Final Project Submission

Please fill out:

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- Student pace: part time
- Scheduled project review date/time:
- Instructor name: NOAH KANDIE
- Blog post URL:

In [1]:
```
# Your code here - remember to use markdown cells for comments as well!
```

OVERVIEW

With sudden increase in original film production in mega companies, Microsoft wants to get an in-depth understanding of the movie industries to help her determine if it's a business they can venture. I used the return on investment as a measure to gauge the profitability of particular movies, looked into most popular publisher and rating and also used production budget against domestic gross to help determine the correction of the two output and also how production budget influence movie output in term of sales.

BUSINESS PROBLEM

The potential problem that microsoft has is basically to determine if they should venture into the movie industry and just get to basically understand the key determiners of the market that influence good outcome in term of sale and basically helping them understand the success of a movie is basically determine by not only common factor like gross income but things also like the publisher so Microsoft has to position itself well to beat key players like Amazon and Netflix. I used these key analysis to help them understand the problem 1.Original language 2.ROI and Production Budget 3.Publishers and Rating It's important for Microsoft to carefully consider both the ROI potential and the publishers they work with in order to make informed decisions about their venture into original movie content.

DATA UNDERSTANDING

The potential problem that microsoft has is basically to determine if they should venture into the movie industry and just get to basically understand the key determiners of the market that influence good outcome in term of sale and success of a movie is basically determine by not only common factor like gross income but things also like the publisher so Microsoft has to position itself well to beat key players like Amazon and Netflix.I used below key analysis to help them understand the problem 1.Return On Investement(ROI) i will get this analyses from the movie budget dataset 2.Production Budget 3.Publishers and Ratings It's important for Microsoft to carefully consider both the ROI potential and the publishers they work with in order to make informed decisions about their venture into original movie content.

In [2]:
```
#imported the necessary tool for data cleaning and analyses.
import pandas as pd
import sqlite3
import csv
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
#Ignore warnings
import warnings
warnings.filterwarnings('ignore')
```

1. Get to answer original language influence on the movie views

In [3]:
```
#import TMDB movie dataset
movies =pd.read_csv('tmdb.movies.csv.gz',index_col = 0)
movies
```

Out[3]:

	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	Harry P th Hallov
1	[14, 12, 16, 10751]	10191	en	How to Train Your Dragon	28.734	2010-03-26	How to T
2	[12, 28, 878]	10138	en	Iron Man 2	28.515	2010-05-07	Ir
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	L C
26513	[18, 53]	485975	en	_EXHIBIT_84xxx_	0.600	2018-05-01	_EXHIBI
26514	[14, 28, 12]	381231	en	The Last One	0.600	2018-10-01	The
26515	[10751, 12, 28]	366854	en	Trailer Made	0.600	2018-06-22	Tra
26516	[53, 27]	309885	en	The Church	0.600	2018-10-05	Th

26517 rows × 9 columns

In [4]:
```
#having gotten the data,an overview of the columns shows the following (genre
```

In [5]:
```
#get to understanding datatype i will be using
movies.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
```

In [6]:
```
#get to see statistical ananlysis of the data
movies.describe()
```

Out[6]:

	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

In [7]:
```
#get to see if there is null values in the data
movies.isnull().sum()
```

