Final Project Submission

Please fill out:

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- **Scheduled project review date/time: 16/04/2023 / 0000HRS**
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- **Blog post URL:**

AN ANALYSIS TO INVESTIGATE THE KIND OF MOVIES THAT ARE PERFORMING WELL AT THE BOX OFFICE IN TERMS OF RATINGS, FOREIGN GROSS AND INSIGHTS.

Business Understanding

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. I am therefore charged with exploring what types of films are currently doing the best at the box office and then translate those findings into actionable insights that the head of Microsoft's new movie studio can use to help decide what type of films to create.

Problem Statement

Microsoft stakeholders and top management are finding it hard understanding the specific movies that are performing well in terms of ratings, foreign gross, insights such as number of votes and genres that performed well. Without understanding these metrics it will be hard for them to create original video content through their movie studio. They are not sure where to start in order to investigate these metrics.

Project's goal

Therefore this project is focused on investigating the above metrics inorder to come up with a decisive action to enable the microsoft studio to create only movies that are going to perform well internationally and be a good investment plan. Only the kind of movies that attract great insights through high number of votes, high foreign gross and higher ratings will be prioritised in the production studio.

In [1]:

```
# importing the python libraries that I will use for this project
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import sqlite3
```

Data Understanding

In this analysis I used three different datasets which are from Box office Mojo, IMDB SQLite Database and The movie Database. The datasets will be cleaned before performing exploratory data analysis. The datasets were chosen since they have data on foreign gross, domestic gross, genres, insights through number of votes the movies attracted and the movie ratings. This will present a clear picture of how different movies performed and thus lead to the stakeholders and top management at Microsoft making informed decisions before production at the new movie studio.

1. BOX OFFICE MOJO DATASET

II. BOX OFFICE MOJO DATASET

I will first start by reading the dataset inorder to understand the data and the kind of measurements that I will use to determine the success of movies

In [2]:

```
bom_df=pd.read_csv("zippedData/bom.movie_gross.csv.gz")
```

In [3]:

```
bom_df
```

Out[3]:

	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

Size of the dataset

The above dataset has 3387 rows and 5 columns

In [4]:

```
bom_df.shape
```

Out[4]:

```
(3387, 5)
```

Checking for missing values

Missing values can occur for a variety of reasons, including measurement error, data entry errors and non-response. The presence of missing data can cause biased estimates, inaccurate results, misleading visualisations as well as a loss of information. By checking, identifying and addressing missing values before analysis, I will be able to increase the accuracy and reliability of my results

In [5]:

```
# getting the sum of all missing values in the dataframe
bom_df.isna().sum()
```

Out[5]:

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

In [6]:

```
# From the dataframe studio column has five missing values, domestic_gross 28 missing val
ues and
# foreign_gross a total of 1350 missing values
```

In [7]:

```
# since studio column has no much significance in this analysis, I decided to drop it
```

In [8]:

```
bom_df.drop(columns=["studio"], inplace=True)
```

In [9]:

```
bom_df
```

Out[9]:

	title	domestic_gross	foreign_gross	year
0	Toy Story 3	415000000.0	652000000	2010
1	Alice in Wonderland (2010)	334200000.0	691300000	2010
2	Harry Potter and the Deathly Hallows Part 1	296000000.0	664300000	2010
3	Inception	292600000.0	535700000	2010
4	Shrek Forever After	238700000.0	513900000	2010
...	...	...	...	...
3382	The Quake	6200.0	NaN	2018
3383	Edward II (2018 re-release)	4800.0	NaN	2018
3384	El Pacto	2500.0	NaN	2018
3385	The Swan	2400.0	NaN	2018
3386	An Actor Prepares	1700.0	NaN	2018

3387 rows × 4 columns

Filling missing values in domestic_gross with its mean

This column cannot be dropped as it is of great significance as a metric for movie perfomance in terms of gross revenue. Therefore missing values will be filled with the mean of domestic_gross

In [10]:

```
bom_df["domestic_gross"].fillna(bom_df["domestic_gross"].mean(),inplace=True)
```

In [11]:

```
bom_df
```

Out[11]:

	title	domestic_gross	foreign_gross	year
0	Toy Story 3	415000000.0	652000000	2010
1	Alice in Wonderland (2010)	334200000.0	691300000	2010
2	Harry Potter and the Deathly Hallows Part 1	296000000.0	664300000	2010
3	Inception	292600000.0	535700000	2010
4	Shrek Forever After	238700000.0	513900000	2010
...	...	...	...	...

	title	domestic_gross	foreign_gross	year
3382	The Quake	6200.0	NaN	2018
3383	Edward II (2018 re-release)	4800.0	NaN	2018
3384	El Pacto	2500.0	NaN	2018
3385	The Swan	2400.0	NaN	2018
3386	An Actor Prepares	1700.0	NaN	2018

