

"INSIGHTS ILLUMINATED : DATA DRIVEN RECOMMENDATIONS FOR MICROSOFT'S MOVIE MAKING ENDEAVORS"

1. Overview Of The Bussiness Problem.

As Microsoft ventures in to movie making,they face the challenge of identifying the best genres to make in a highly competitive industry.Microsoft requires insights derived from an analysis of movie datasets.

Therefore, this analysis is to inform the managers and decision makers on the type of movies that are likely to captivate audiences.

The tools that were used for the data analysis were python,a programming language for exploratory data analysis together with Matplotlib for data manipulation.Jupyter notebook for data analysis workflows and Seaborn was used to generate insightful plots and charts to communicate findings effectively.

STEP 1: IMPORT THE NECCESARY LIBRARIES

```
In [2]: import csv
import pandas as pd
import matplotlib as plt
import seaborn as sns
import numpy as np
```

STEP 2: IMPORTING AND JOINING THE DATASETS

```
In [3]: df1 = pd.read_csv(r"c:\Users\Ruth\Downloads\dsc-phase-1-project-v2-4-master\dsc-phase-1-
df2 = pd.read_csv(r"c:\Users\Ruth\Downloads\dsc-phase-1-project-v2-4-master\dsc-phase-1-
```

Joining the datasets

```
In [4]: df3 = df1.merge(df2)
```

STEP 3 : DATA UNDERSTANDING

```
.Dataframe shape
.Columns
.dtypes
.Description
.Info
```

```
In [5]: df3.shape
```

```
Out[5]: (2703, 14)
```

```
In [6]: df3.columns
```

```
Out[6]: Index(['Unnamed: 0', 'genre_ids', 'id', 'original_language', 'original_title',
'popularity', 'release_date', 'title', 'vote_average', 'vote_count',
'studio', 'domestic_gross', 'foreign_gross', 'year'],
dtype='object')
```

```
In [7]: df3.head(10)
```

```
Out[7]:   Unnamed: 0  genre_ids  id  original_language  original_title  popularity  release_date  title  vote_av
```

0	1	[14, 12, 16, 10751]	10191		en	How to Train Your Dragon	28.734	2010-03-26	How to Train Your Dragon
1	2	[12, 28, 878]	10138		en	Iron Man 2	28.515	2010-05-07	Iron Man 2
2	4	[28, 878, 12]	27205		en	Inception	27.920	2010-07-16	Inception
3	7	[16, 10751, 35]	10193		en	Toy Story 3	24.445	2010-06-17	Toy Story 3
4	8	[16, 10751, 35]	20352		en	Despicable Me	23.673	2010-07-09	Despicable Me
5	9	[16, 28, 35, 10751, 878]	38055		en	Megamind	22.855	2010-11-04	Megamind
6	12	[53, 12, 28]	27578		en	The Expendables	21.517	2010-08-03	The Expendables
7	13	[16, 10751]	38757		en	Tangled	21.511	2010-11-24	Tangled
8	15	[12, 14, 18, 10749]	24021		en	The Twilight Saga: Eclipse	20.340	2010-06-23	The Twilight Saga: Eclipse
9	16	[28, 53, 878]	20504		en	The Book of Eli	18.985	2010-01-11	The Book of Eli

In [8]:

df3.dtypes

Out[8]:

Unnamed: 0 int64
 genre_ids object
 id int64
 original_language object
 original_title object
 popularity float64
 release_date object
 title object
 vote_average float64
 vote_count int64
 studio object
 domestic_gross float64
 foreign_gross object
 year int64
 dtype: object

In [9]:

df3.tail(5)

Out[9]:

Unnamed: 0 genre_ids id original_language original_title popularity release_date title vote_

2698	25090	[16, 10751, 12]	455842	en	Elliot: The Littlest Reindeer	2.903	2018-11-30	Elliot: The Littlest Reindeer	
2699	25148	[28, 12, 16]	332718	en	Bilal: A New Breed of Hero	2.707	2018-02-02	Bilal: A New Breed of Hero	
2700	25189	[35]	498919	es	La Boda de Valentina	2.550	2018-02-09	La Boda de Valentina	
2701	25307	[18]	470641	hi	मुक़ाबला	2.276	2018-01-12	Mukkabaaz	
2702	26409	[10749, 18]	551634	zh	你好，之华	0.600	2018-11-09	Last Letter	

```
In [10]: df3.describe()
```

```
Out[10]:
```