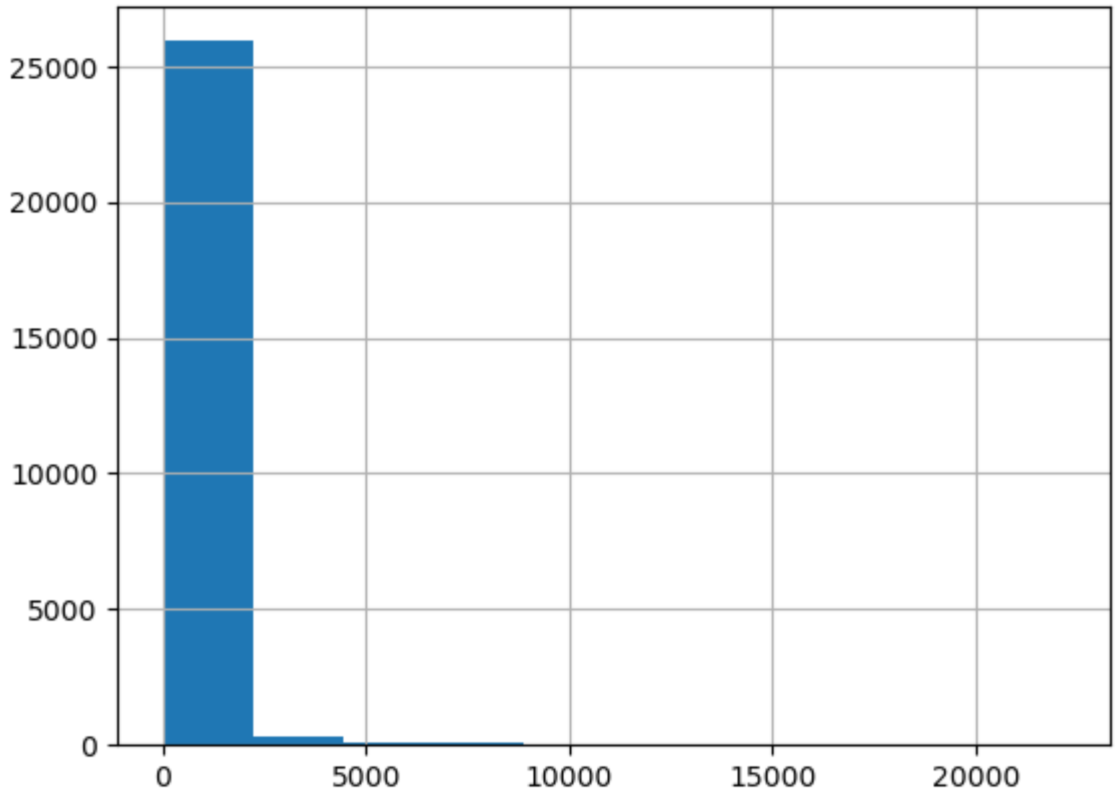
Out[7]:
```
genre_ids            0
id                   0
original_language    0
original_title       0
popularity           0
release_date         0
title                0
vote_average         0
vote_count           0
dtype: int64
```

In [8]:
```
#get to see the key values in the dataset
movies.keys()
```

Out[8]:
```
Index(['genre_ids', 'id', 'original_language', 'original_title', 'popularity
',
       'release_date', 'title', 'vote_average', 'vote_count'],
      dtype='object')
```

In [9]:
```
#get to create an histogram for the vote count column to have an insight of ho
movies['vote_count'].hist()
```

Out[9]: <AxesSubplot:>



In [10]:
```
#get to get in the vote count column those above 20000
movies[movies['vote_count']>20000]
```

Out[10]:

	genre_ids	id	original_language	original_title	popularity	release_date	title	vo
4	[28, 878, 12]	27205	en	Inception	27.920	2010-07-16	Inception	
17383	[28, 12, 35]	293660	en	Deadpool	35.067	2016-02-12	Deadpool	

In [11]:
```
#above shows the two movies that had a value count of more than 20000
```

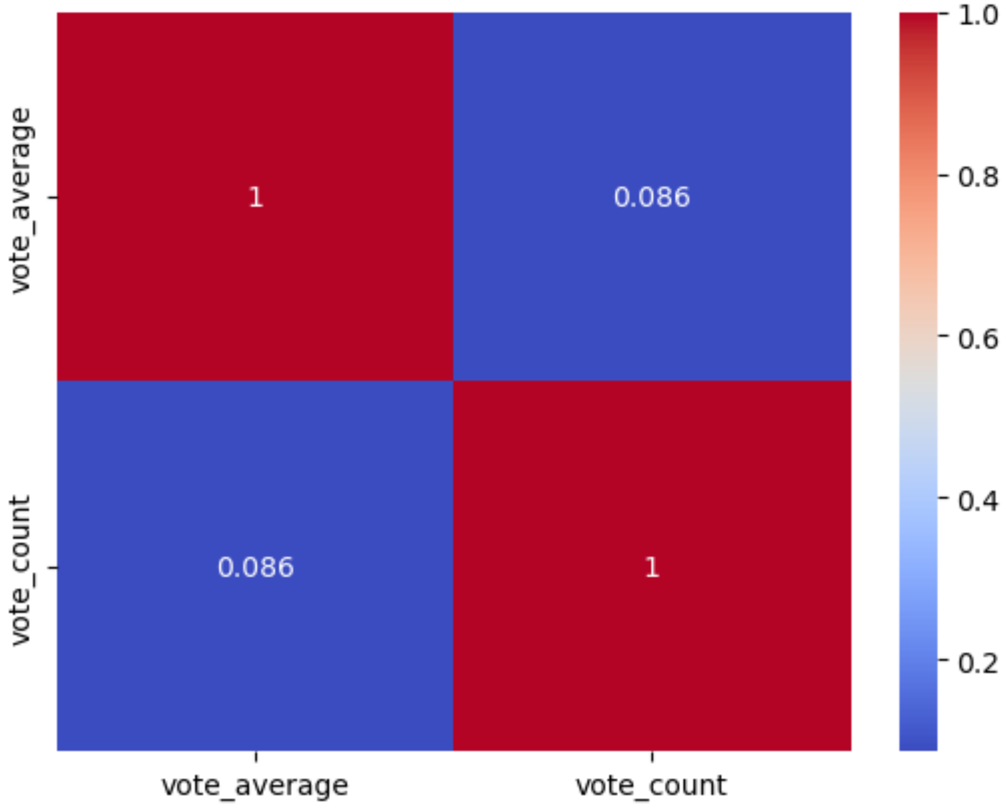
In [12]:
```
#the correlation btw vote_average and vote_count is weak positive correlation
movies_corr =movies[['vote_average', 'vote_count']].corr()
movies_corr
```

