
bom_movies_gross_df['year'].unique()
```

Out[183]:
```
array([2010, 2011, 2012, 2013, 2014, 2015, 2016, 2017, 2018], dtype=int64)
```

In [184]:
```
#Grouping.
studio_gross_title = bom_movies_gross_df.groupby("title")["domestic_gross"].sui
print(studio_gross_title)
```

```
                               title  domestic_gross
0                                '71       1300000.0
1              1,000 Times Good Night        53900.0
2                 10 Cloverfield Lane      72100000.0
3                            10 Years        203000.0
4                          1001 Grams         11000.0
...                               ...             ...
3381                      Zoolander 2      28800000.0
3382                         Zootopia     341300000.0
3383                          [Rec] 2         27800.0
3384                          mother!      17800000.0
3385  xXx: The Return of Xander Cage      44900000.0

[3386 rows x 2 columns]
```

In [185]:
```
studio_gross = bom_movies_gross_df.groupby("studio")["domestic_gross"].sum().r
print(studio_gross)
```

```
    studio  domestic_gross
0       3D       6100000.0
1      A23        164200.0
2      A24     324194200.0
3      ADC        248200.0
4       AF       2142900.0
..     ...             ...
253     XL        458000.0
254    YFG       1100000.0
255   Yash      33031400.0
256    Zee       1100000.0
257  Zeit.       5663500.0