	Unnamed: 0	id	popularity	vote_average	vote_count	domestic_gross	year
count	2703.000000	2703.000000	2703.000000	2703.000000	2703.000000	2.682000e+03	2703.000000
mean	11686.778024	213291.491306	10.002752	6.418572	1358.194599	3.629150e+07	2014.044395
std	7459.175381	139706.978070	7.294182	0.916424	2408.885097	7.734897e+07	2.440458
min	1.000000	1771.000000	0.600000	0.000000	1.000000	1.000000e+02	2010.000000
25%	5289.000000	76493.500000	5.881000	5.900000	78.000000	2.000000e+05	2012.000000
50%	11319.000000	209249.000000	8.627000	6.500000	393.000000	3.800000e+06	2014.000000
75%	17675.000000	334521.500000	12.698500	7.000000	1440.000000	3.882500e+07	2016.000000
max	26506.000000	574534.000000	80.773000	10.000000	22186.000000	9.367000e+08	2018.000000

```
In [11]: df3.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2703 entries, 0 to 2702
Data columns (total 14 columns):
 #   Column                Non-Null Count  Dtype
---  -
 0   Unnamed: 0            2703 non-null   int64
 1   genre_ids             2703 non-null   object
 2   id                   2703 non-null   int64
 3   original_language     2703 non-null   object
 4   original_title        2703 non-null   object
 5   popularity            2703 non-null   float64
 6   release_date          2703 non-null   object
 7   title                 2703 non-null   object
 8   vote_average          2703 non-null   float64
 9   vote_count            2703 non-null   int64
10   studio                2702 non-null   object
11   domestic_gross        2682 non-null   float64
12   foreign_gross         1723 non-null   object
13   year                  2703 non-null   int64
dtypes: float64(3), int64(4), object(7)
memory usage: 295.8+ KB
```

STEP 4 :DATA PREPARATION

```
.checking missing values in dataset
.dropping the missing values
.visualizing and percentage of missing values
.Identifying duplicated data
```

```
In [12]: print('Any missing value?', df3.isnull().values.any())
```

```
Any missing value? True
```

```
In [13]: df3.isnull().sum()
```

```
Out[13]:
```

Unnamed: 0	0
genre_ids	0
id	0
original_language	0
original_title	0
popularity	0
release_date	0
title	0
vote_average	0
vote_count	0

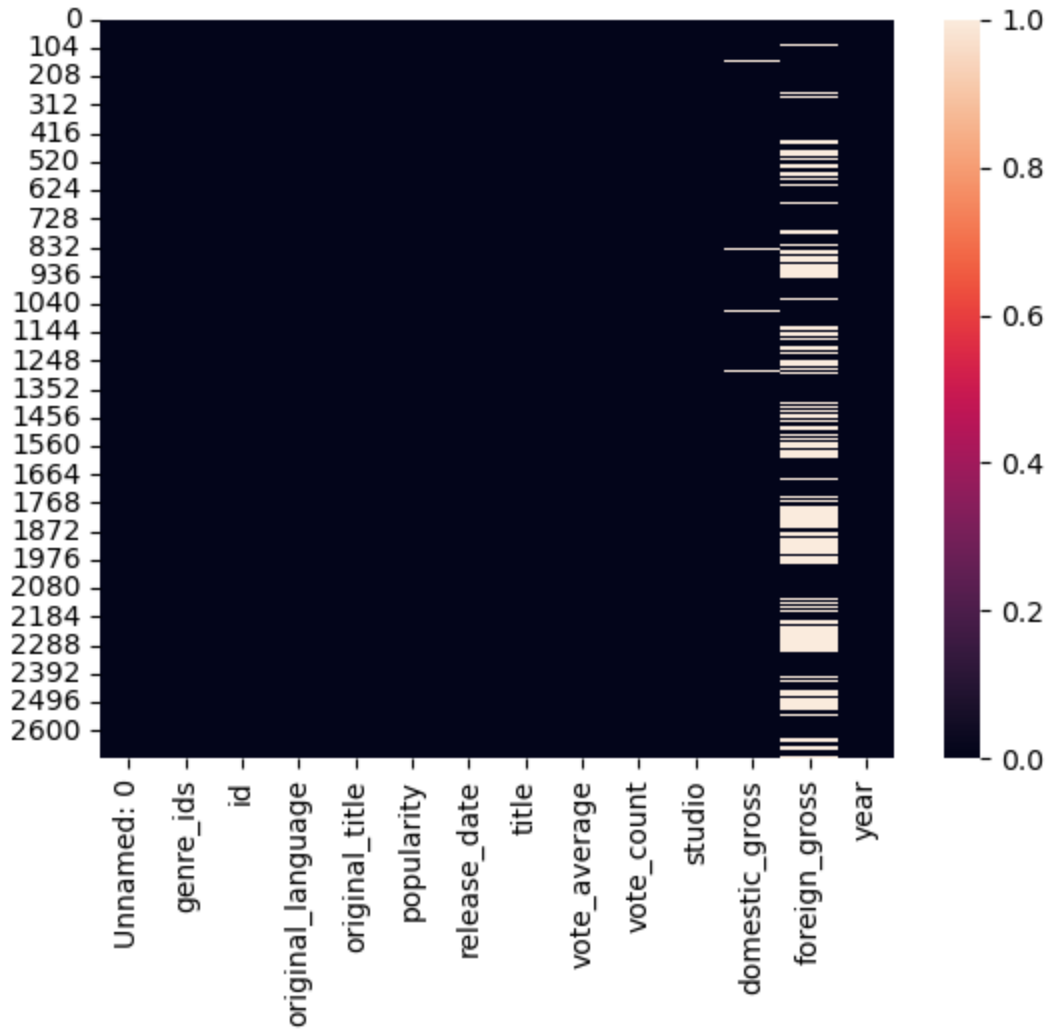
```

studio      1
domestic_gross    21
foreign_gross    980
year          0
dtype: int64