Out[12]:

	vote_average	vote_count
vote_average	1.00000	0.08637
vote_count	0.08637	1.00000

In [13]:
```
# the seaborn graph assist to clearly show the correlation of the two and as p
sns.heatmap(movies_corr, cmap ='coolwarm', annot =True)
```

Out[13]: <AxesSubplot:>



In [14]:
```
#another insight is the relation of the movies and the languages used and most
movies['original_language'].value_counts()
```

Out[14]:
```
en    23291
fr      507
es      455
ru      298
ja      265
      ...
bo        1
si        1
sl        1
hz        1
dz        1
Name: original_language, Length: 76, dtype: int64
```

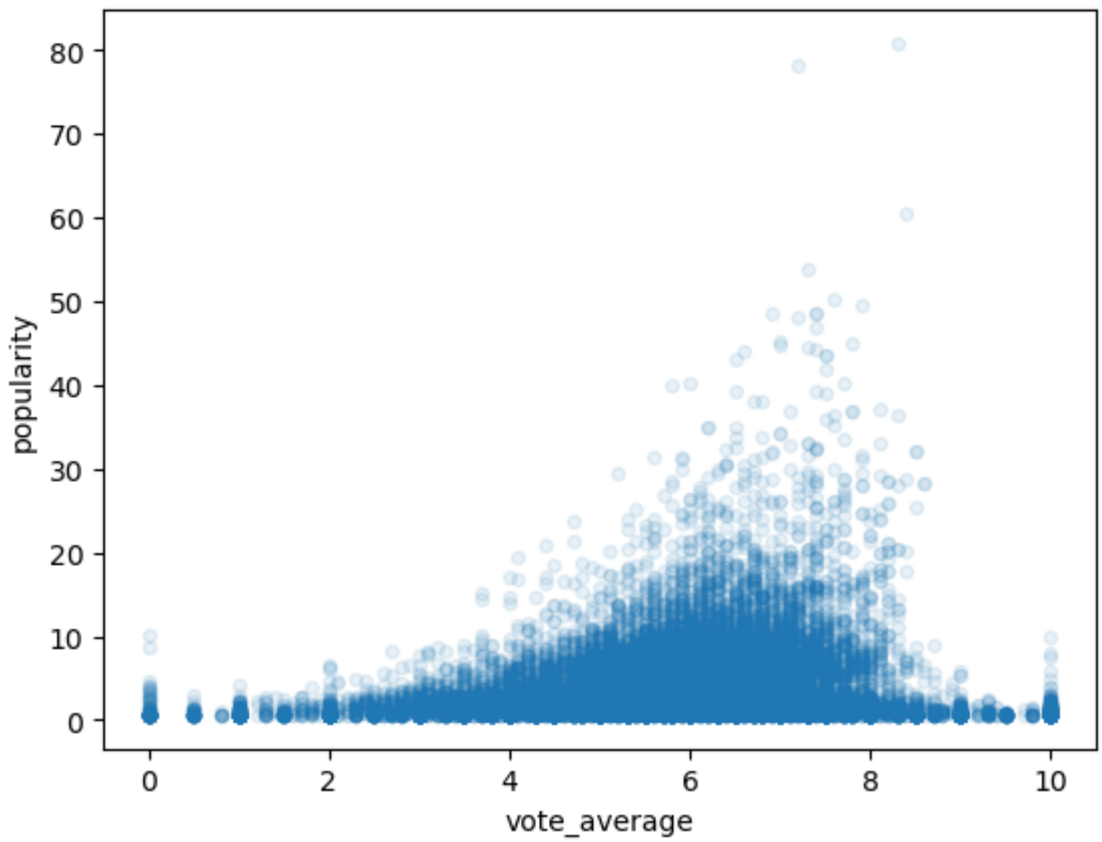
In [15]:
```
#the correlation btw vote_average and popularity is weak positive correlation
movies_pop =movies[['popularity', 'vote_average']].corr()
movies_pop
```