3387 rows × 4 columns

In [12]:

```
bom_df.isna().sum()
```

Out[12]:

```
title                0
domestic_gross       0
foreign_gross     1350
year                 0
dtype: int64
```

In [13]:

```
# domestic_gross has 0 missing values after filling with mean
```

Addressing missing values in foreign_gross

For foreign gross I made an assumption that the missing values are as a result of the movies having 0 international sales This might have been due to no international releases for those movies that have missing values Therefore the best strategy was to fill with 0s since this column is vital in the analysis and cannot be dropped

In [14]:

```
bom_df["foreign_gross"].fillna(0, inplace=True)
```

In [15]:

```
bom_df
```

Out[15]:

	title	domestic_gross	foreign_gross	year
0	Toy Story 3	415000000.0	652000000	2010
1	Alice in Wonderland (2010)	334200000.0	691300000	2010
2	Harry Potter and the Deathly Hallows Part 1	296000000.0	664300000	2010
3	Inception	292600000.0	535700000	2010
4	Shrek Forever After	238700000.0	513900000	2010
...	...	...	...	...
3382	The Quake	6200.0	0	2018
3383	Edward II (2018 re-release)	4800.0	0	2018
3384	El Pacto	2500.0	0	2018
3385	The Swan	2400.0	0	2018
3386	An Actor Prepares	1700.0	0	2018

3387 rows × 4 columns

In [16]:

```
bom_df.isna().sum()
```

Out[16]:

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

In [17]:

```
# There are no missing values in the dataframe now
```

Checking for duplicates in the data

By identifying and removing duplicates, I want to ensure that each observation in the Box office Mojo dataset is represented only once. This will help to ensure data accuracy, efficiency, and consistency, and thus help in obtaining reliable and meaningful insights from the data.

In [18]:

```
bom_df.duplicated().value_counts()
```

Out[18]:

```
False    3387
dtype: int64
```

In [19]:

```
# False indicates that the data has no duplicates
```

Identfying top 20 movies with high foreign gross

In [20]:

```
# Converting foreign gross to numeric type

bom_df["foreign_gross"] = pd.to_numeric(bom_df["foreign_gross"], errors="coerce")
# Sorting
top_20_df=bom_df.sort_values("foreign_gross", ascending=False).head(20)
top_20_df
```

Out[20]:

	title	domestic_gross	foreign_gross	year
328	Harry Potter and the Deathly Hallows Part 2	381000000.0	960500000.0	2011
1875	Avengers: Age of Ultron	459000000.0	946400000.0	2015
727	Marvel's The Avengers	623400000.0	895500000.0	2012
3081	Jurassic World: Fallen Kingdom	417700000.0	891800000.0	2018
1127	Frozen	400700000.0	875700000.0	2013
2764	Wolf Warrior 2	2700000.0	867600000.0	2017
1477	Transformers: Age of Extinction	245400000.0	858600000.0	2014
1876	Minions	336000000.0	823400000.0	2015
3083	Aquaman	335100000.0	812700000.0	2018
1128	Iron Man 3	409000000.0	805800000.0	2013
330	Pirates of the Caribbean: On Stranger Tides	241100000.0	804600000.0	2011
728	Skyfall	304400000.0	804200000.0	2012
329	Transformers: Dark of the Moon	352400000.0	771400000.0	2011
2761	Despicable Me 3	264600000.0	770200000.0	2017
[illegible]	Beauty and the Beast (2017)	[illegible]	[illegible]	[illegible]