```

```
In [14]: sns.heatmap(df3.isnull())
```

```
Out[14]: <Axes: >
```



```
In [15]: df_missing = df3.isnull().sum() * 100 / len(df3)
print(df_missing)
```

```

Unnamed: 0      0.000000
genre_ids      0.000000
id             0.000000
original_language 0.000000
original_title  0.000000
popularity      0.000000
release_date    0.000000
title          0.000000
vote_average    0.000000
vote_count      0.000000
studio         0.036996
domestic_gross  0.776915
foreign_gross   36.256012
year           0.000000
dtype: float64

```

```
In [16]: df=df3.dropna(axis=0,)
print(df)
```

	Unnamed: 0	genre_ids	id	original_language	\
0	1	[14, 12, 16, 10751]	10191	en	
1	2	[12, 28, 878]	10138	en	
2	4	[28, 878, 12]	27205	en	
3	7	[16, 10751, 35]	10193	en	
4	8	[16, 10751, 35]	20352	en	
...
2682	24335	[12, 80, 10751, 35]	425148	en	
2686	24465	[35, 10749, 18, 9648]	522921	zh	
2689	24494	[12, 35, 14]	497984	zh	
2693	24646	[18, 10749]	446132	fr	
2699	25148	[28, 12, 16]	332718	en	

		original_title	popularity	release_date	\
0	How to Train Your Dragon	28.734	2010-03-26		
1	Iron Man 2	28.515	2010-05-07		
2	Inception	27.920	2010-07-16		
3	Toy Story 3	24.445	2010-06-17		
4	Despicable Me	23.673	2010-07-09		
...
2682	Show Dogs	7.904	2018-05-18		
2686	超时空同居	6.840	2018-05-17		
2689	捉妖记2	6.637	2018-02-14		
2693	Gauguin: Voyage de Tahiti	5.553	2018-07-11		
2699	Bilal: A New Breed of Hero	2.707	2018-02-02		

		title	vote_average	vote_count	studio	\
0	How to Train Your Dragon	7.7	7610	P/DW		
1	Iron Man 2	6.8	12368	Par.		
2	Inception	8.3	22186	WB		
3	Toy Story 3	7.7	8340	BV		
4	Despicable Me	7.2	10057	Uni.		
...
2682	Show Dogs	5.9	92	Global Road		
2686	How Long Will I Love U	7.4	11	WGUSA		
2689	Monster Hunt 2	6.3	14	LGF		
2693	Gauguin: Voyage to Tahiti	5.6	48	Cohen		
2699	Bilal: A New Breed of Hero	6.8	54	VE		

	domestic_gross	foreign_gross	year
0	217600000.0	277300000	2010
1	312400000.0	311500000	2010
2	292600000.0	535700000	2010
3	415000000.0	652000000	2010
4	251500000.0	291600000	2010
...
2682	179000000.0	21300000	2018
2686	747000.0	82100000	2018
2689	706000.0	361000000	2018
2693	200000.0	3100000	2018
2699	491000.0	1700000	2018

[1701 rows x 14 columns]

In [17]: `df.isna().sum()`

Out[17]:

Unnamed: 0	0
genre_ids	0
id	0
original_language	0
original_title	0
popularity	0
release_date	0
title	0
vote_average	0
vote_count	0

```
studio      0
domestic_gross  0
foreign_gross  0
year        0
dtype: int64
```

```
In [18]: df.duplicated()
```

```
Out[18]: 0      False
1      False
2      False
3      False
4      False
...
2682   False
2686   False
2689   False
2693   False
2699   False
Length: 1701, dtype: bool
```

```
In [19]: df.isna().sum()
```

```
Out[19]: Unnamed: 0      0
genre_ids      0
id             0
original_language  0
original_title  0
popularity     0
release_date   0
title          0
vote_average   0
vote_count     0
studio         0
domestic_gross  0
foreign_gross   0
year           0
dtype: int64
```