Out[15]:

	popularity	vote_average
popularity	1.000000	0.065273
vote_average	0.065273	1.000000

In [16]:
```
#create a scatterplot for the vote average and popularity
movies.plot.scatter(x ='vote_average',y= 'popularity', alpha= .1)
```

Out[16]:
```
<AxesSubplot:xlabel='vote_average', ylabel='popularity'>
```



2.Analyse the TN dataset to get more insight on ROI

In [17]:
```
#import movie budget dataset
movie_budgets =pd.read_csv('tn.movie_budgets.csv.gz')
movie_budgets
```

Out[17]:

	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

In [18]:
```
#get to see the statistical analyses of the data like mean
movie_budgets.describe()
```

Out[18]:

	id
count	5782.000000
mean	50.372363
std	28.821076
min	1.000000
25%	25.000000
50%	50.000000
75%	75.000000
max	100.000000

In [19]:
```
#get to see datatype
movie_budgets.dtypes
```

Out[19]:
```
id                    int64
release_date         object
movie                object
production_budget    object
domestic_gross       object
worldwide_gross      object
dtype: object
```

In [20]:
```
#get to see if the data has null values
movie_budgets.isnull().any()
```

Out[20]:
```
id                   False
release_date         False
movie                False
production_budget    False
domestic_gross       False
worldwide_gross      False
dtype: bool
```

In [21]:
```
#movie_budgets_corr =movie_budgets[['domestic_gross','foreign_gross']].corr()
#movie_budgets_corr
```

In [22]:
```
#get to remove the $ and '' values in the data to help do further statistical
movie_budgets['domestic_gross'] = pd.to_numeric(movie_budgets['domestic_gross'
movie_budgets['production_budget'] =pd.to_numeric(movie_budgets['production_bu
movie_budgets['worldwide_gross'] = pd.to_numeric(movie_budgets['worldwide_gros
movie_budgets
```

Out[22]:

	id	release_date	movie	production_budget	domestic_gross	worldwide_gross
0	1	Dec 18, 2009	Avatar	425000000	760507625	2776345279
1	2	May 20, 2011	Pirates of the Caribbean: On Stranger Tides	410600000	241063875	1045663875
2	3	Jun 7, 2019	Dark Phoenix	350000000	42762350	149762350
3	4	May 1, 2015	Avengers: Age of Ultron	330600000	459005868	1403013963
4	5	Dec 15, 2017	Star Wars Ep. VIII: The Last Jedi	317000000	620181382	1316721747
...	...	...	...	...	...	...
5777	78	Dec 31, 2018	Red 11	7000	0	0
5778	79	Apr 2, 1999	Following	6000	48482	240495
5779	80	Jul 13, 2005	Return to the Land of Wonders	5000	1338	1338
5780	81	Sep 29, 2015	A Plague So Pleasant	1400	0	0
5781	82	Aug 5, 2005	My Date With Drew	1100	181041	181041

5782 rows × 6 columns

In [23]:
```
#get to calculate the ROI by substracting production budget from the domestic 
#i have calculated the return of investment based on the difference of domesti
movie_budgets['ROI'] = movie_budgets['domestic_gross'] - movie_budgets['produc
movie_budgets
```