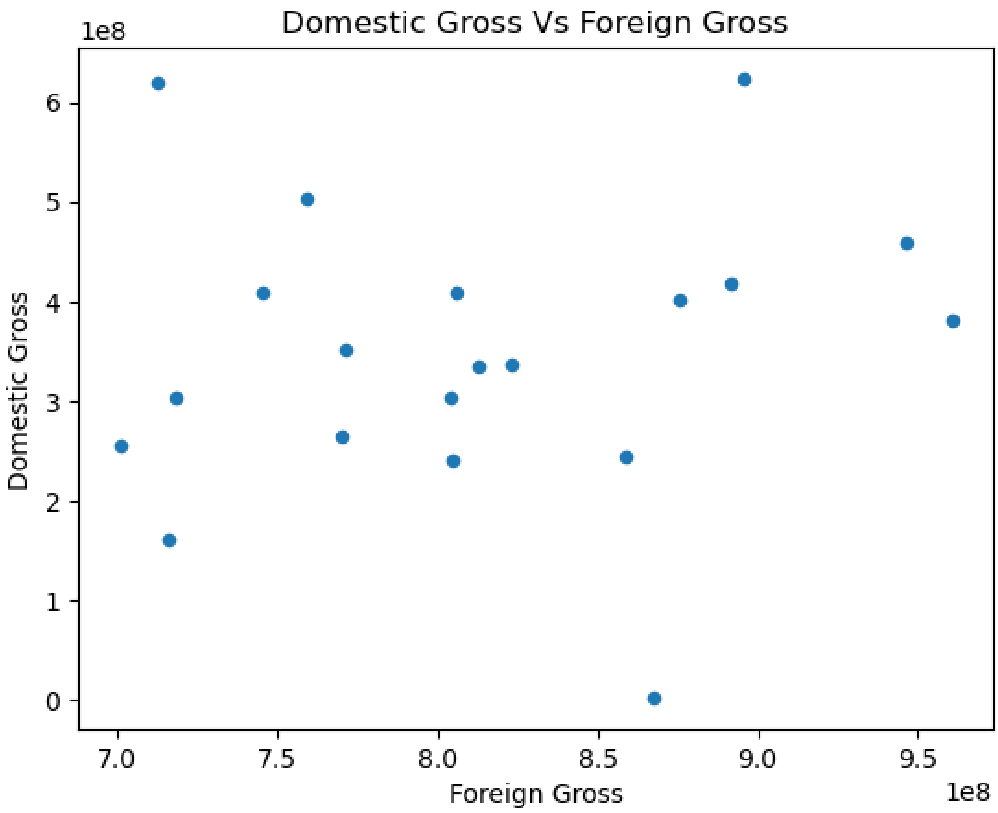
	title	domestic_gross	foreign_gross	year
2759	Beauty and the Beast (2017)	504000000.0	759500000.0	2017
2322	Captain America: Civil War	408100000.0	745200000.0	2016
730	The Hobbit: An Unexpected Journey	303000000.0	718100000.0	2012
731	Ice Age: Continental Drift	161300000.0	715900000.0	2012
2758	Star Wars: The Last Jedi	620200000.0	712400000.0	2017
1478	The Hobbit: The Battle of the Five Armies	255100000.0	700900000.0	2014

In [21]:

```
# Identifying the relationship between foreign gross and domestic gross
# Creating a scatter plot
top_20_df.plot.scatter("foreign_gross","domestic_gross")
plt.ylabel("Domestic Gross")
plt.xlabel("Foreign Gross")
plt.title("Domestic Gross Vs Foreign Gross")
plt.show
```

Out[21]:

```
<function matplotlib.pyplot.show(close=None, block=None)>
```



2. IMDB SQLITE DATABASE

In this Database with several tables, I picked only two tables; movie_ratings and movie_basics which contain valuable data such as average rating and number of votes which will be used as metrics of movie perfomance.

I will join the two tables into one using the key "movie_id" which uniquely identifies the movies. Everything from the two tables will be selected and start filtering on irrelevant data and columns.

In [22]:

```
conn=sqlite3.connect("zippedData/im.db/im.db")
imdb_df=pd.read_sql("""
SELECT *
FROM movie_ratings
JOIN movie_basics
 ON movie_ratings.movie_id= movie_basics.movie_id
""",conn)
imdb_df
```

Out[22]:

	movie_id	averagerating	numvotes	movie_id	primary_title	original_title	start_year	runtime_minutes	
0	tt10356526	8.3	31	tt10356526	Laiye Je Yaarian	Laiye Je Yaarian	2019	117.0	
1	tt10384606	8.9	559	tt10384606	Borderless	Borderless	2019	87.0	
2	tt1042974	6.4	20	tt1042974	Just Inès	Just Inès	2010	90.0	
3	tt1043726	4.2	50352	tt1043726	The Legend of Hercules	The Legend of Hercules	2014	99.0	Action,Adve
4	tt1060240	6.5	21	tt1060240	Até Onde?	Até Onde?	2011	73.0	My
...	...	...	...	...	...	...	...	...	
73851	tt9805820	8.1	25	tt9805820	Caisa	Caisa	2018	84.0	
73852	tt9844256	7.5	24	tt9844256	Code Geass: Lelouch of the Rebellion - Glorifi...	Code Geass: Lelouch of the Rebellion Episode III	2018	120.0	Action,Ani
73853	tt9851050	4.7	14	tt9851050	Sisters	Sisters	2019	NaN	
73854	tt9886934	7.0	5	tt9886934	The Projectionist	The Projectionist	2019	81.0	
73855	tt9894098	6.3	128	tt9894098	Sathru	Sathru	2019	129.0	

73856 rows × 9 columns

Size of the IMDB dataset

The dataframe has 73856 rows and 9 columns

Dropping duplicating and irrelevant columns

In this dataframe that I have obtained from an SQLite database, movie_id columns appears twice and thus the need to drop one or even both since they are not that significant in my analysis.