[258 rows x 2 columns]
```

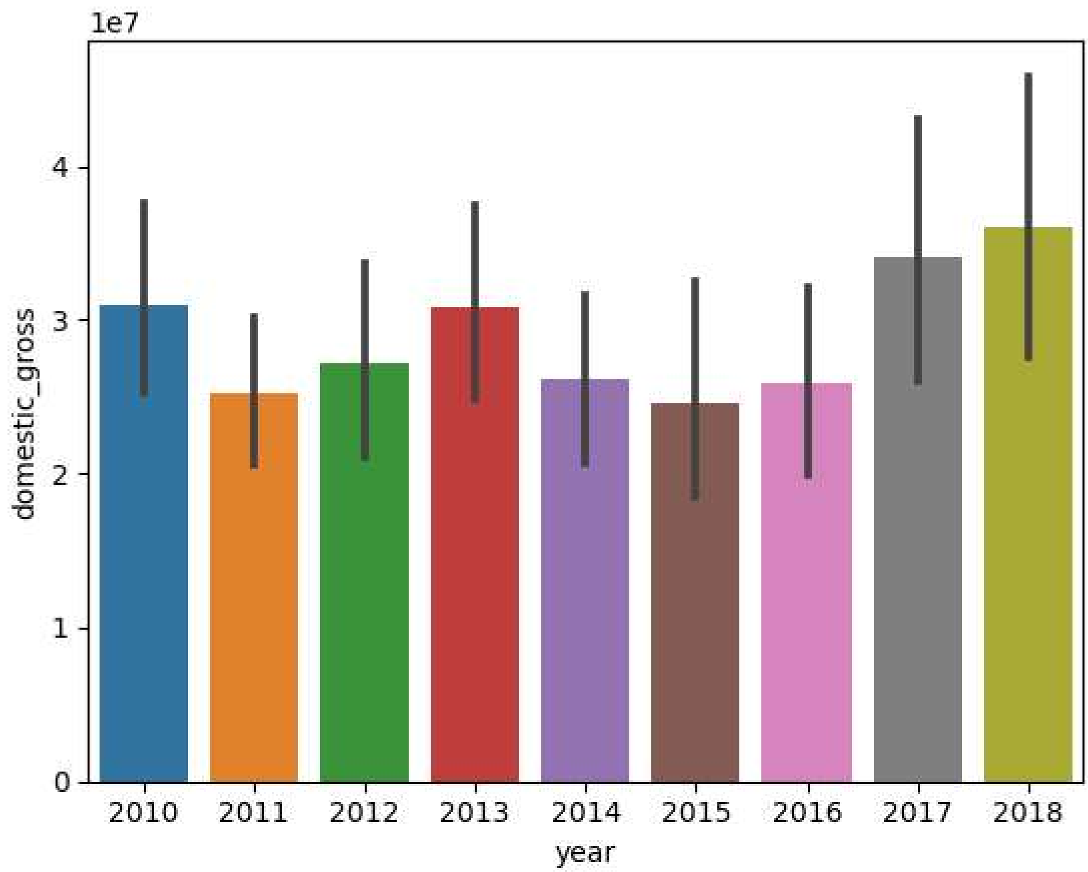
In [186]:
```
bom_movies_gross_df.head()
```

Out[186]:

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

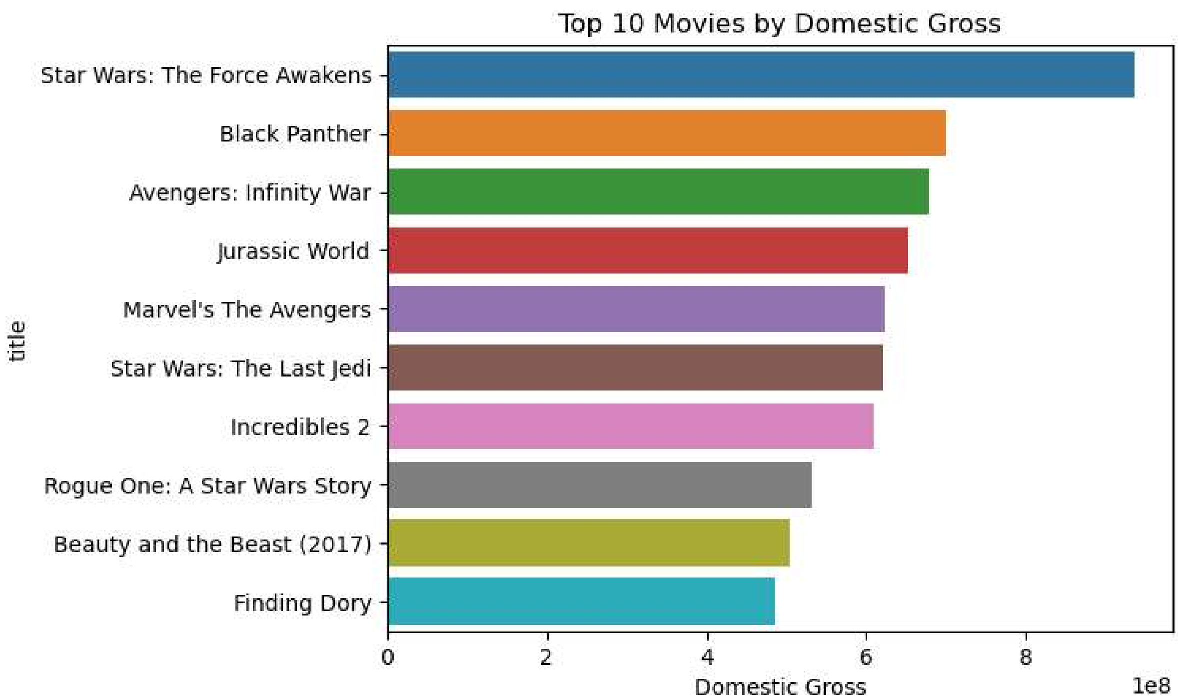
DATA ANALYSIS AND VISUALIZATION.

In [187]:
```
#Linegraph
sns.barplot(x='year', y='domestic_gross', data=bom_movies_gross_df)
plt.show()
```



The above is a line graph that shows the trend in average domestic gross earnings for movies over the years in the dataset. The year 2018 generated the highest domestic gross income followed by 2017, 2013, 2010, 2012, 2014, 2016, 2011 and 2015 in that order.

In [188]:
```
# Sort the dataset by domestic gross in descending order
bom_movies_gross_df = bom_movies_gross_df.reset_index()

sorted_data = bom_movies_gross_df.sort_values('domestic_gross', ascending=Fals

 # Selecting the top 10 movies by domestic gross
top_10 = sorted_data.head(10)

# Create the bar chart
sns.barplot(x="domestic_gross", y="title", data = top_10, orient = "h")
plt.xlabel("Domestic Gross")
plt.ylabel("title")
plt.title("Top 10 Movies by Domestic Gross")
plt.show()
```



The above is a horizontal bar chart of the top 10 movies by domestic gross, with the movie titles on the y-axis and the domestic gross on the x-axis. Star Wars: The Force Awakens generated the highest domestic gross revenue followed by Black Panther, Avengers: Infinity War, Jurassic World, Marvel's The Avengers, Star Wars: The Last jedi, Incredibles 2, Rogue One: A star Wars Story, Beauty and the Beast(2017) while the least was generated by Finding Dory.

FINDINGS

Domestic gross revenue was generated highest in the year 2018, then 2017, 2013, 2010, 2012, 2014, 2016, 2011 with the least being in 2015.

RECOMMENDATIONS

I would recommend Microsoft to produce Star Wars:The Force Awakens, Black Panther and Avengers: Infinity War movies since they generated the highest domestic gross income.