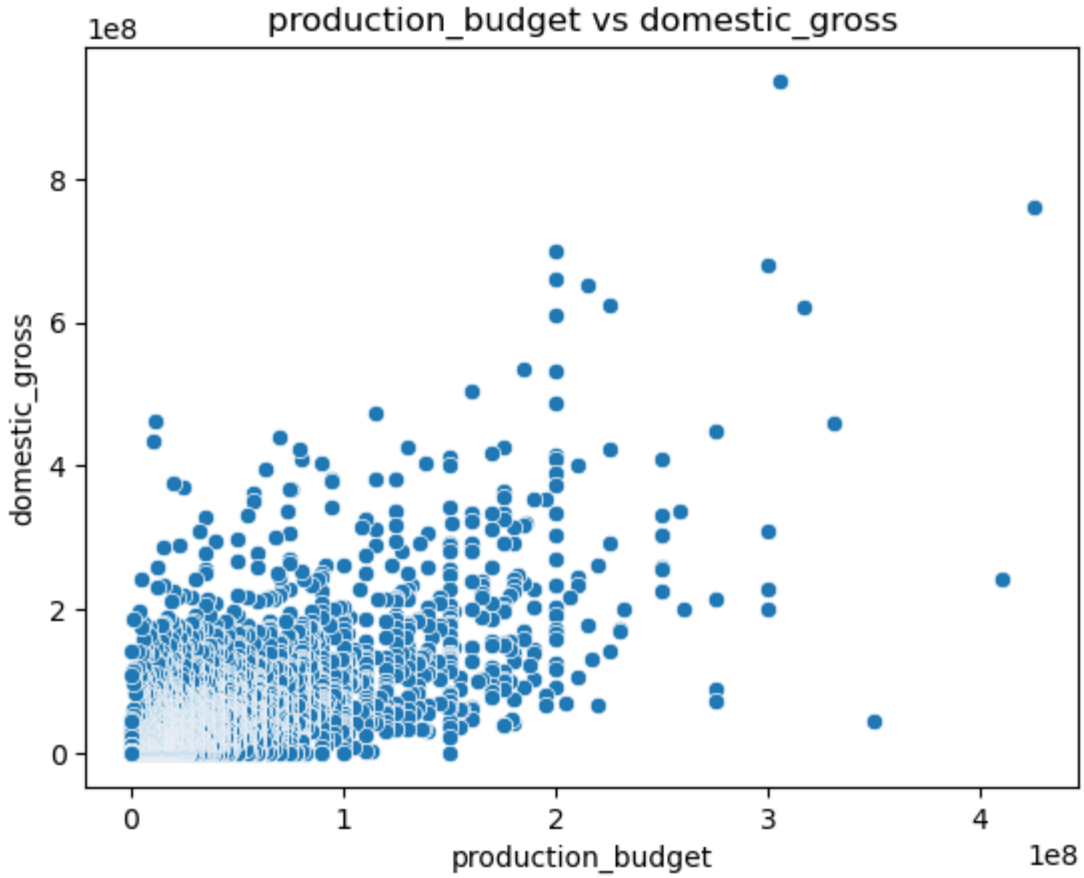
Out[23]:

	id	release_date	movie	production_budget	domestic_gross	worldwide_gross	
0	1	Dec 18, 2009	Avatar	425000000	760507625	2776345279	33550
1	2	May 20, 2011	Pirates of the Caribbean: On Stranger Tides	410600000	241063875	1045663875	-16953
2	3	Jun 7, 2019	Dark Phoenix	350000000	42762350	149762350	-30723
3	4	May 1, 2015	Avengers: Age of Ultron	330600000	459005868	1403013963	12840
4	5	Dec 15, 2017	Star Wars Ep. VIII: The Last Jedi	317000000	620181382	1316721747	30318
...	...	...	...	...	...	...	
5777	78	Dec 31, 2018	Red 11	7000	0	0	-
5778	79	Apr 2, 1999	Following	6000	48482	240495	4
5779	80	Jul 13, 2005	Return to the Land of Wonders	5000	1338	1338	-
5780	81	Sep 29, 2015	A Plague So Pleasant	1400	0	0	-
5781	82	Aug 5, 2005	My Date With Drew	1100	181041	181041	17