In [23]:

```
#Dropping movie_id columns
imdb_df.drop(columns=["movie_id"],inplace=True)
```

In [24]:

```
imdb_df
```

Out[24]:

	averagerating	numvotes	primary_title	original_title	start_year	runtime_minutes	genres
0	8.3	31	Laiye Je Yaarian	Laiye Je Yaarian	2019	117.0	Romance
1	8.9	559	Borderless	Borderless	2019	87.0	Documentary
2	6.4	20	Just Inès	Just Inès	2010	90.0	Drama
3	4.2	50352	The Legend of Hercules	The Legend of Hercules	2014	99.0	Action,Adventure,Fantasy
4	6.5	21	Até Onde?	Até Onde?	2011	73.0	Mystery,Thriller
...	...	...	...	...	...	...	...
73851	8.1	25	Caisa	Caisa	2018	84.0	Documentary
73852	7.5	24	Code Geass: Lelouch of the Rebellion -	Code Geass: Lelouch of the Rebellion Episode	2018	120.0	Action,Animation,Sci-Fi

	averagerating	numvotes	primary_title	original_title	start_year	runtime_minutes	genres
73853	4.7	14	Sisters	Sisters	2019	NaN	Action,Drama
73854	7.0	5	The Projectionist	The Projectionist	2019	81.0	Documentary
73855	6.3	128	Sathru	Sathru	2019	129.0	Thriller

73856 rows × 7 columns

My columns of interest are the averagerating and numvotes which will be used as metrics for movie perfomance

Checking for missing values

In [25]:

```
imdb_df.isna().sum()
```

Out[25]:

```
averagerating        0
numvotes             0
primary_title        0
original_title       0
start_year           0
runtime_minutes   7620
genres             804
dtype: int64
```

Decision made

Runtime_minutes has a total of 7620 missing values and genres 804 missing values. Runtime minutes will be dropped since there is no much use in this analysis and genres will be kept since it will enable me to understand the kind of movie genres that perfomed well.

In [26]:

```
imdb_df.drop(columns=["runtime_minutes"], inplace=True)
```

In [27]:

```
imdb_df
```

Out[27]:

	averagerating	numvotes	primary_title	original_title	start_year	genres
0	8.3	31	Laiye Je Yaarian	Laiye Je Yaarian	2019	Romance
1	8.9	559	Borderless	Borderless	2019	Documentary
2	6.4	20	Just Inès	Just Inès	2010	Drama
3	4.2	50352	The Legend of Hercules	The Legend of Hercules	2014	Action,Adventure,Fantasy
4	6.5	21	Até Onde?	Até Onde?	2011	Mystery,Thriller
...	...	...	...	...	...	...
73851	8.1	25	Caisa	Caisa	2018	Documentary
73852	7.5	24	Code Geass: Lelouch of the Rebellion - Glorifi...	Code Geass: Lelouch of the Rebellion Episode III	2018	Action,Animation,Sci-Fi
73853	4.7	14	Sisters	Sisters	2019	Action,Drama
73854	7.0	5	The Projectionist	The Projectionist	2019	Documentary
73855	6.3	128	Sathru	Sathru	2019	Thriller

73856 rows × 6 columns

Checking for duplicates in the data

In [28]:

```
imdb_df.duplicated().value_counts()
```

Out[28]:

```
False    73856
dtype: int64
```

In [29]:

```
# This indicates that there are no duplicates in the data
```

Plotting Top 15 movie genres with many votes

In [30]:

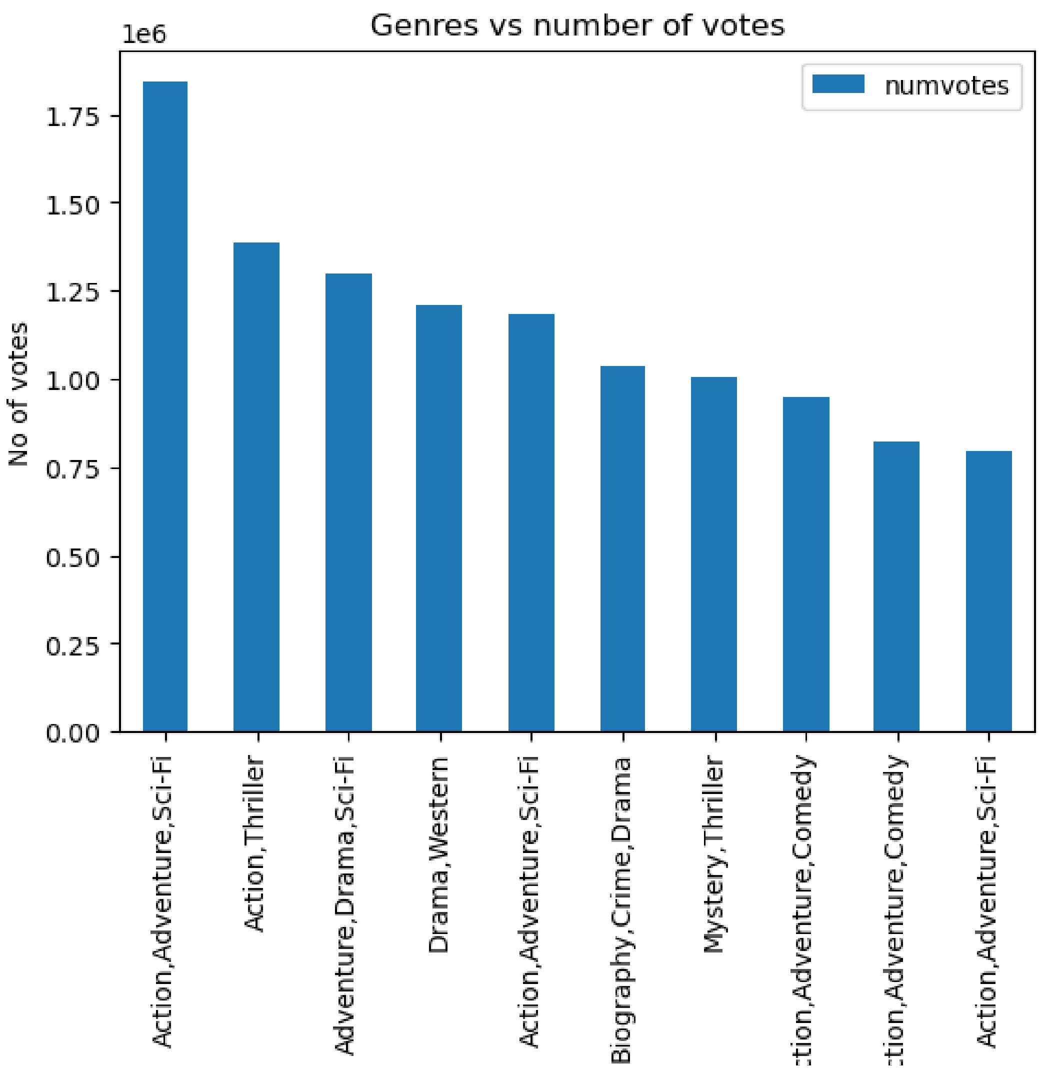
```
#Sorting top 15 movies with high number of votes in descending order

top_15_df=imdb_df.sort_values("numvotes", ascending=False).head(10)
```

In [31]:

```
# Creating a bar chart
top_15_df.plot.bar("genres","numvotes")
plt.xlabel("Genres")
plt.ylabel("No of votes")
plt.title("Genres vs number of votes")
plt.show
```

Out[31]:

```
<function matplotlib.pyplot.show(close=None, block=None)>
```



3. THE MOVIE DATABASE

This dataset will be important in obtaining data for movie popularity, vote average and the vote count of different movies which will be vital in the analysis

In [32]:

```
tmdb_df=pd.read_csv("zippedData/tmdb.movies.csv.gz", index_col=0)
#index_col=0 was used to avoid having two index columns
```

In [33]:

```
tmdb_df
```

Out[33]:

	genre_ids	id	original_language	original_title	popularity	release_date	title	vote_average	vote_
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	7.7	
1	[14, 12, 16, 10751]	10191	en	How to Train Your Dragon	28.734	2010-03-26	How to Train Your Dragon	7.7	
2	[12, 28, 878]	10138	en	Iron Man 2	28.515	2010-05-07	Iron Man 2	6.8	
3	[16, 35, 10751]	862	en	Toy Story	28.005	1995-11-22	Toy Story	7.9	
4	[28, 878, 12]	27205	en	Inception	27.920	2010-07-16	Inception	8.3	
...	...	...	...	...	...	...	...	...	
26512	[27, 18]	488143	en	Laboratory Conditions	0.600	2018-10-13	Laboratory Conditions	0.0	
26513	[18, 53]	485975	en	_EXHIBIT_84xxx_	0.600	2018-05-01	_EXHIBIT_84xxx_	0.0	
26514	[14, 28, 12]	381231	en	The Last One	0.600	2018-10-01	The Last One	0.0	
26515	[10751, 12, 28]	366854	en	Trailer Made	0.600	2018-06-22	Trailer Made	0.0	
26516	[53, 27]	309885	en	The Church	0.600	2018-10-05	The Church	0.0	

26517 rows × 9 columns

Size of the the movie database

The dataframe has 26517 rows and 9 columns

In [34]:

```
#The next step will be dropping unnecessary columns by creating a list of unnecessary col
umns
unnecessary_cols=["genre_ids","id","original_language","original_title","release_date"]
#Dropping the columns
tmdb_df.drop(columns=unnecessary_cols,inplace=True)
```