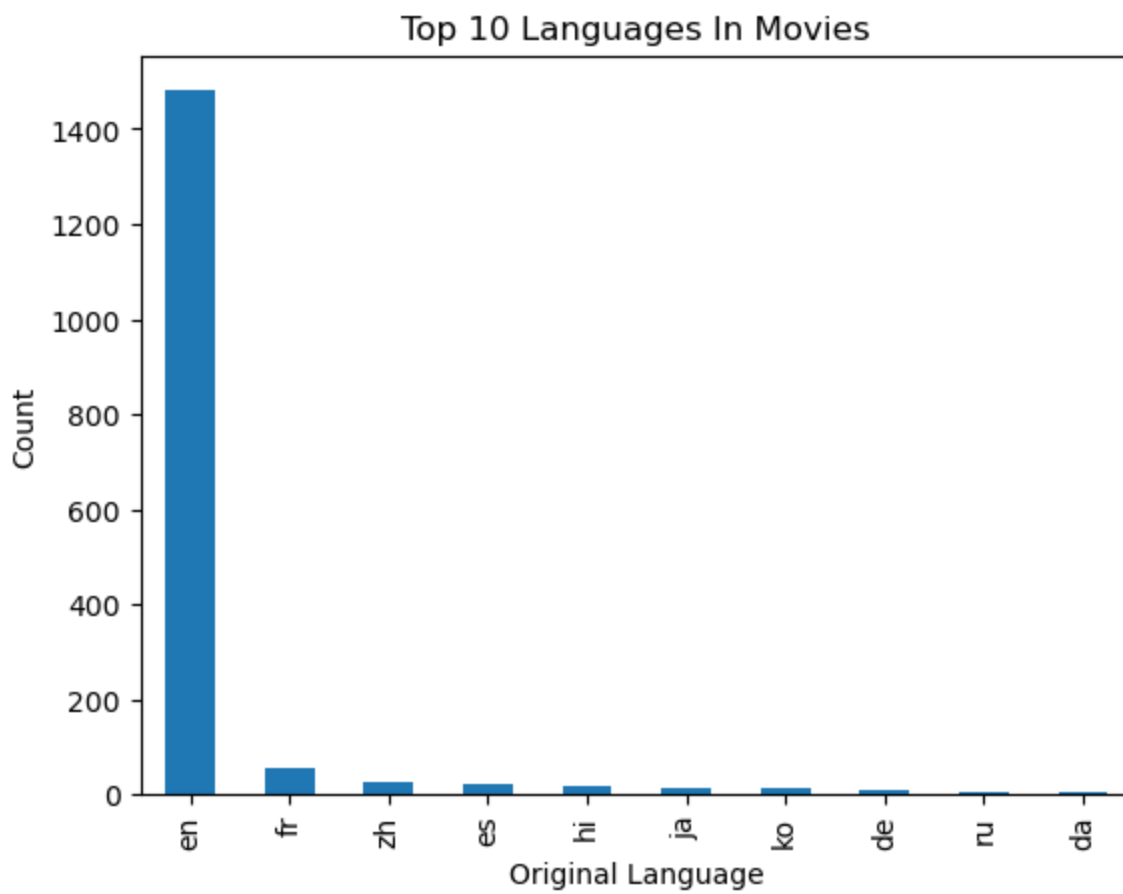
STEP 5:FEATURE UNDERSTANDING (Univariate Analysis)

```
.plotting feature distributions.
. Top 10 Languages using Bar Plot
. Top Vote Count Using Histogram
```

Language analysis

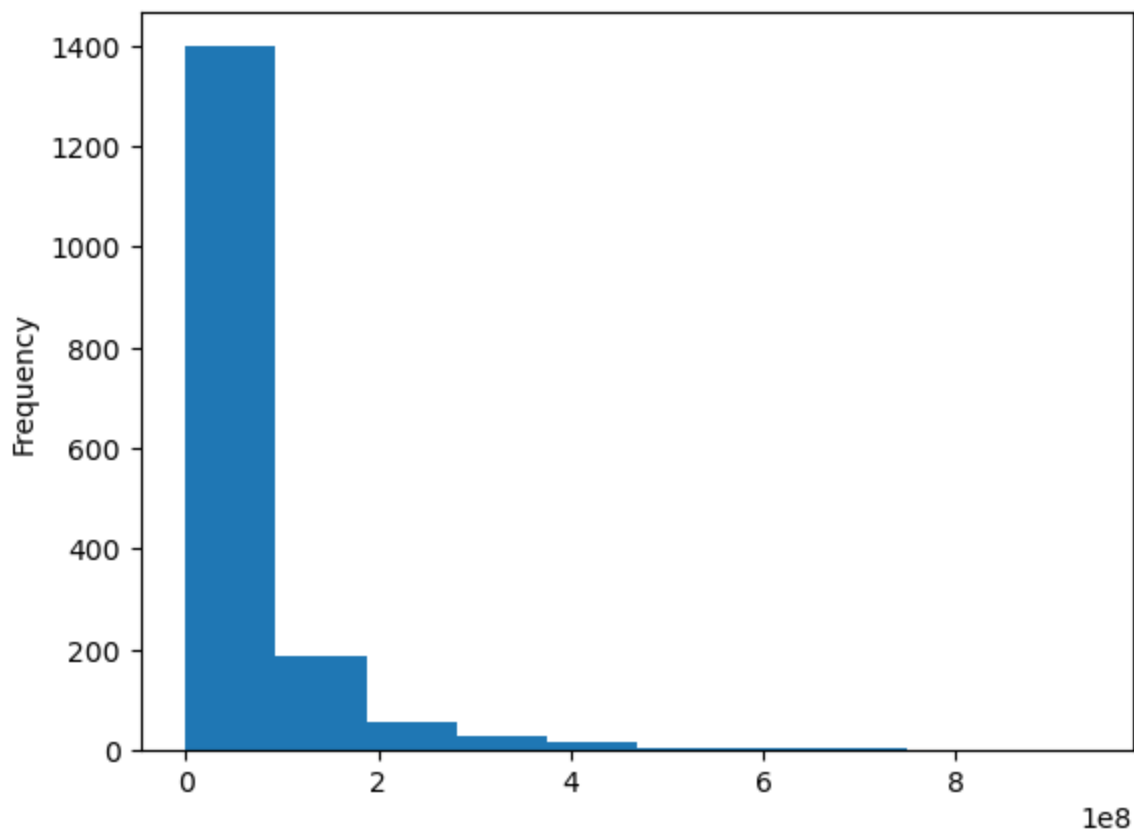
```
In [20]: ax=df['original_language'].value_counts().head(10).plot(kind="bar",title="Top 10 Languages")
ax.set_xlabel('Original Language')
ax.set_ylabel('Count')
```

```
Out[20]: Text(0, 0.5, 'Count')
```



```
In [21]: df["domestic_gross"].plot(kind='hist')
```