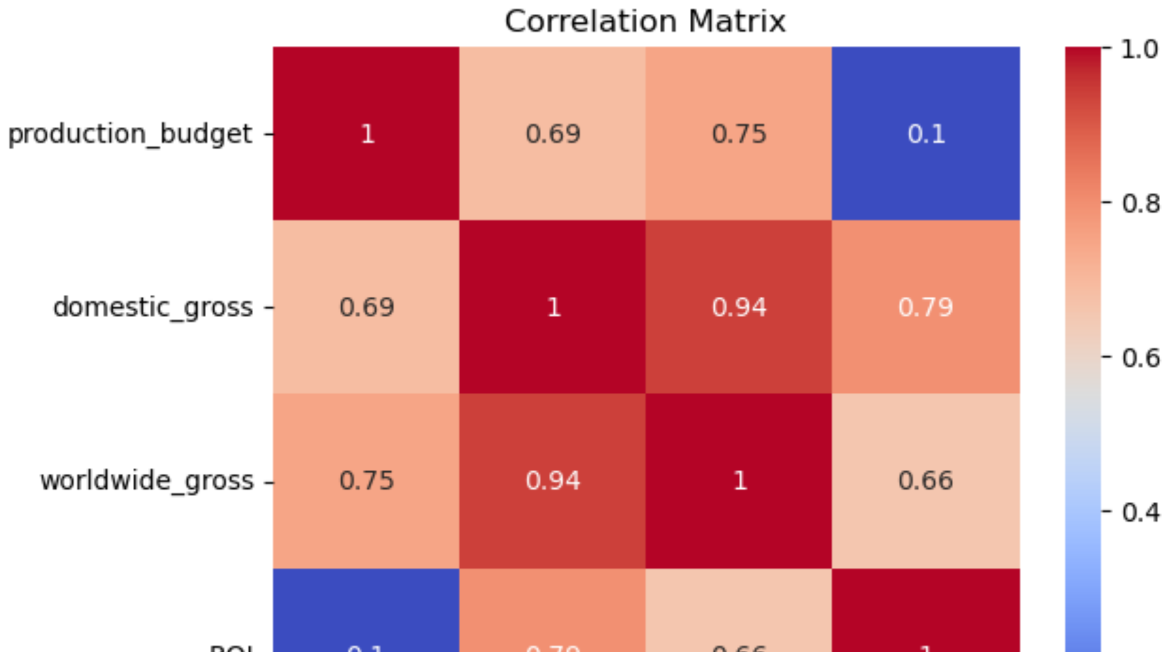
5782 rows × 7 columns

In [24]:
```
#create a scatterplot
sns.scatterplot(data=movie_budgets,x='production_budget', y='domestic_gross')
plt.title('production_budget vs domestic_gross')
```

Out[24]: Text(0.5, 1.0, 'production_budget vs domestic_gross')



In [25]:
```
# Compute the correlation matrix
corr = movie_budgets[['production_budget', 'domestic_gross', 'worldwide_gross'

# Create heatmap of the correlation matrix
sns.heatmap(corr, annot=True, cmap='coolwarm')
plt.title('Correlation Matrix')
plt.show()
```



In [26]:
```
# Get the movie with the highest ROI
highest_ROI_movie = movie_budgets.loc[movie_budgets['ROI'].idxmax(), 'movie']
print(f"Highest ROI movie: {highest_ROI_movie}")
```

```
Highest ROI movie: Star Wars Ep. VII: The Force Awakens
```

In [27]:
```
# Get the movie with the highest domestic gross
highest_domestic_gross_movie = movie_budgets.loc[movie_budgets['domestic_gross
print(f"Highest domestic gross movie: {highest_domestic_gross_movie}")
```

```
Highest domestic gross movie: Star Wars Ep. VII: The Force Awakens
```

In [28]:
```
#this two previous finds supports my correlation matrix on the correction betw
```

In [29]:
```
highest_production_budget_movie = movie_budgets.loc[movie_budgets['production_
print(f"Highestproduction budget movie: {highest_production_budget_movie}")
```

```
Highestproduction budget movie: Avatar
```

In [30]:
```
#avatar had the highest prouction budget meaning production budget doesnt mean
```