In [35]:

```
tmdb_df
```

Out[35]:

	popularity	title	vote_average	vote_count
0	33.533	Harry Potter and the Deathly Hallows: Part 1	7.7	10788
1	28.734	How to Train Your Dragon	7.7	7610
2	28.515	Iron Man 2	6.8	12368
3	28.005	Toy Story	7.9	10174
4	27.920	Inception	8.3	22186
...	...	...	...	...
26512	0.600	Laboratory Conditions	0.0	1
26513	0.600	_EXHIBIT_84xxx_	0.0	1
26514	0.600	The Last One	0.0	1
26515	0.600	Trailer Made	0.0	1
26516	0.600	The Church	0.0	1

26517 rows × 4 columns

Checking for missing values

In [36]:

```
tmdb_df.isna().sum()
```

Out[36]:

```
popularity      0
title           0
vote_average    0
vote_count      0
dtype: int64
```

In [37]:

```
### There are no missing values in the movie database
```

Checking for duplicates

In [38]:

```
tmdb_df.duplicated().value_counts()
```

Out[38]:

```
False    25493
True      1024
dtype: int64
```

In [39]:

```
# There are 9428 duplicated values in the dataframe
```

In [40]:

```
#Dropping the duplicates

tmdb_df=tmdb_df.drop_duplicates()
```

In [41]:

```
#confirming that the duplicates were dropped
tmdb_df.duplicated().value_counts()
```

Out[41]:

```
False    25493
dtype: int64
```

In [42]:

```
# The duplicates have been gotten rid of
```

Top 10 popular movies

In [43]:

```
#sorting top 10

top_10=tmdb_df.sort_values("popularity", ascending=False).head(10)
top_10
```

Out[43]:

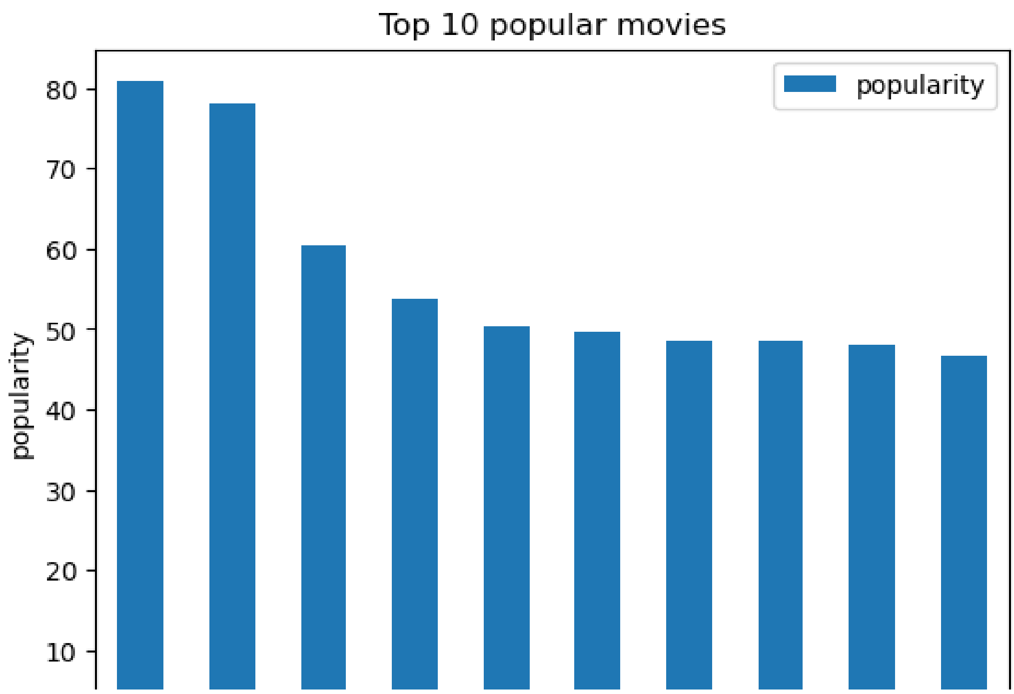
	popularity	title	vote_average	vote_count
23811	80.773	Avengers: Infinity War	8.3	13948
11019	78.123	John Wick	7.2	10081
23812	60.534	Spider-Man: Into the Spider-Verse	8.4	4048
11020	53.783	The Hobbit: The Battle of the Five Armies	7.3	8392
5179	50.289	The Avengers	7.6	19673
11021	49.606	Guardians of the Galaxy	7.9	17958
20617	48.571	Blade Runner 2049	7.4	6679
23814	48.508	Fantastic Beasts: The Crimes of Grindelwald	6.9	4870
23815	48.057	Ralph Breaks the Internet	7.2	2626
20618	46.775	Spider-Man: Homecoming	7.4	11585