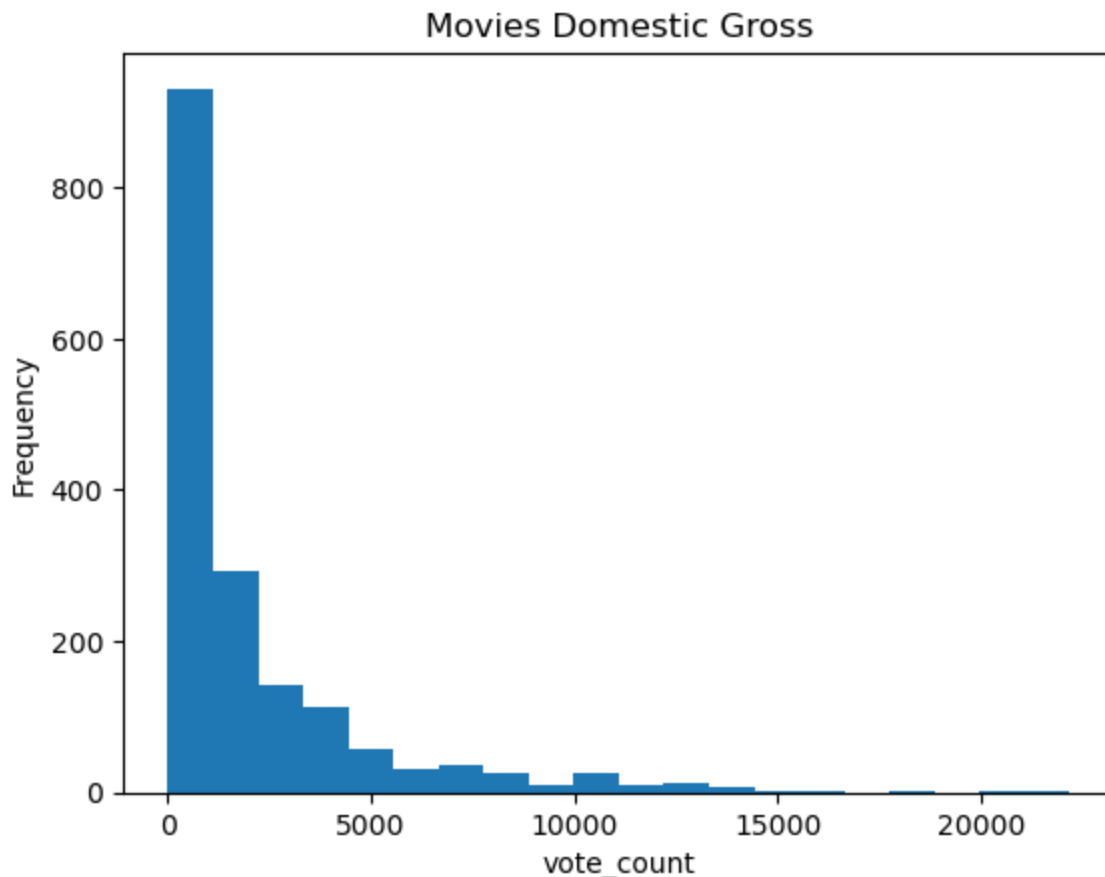
```
Out[21]: <Axes: ylabel='Frequency'>
```



From the above distribution of the top languages used, English has dominated the global box office. By producing movies in English, Microsoft can align themselves with established industry norms.

```
In [22]: ax = df["vote_count"].plot(kind = 'hist',bins = 20,title = 'Movies Domestic Gross')
ax.set_xlabel('vote_count')
```

```
Out[22]: Text(0.5, 0, 'vote_count')
```



Gross revenue is an indicator of a movie's financial success. Here, we can identify patterns and trends in revenue generation helping to predict the viability of their movie projects. This information can guide to assess the performance of their movies compared to competitors.