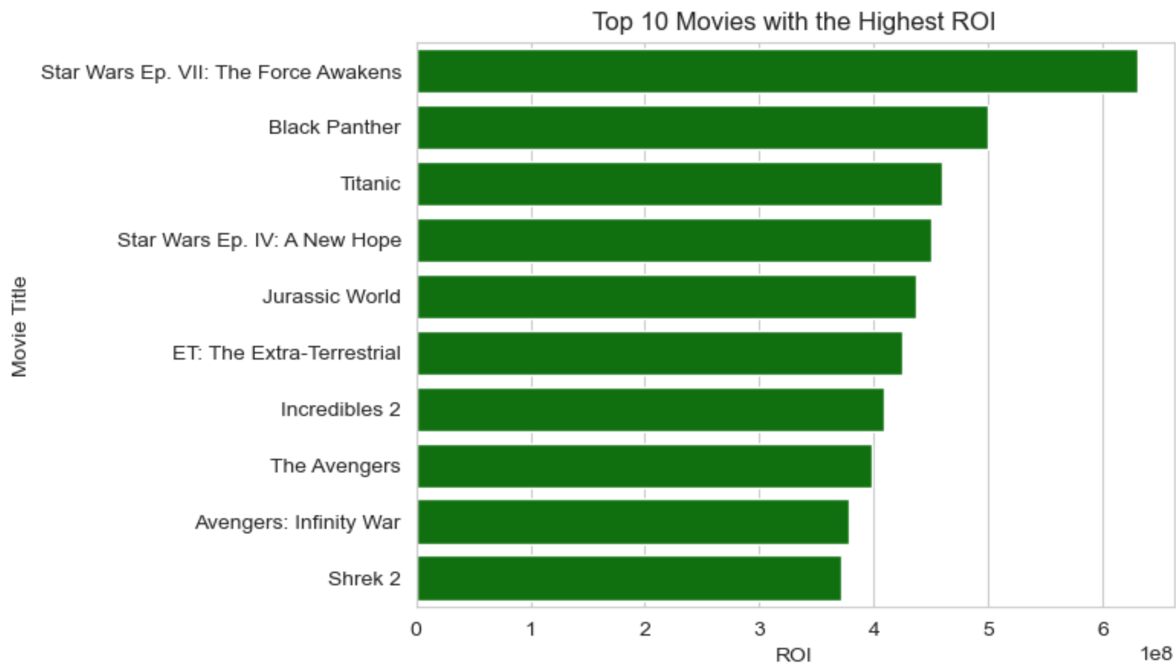
In [31]:
```
#Determine the movies that made losses in terms of ROI
# Filter the rows where ROI is negative
negative_ROI_movies = movie_budgets.loc[movie_budgets['ROI'] < 0, 'movie']

# Print the movies with negative ROI
print(negative_ROI_movies)
```

```
1       Pirates of the Caribbean: On Stranger Tides
2                                      Dark Phoenix
8                                    Justice League
9                                           Spectre
11                            Solo: A Star Wars Story
                            ...
5772                                      Newlyweds
5776                                The Mongol King
5777                                         Red 11
5779                    Return to the Land of Wonders
5780                           A Plague So Pleasant
Name: movie, Length: 3105, dtype: object
```

In [32]:
```
# Sort the DataFrame by ROI in descending order
sorted_movie = movie_budgets.sort_values('ROI', ascending=False)

# Get the top 10 movies with the highest ROI
top_10_ROI_movies = sorted_movie.head(10)

# Display the top 10 movies
print(top_10_ROI_movies[['movie', 'ROI']])
```

```
                                movie        ROI
5     Star Wars Ep. VII: The Force Awakens  630662225
41                           Black Panther  500059566
42                                 Titanic  459363944
3464            Star Wars Ep. IV: A New Hope  449998007
33                          Jurassic World  437270625
3525             ET: The Extra-Terrestrial  424610554
43                            Incredibles 2  408581744
26                            The Avengers  398279547
6                    Avengers: Infinity War  378815482
692                                Shrek 2  371226247
```

In [33]:
```
# Create a horizontal bar chart of the top 10 movies with the highest ROI
sns.set_style('whitegrid')
sns.barplot(data=top_10_ROI_movies, x='ROI', y='movie', color='green')
plt.xlabel('ROI')
plt.ylabel('Movie Title')
plt.title('Top 10 Movies with the Highest ROI')

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



Identify the movies with highest ROI for the last 10 years

In [*]:
```
#identify the movies with highest ROI for the last 10 years having resetted th
#reset the release_date column as a datetime and set it as the index column
# Convert the release_date column to datetime and set it as index
movie_budgets['release_date'] = pd.to_datetime(movie_budgets['release_date'])
movie_budgets.set_index('release_date', inplace=True)