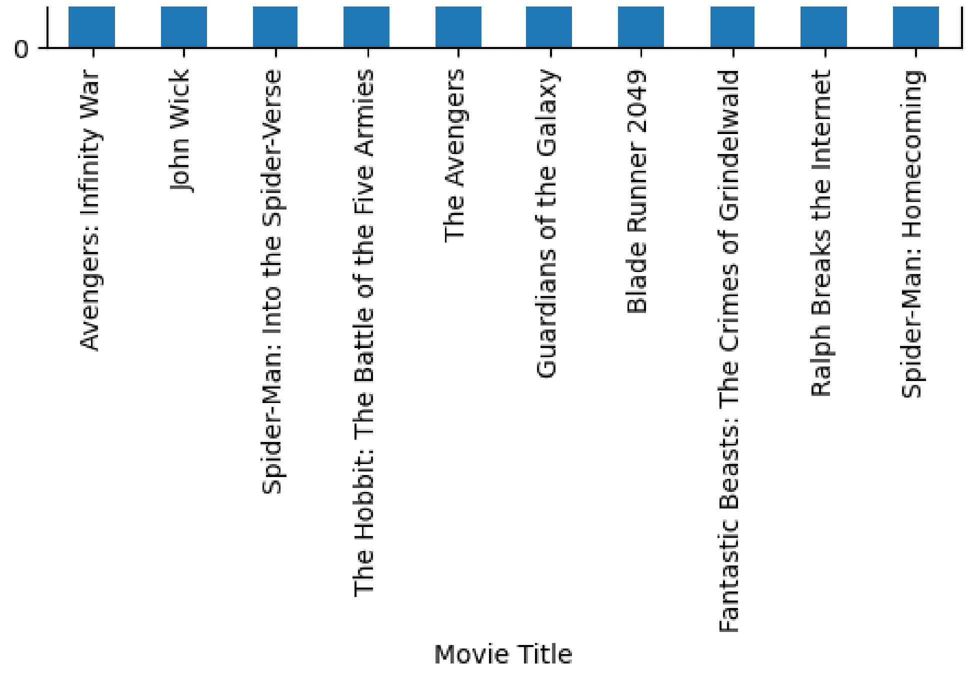
In [44]:

```
top_10.plot.bar("title", "popularity")
plt.xlabel("Movie Title")
plt.ylabel("popularity")
plt.title("Top 10 popular movies")
```