STEP 5 :FEATURE RELATIONSHIPS

(1) Top 10 Highest Gross Movie Titles

(2) Top 10 Movies With Highest Vote Count

(3) Comparing popularity vs domestic gross

(1) Top 10 Highest Gross Movie Titles

```
In [23]: df.nlargest(10,"domestic_gross")['title']
```

```
Out[23]: 1624    Star Wars: The Force Awakens
1625    Star Wars: The Force Awakens
608      Black Panther
609      Black Panther
2550    Avengers: Infinity War
1639      Jurassic World
2319    Star Wars: The Last Jedi
2320    Star Wars: The Last Jedi
2559      Incredibles 2
2009    Rogue One: A Star Wars Story
Name: title, dtype: object
```

```
In [24]: top_ten = df.nlargest(10,"domestic_gross")[['title',"domestic_gross"]].set_index('title')
```

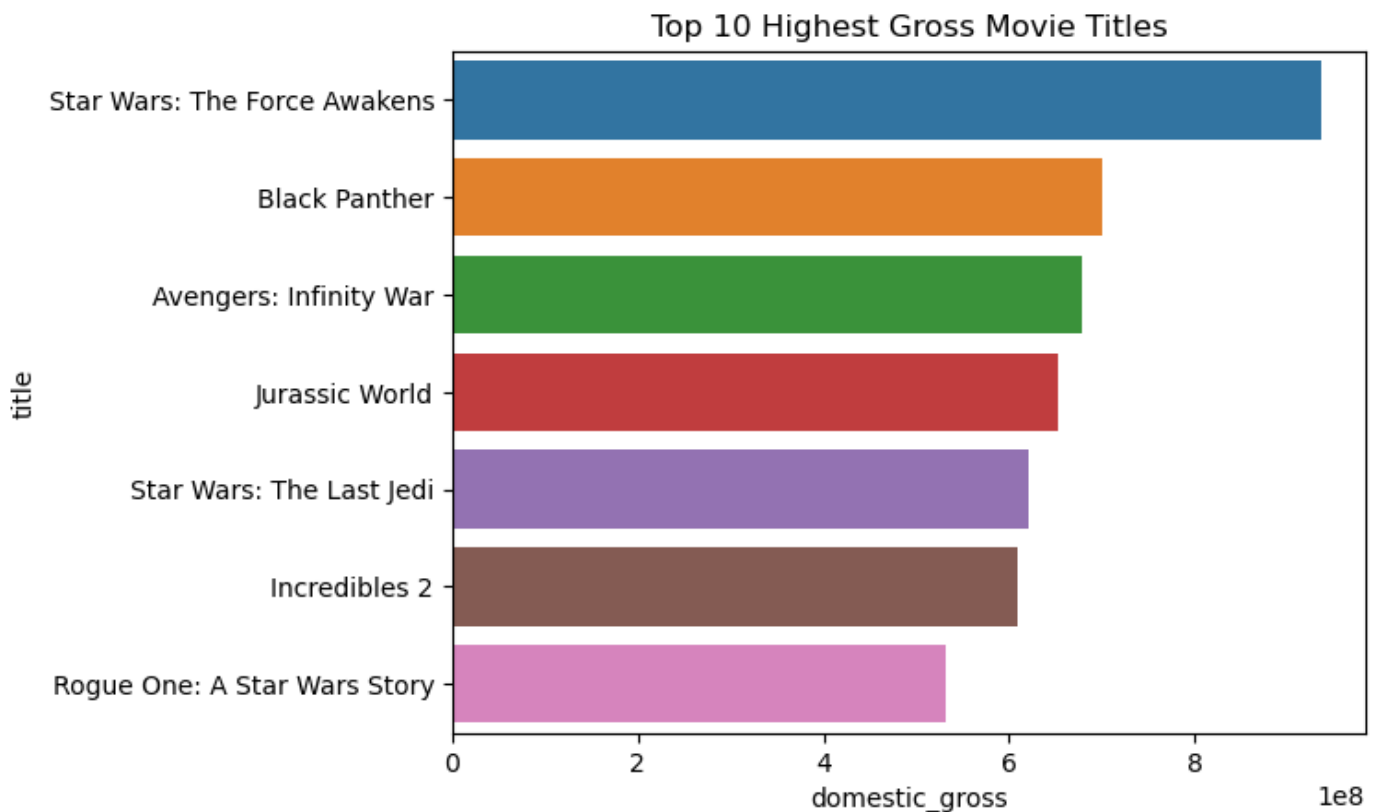


```
print(top_ten)
```

	domestic_gross
title	
Star Wars: The Force Awakens	936700000.0