# Filter the DataFrame to only include the rows from the past 10 years
ten_years_ago = pd.to_datetime('today') - pd.DateOffset(years=10)
filtered_df = movie_budgets.loc[movie_budgets.index >= ten_years_ago]

# Sort the DataFrame by ROI in descending order and retrieve the top 10 movies
sorted_df = filtered_df.sort_values('ROI', ascending=False)
top_10_ROI_movies = sorted_df.head(10)

# Print out the top 10 movies with their ROI values
print(top_10_ROI_movies[['movie', 'ROI']])
```

In [*]:
```
# Create a bar plot of the top 10 movies by ROI
sns.set_style('darkgrid')
plt.figure(figsize=(10, 6))
sns.barplot(x='movie', y='ROI', data=top_10_ROI_movies)
plt.title('Top 10 Movies by ROI in the Past 10 Years')
plt.xlabel('Movie')
plt.ylabel('ROI')
plt.xticks(rotation=45, ha='right')
plt.tight_layout()
plt.show()
```

3.Analyse the review dataset to get an insight of the publisher and rating

In [*]:
```
review = pd.read_csv('reviews.tsv' ,sep ='\t',encoding = 'latin')
review
```

In [*]:
```
review['publisher'].unique()
```

In [*]:
```
review['rating'].unique()
```

In [*]:
```
#The ratings appear to be in different formats
#such as letter grades (A+, A, B-, etc.)
# percentages (e.g. 80%)
#fractions (e.g. 3/5), and
#even non-numeric characters (such as 'N' and 'T').
```

In [*]:
```
#create a function that takes each rating as an input
#checks its format,
#converts it to a numerical rating on a scale of 1 to 10.
def convert_rating(rating):
    try:
        if '/' in rating:
            numer, denom = rating.split('/')
            return round(int(numer)/int(denom)*10, 1)
        elif '-' in rating:
            left, right = rating.split('-')
            return round((int(left) + int(right))/2, 1)
        elif rating in ['N', 'R', 'T']:
            return None
        else:
            return float(rating)
    except:
        return None
```

In [*]:
```
#apply this function to each element in the ratings column using the apply() m
# create a new column showing the ratings in numeric.
# Identify the publisher who had the highest rating.
review['numeric_rating'] = review['rating'].apply(convert_rating)
review
```

In [*]:
```
#calculate the highest rated publisher
highest_rated_publisher = review.groupby('publisher')['numeric_rating'].mean()
print("The highest rated publisher is:", highest_rated_publisher)
```

In [*]:
```
#get the top ten publishers
top_ten_publishers = review.groupby('publisher')['numeric_rating'].mean().sort
print(top_ten_publishers)
```

In [*]:
```
# Explore fresh distribution
sns.catplot(x="fresh", kind="count", data=review)
```

In [*]:
```
#The dataset has more fresh movies as compared to rotten.
#movies with a score above 70% are considered to be fresh while movies with a
```

CONCLUSIONS

The three key factor I used for analysis show that ROI is important and this is basically determined by production cost against domestic gross and also the language of the movie will influence production and English is the most preferred movie type as it attracts more audience hence mostly watched and lastly publishers and their rating is a key factor as they will assist push for sales and good rating. Top known publisher in the industry plays a key role in pushing for movies sales.

RECOMMENDATION

Consider investing in movies with higher production budgets: Since there is a positive correlation between production budget and domestic gross, investing in movies with higher production budgets may be more likely to yield higher returns. However, it's important to keep in mind that higher production budgets also come with higher risks.

Look for movies with good ratings: Movies with good ratings, especially those from top publishers, may be more likely to attract audiences and generate higher ticket sales. Investing in movies with good ratings can help minimize the risk of a box office flop.

Diversify your investments: While there is a positive correlation between production budget and domestic gross, it's important to diversify your investments to minimize risk. Investing in a variety of movies with different production budgets, genres, and ratings can help spread out the risk and increase the likelihood of a successful investment portfolio.

Consider the overall market trends: It's important to consider the overall market trends and consumer preferences when making investment decisions in the movie industry. For example, if streaming services are becoming more popular, it may be wise to invest in movies that have the potential to perform well on streaming platforms. Keeping up with the latest market trends can help you make informed investment decisions.