Out[44]:

```
Text(0.5, 1.0, 'Top 10 popular movies')
```

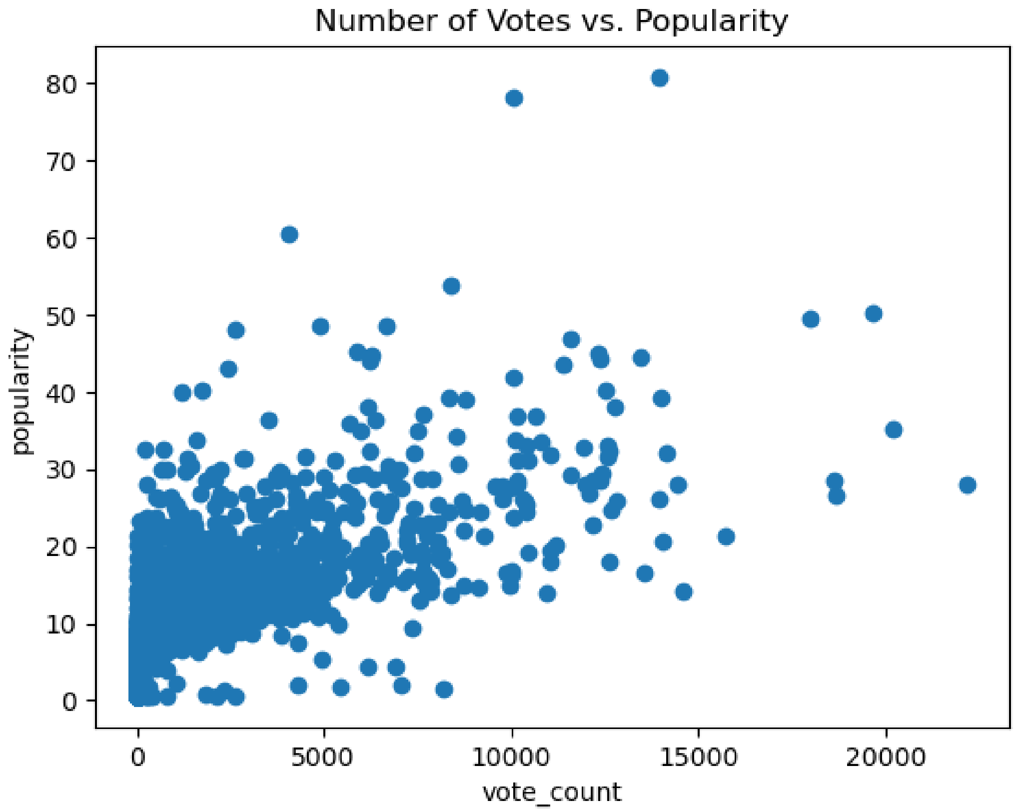




Correlation between Vote count and Movie popularity

In [45]:

```
# plotting a scatter plot
plt.scatter(tmdb_df["vote_count"], tmdb_df["popularity"])

# Add axis labels and a title to the plot
plt.ylabel("popularity")
plt.xlabel("vote_count")
plt.title("Number of Votes vs. Popularity")

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



DISCUSSION

There is a low positive correlation between popularity and vote count of movies

MERGING THE DATASETS

The three datasets will then be merged for Exploratory Data Analysis to take place. Merging the datasets is vital since data will be combined from different sources to gain a more concise and complete information. It will also increase the sample size thus improving the accuracy and reliability of my analysis.

In [46]:

```
to_merge=[bom_df, imdb_df, tmdb_df]

merged_df=pd.concat(to_merge)
```

In [47]:

```
irrelevant_columns=["year","primary_title","original_title","start_year"]
merged_df.drop(columns=irrelevant_columns, inplace=True)
merged_df
```

Out[47]:

	title	domestic_gross	foreign_gross	averagerating	numvotes	genres	popularity	vote_average	vote_cou
0	Toy Story 3	415000000.0	652000000.0	NaN	NaN	NaN	NaN	NaN	Na
1	Alice in Wonderland (2010)	334200000.0	691300000.0	NaN	NaN	NaN	NaN	NaN	Na
2	Harry Potter and the Deathly Hallows Part 1	296000000.0	664300000.0	NaN	NaN	NaN	NaN	NaN	Na
3	Inception	292600000.0	535700000.0	NaN	NaN	NaN	NaN	NaN	Na
4	Shrek Forever After	238700000.0	513900000.0	NaN	NaN	NaN	NaN	NaN	Na
...	...	...	...	...	...	...	...	...	
26512	Laboratory Conditions	NaN	NaN	NaN	NaN	NaN	0.6	0.0	1
26513	_EXHIBIT_84xxx_	NaN	NaN	NaN	NaN	NaN	0.6	0.0	1
26514	The Last One	NaN	NaN	NaN	NaN	NaN	0.6	0.0	1
26515	Trailer Made	NaN	NaN	NaN	NaN	NaN	0.6	0.0	1
26516	The Church	NaN	NaN	NaN	NaN	NaN	0.6	0.0	1

102736 rows × 9 columns

FINDINGS AND CONCLUSIONS

Different observations were noted when perfoming exploratory data analysis. These findings are explained below;

1. **It was observed there was low positive correlation between domestic gross and foreign gross, which meant there little relationship between the two. Movies released between 2011 to 2018 earned the highest foreign gross.**

1. **While analysing the top 15 genres with top number of votes received, it was observed that Action, Adventure, Sci-fi, Thriller, Drama, Comedy and Crime attracted a lot of insights from different people who voted.**

1. **While analysis top 10 popular movies, it was observed that sci-fi and action movies were the most popular, with Avengers: Infinity war topping with 80.773% popularity followed closely by John Wick with 78.123% and Spider Man: Into the spider verse with 60.534% popularity.**

1. **The final observation was that there was low positive correlation between number of votes and average**

rating of movies.

RECOMMENDATIONS

Different recommendations were derived from the findings;

1.) It would be imperative for the stakeholders and top management at Microsoft to prioritise production of movies similar to those released between the year 2011 and 2018 since they earned the highest foreign gross. The top four earners included; a) Harry potter and the deathly hallows part 2 (2011)

b) Avengers: Age of Ultron (2015)

c) Marvel's The Avengers (2012)

d) Jurrasic World: Fallen Kingdom (2018)

Since the top four earners were all Sci-fi movies, then Microsoft would have a great return on investment by creating Sci-Fi movies.

Foreign gross would lead to higher international sales. Higher foreign gross means there is also higher domestic sales, but higher domestic gross does not equate to higher foreign gross since from the scatter plot there is low positive relationship between the two variables.

2.) For Microsoft studio to create awareness of their existence and new products, it is recommended they focus more on Sci-Fi, Action, Adventure, Thriller, Drama, Crime and Comedy since they attracted the most votes from movie fans leading to high insights.

3.) For Microsoft to gain popularity and return on investments they should prioritise Sci-fi and Action movies such as Avengers: Infinity war topping with 80.773% popularity, John Wick with 78.123% and Spider Man: Into the spider verse with 60.534% popularity. This would ensure that the created movies at Microsoft studio attract great popularity leading to high international sales.

In [ ]:

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