Star Wars: The Force Awakens	936700000.0
Black Panther	700100000.0
Black Panther	700100000.0
Avengers: Infinity War	678800000.0
Jurassic World	652300000.0
Star Wars: The Last Jedi	620200000.0
Star Wars: The Last Jedi	620200000.0
Incredibles 2	608600000.0
Rogue One: A Star Wars Story	532200000.0

```
In [27]: ax = sns.barplot(x="domestic_gross",y=top_ten.index,data=top_ten)
ax.set_title('Top 10 Highest Gross Movie Titles')
```

```
Out[27]: Text(0.5, 1.0, 'Top 10 Highest Gross Movie Titles')
```



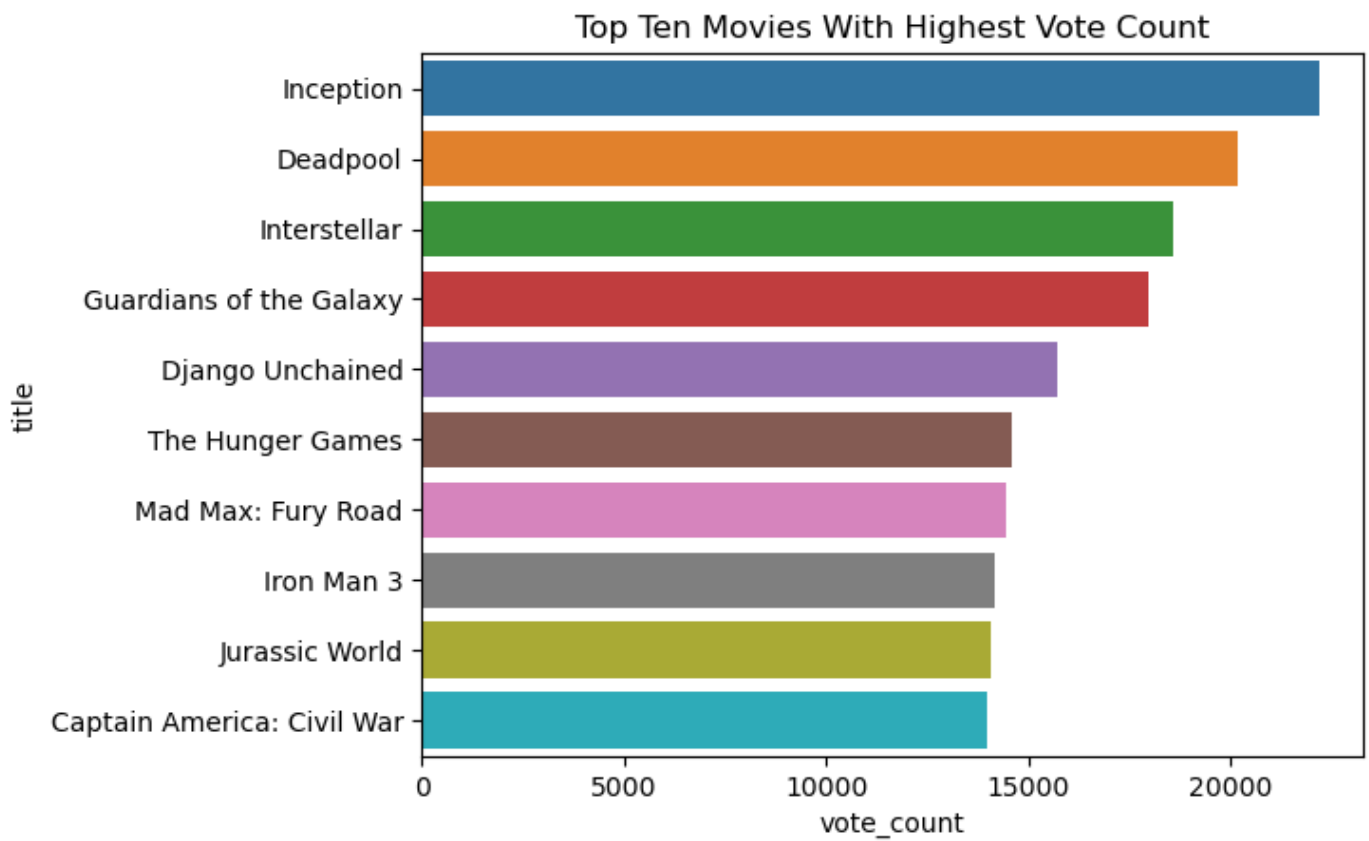
1. I recommend that Microsoft should focus on the genres and themes that have performed well based on the above dataset which was the movies with the highest revenue. Essentially, action, adventure and fantasy have consistently performed well. This will help to appeal to a wider demographic

(2) Movies With Highest Votes Count

```
In [ ]: top10 = df.nlargest(10,"vote_count")[['title',"vote_count"]].set_index('title')
```

```
In [ ]: ax = sns.barplot(x="vote_count",y=top10.index,data=top10)
ax.set_title('Top Ten Movies With Highest Vote Count')
```

```
Out[ ]: Text(0.5, 1.0, 'Top Ten Movies With Highest Vote Count')
```

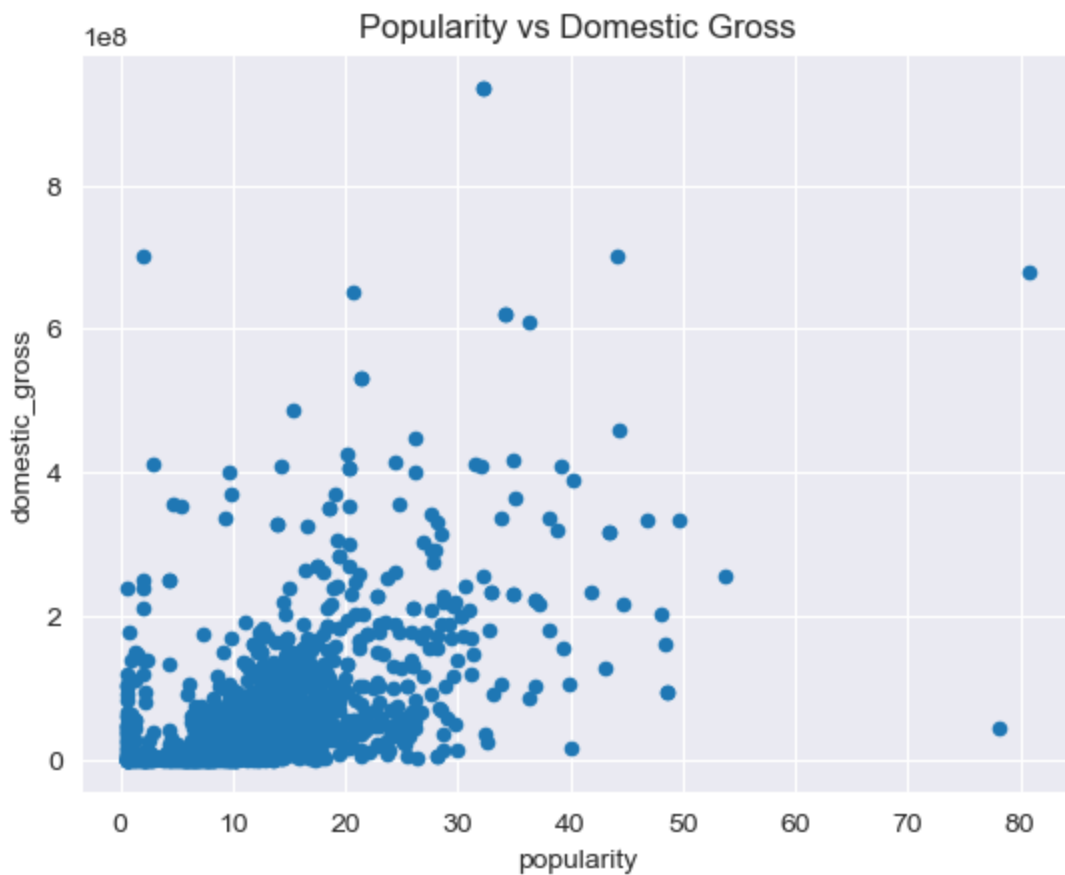


1. I recommend that In order to resonate with the audience, Microsoft should deliver movies that are visually stunning,intellectually stimulating and emotionally resonant. Invest in top tier talent,production resources that earn votes

(3) Comparing popularity vs domestic gross

```
In [ ]: df.plot(kind = 'scatter', x= 'popularity', y = "domestic_gross",title = "Popularity vs D
```

```
Out[ ]: <Axes: title={'center': 'Popularity vs Domestic Gross'}, xlabel='popularity', ylabel='do  
mestic_gross'>
```



1. Microsoft should prioritize projects that demonstrate potential for both popularity and revenue . From the above scatterplot,high popular movies may attract audiences but may not always translate to substantial box office gross.

In a nutshell, based on the analysis of the movie dataset,i recommend that Microsoft prioritizes genres and themes that have demonstrated the highest revenue,popularity and vote count. By understanding the audience Microsoft can tailor the movies to engage the target audience

I would like to extend my sincere gratitude to Microsoft for the opportunity to work on this project. It has been a great experience to delve in to the movie datasets and provide insights to support Microsoft's venture in to movie making. Should you have any further questions,please reach out.Thank you once again for the opportunity to contribute to this exciting project.