ANALYSIS OF FACTORS TO CONSIDER WHEN STARTING A MOVIE BUSINESS

In this analysis, I will explore 3 data sets,namely: 'bom.movie_gross.csv','tmdb.movies.csv' and 'tn.movie_budgets.csv'. I will use the data sets to explore the types of movies that are best perfoming by examining 4 key metrics:title, production budget,popularity and vote_count. My goal is to analyze the metrics, to find actionable insights that will be crucial to Microsoft when seting up the new movie production business.

Analysis of the 'bom.movie_gross.csv' data set to determine if the title of the movie has an effect on the revenue it generates.

First we import the libraries we will use for analyzing the dataset

In [24]:
```
#importing libraries to use for the analysis
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt

%matplotlib inline
```

In [3]:
```
#opening up the file so that we can parse the data
file_path = "C:/Users/ADMIN/dsc-phase-1-project-v2-4/zippedData/bom.movie_gross.csv.gz"

# Load the gzip compressed CSV file into a pandas dataframe
df = pd.read_csv(file_path, compression='gzip', encoding='ISO-8859-1')

# Display the first few rows of the dataframe
print(df.head())
```

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

  foreign_gross  year
0     652000000  2010
1     691300000  2010
2     664300000  2010
3     535700000  2010
4     513900000  2010
```

In [4]:
```
#getting an overview of the data
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3387 entries, 0 to 3386
Data columns (total 5 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   title           3387 non-null   object
 1   studio          3382 non-null   object
 2   domestic_gross  3359 non-null   float64
 3   foreign_gross   2037 non-null   object
```

```
 4   year             3387 non-null   int64
dtypes: float64(1), int64(1), object(3)
memory usage: 132.4+ KB
```

From the overview, we can deduce that the "foreign_gross" and "domesti_gross" columns have some missing values/data. First we find out how many values are missing in each

In [42]:
```
num_of_missing_values = df[["domestic_gross", "foreign_gross"]].isnull().sum()
num_of_missing_values
```

Out[42]:
```
domestic_gross      28
foreign_gross     1350
dtype: int64
```

Since the foreign column has a lot of missing data,we are going to delete it. For the domestic_gross column, we are going to replace the missing values with the most appropiate statistical measure since the missing values are few.

first we delete the "foreign_gross"

In [43]:
```
df = df.drop("foreign_gross", axis=1)
print(df)
```

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

      year
0     2010
1     2010
2     2010
3     2010
4     2010
...    ...
3382  2018
3383  2018
3384  2018
3385  2018
3386  2018

[3387 rows x 4 columns]
```

To determine the best option to replace missing values in a dataset, we need to consider the characteristics of the data, such as the distribution, range, and variability of the values

In [5]:
```
#statical characteristics of 'domestic_gross' column
(df[["domestic_gross"]]).describe()
```

Out[5]:

	domestic_gross
count	3.359000e+03
mean	2.874585e+07
std	6.698250e+07

min	1.000000e+02
25%	1.200000e+05
50%	1.400000e+06
75%	2.790000e+07
max	9.367000e+08

Since the missing values are few and the data is not widely distributed as per the standard deviation, we shall replace the missing values in the "domestic_gross" column with the mean.

In [6]:
```
mean_domestic_gross = 2.874585e+07
```

In [7]:
```
#replacing missing values with the mean
df['domestic_gross'] = df['domestic_gross'].fillna(mean_domestic_gross)
df.head()
```

Out[7]:

	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

In [8]:
```
#confirming missing values are replaced
df[["domestic_gross"]].isnull().sum()
```

Out[8]:
```
domestic_gross    0
dtype: int64
```

Analysis of what title of movies did well domestically, in terms of sales.

In [9]:
```
movie_sales_in_ASC_order = df.sort_values('domestic_gross', ascending=False,)
movie_sales_in_ASC_order.head(30)
```

Out[9]:

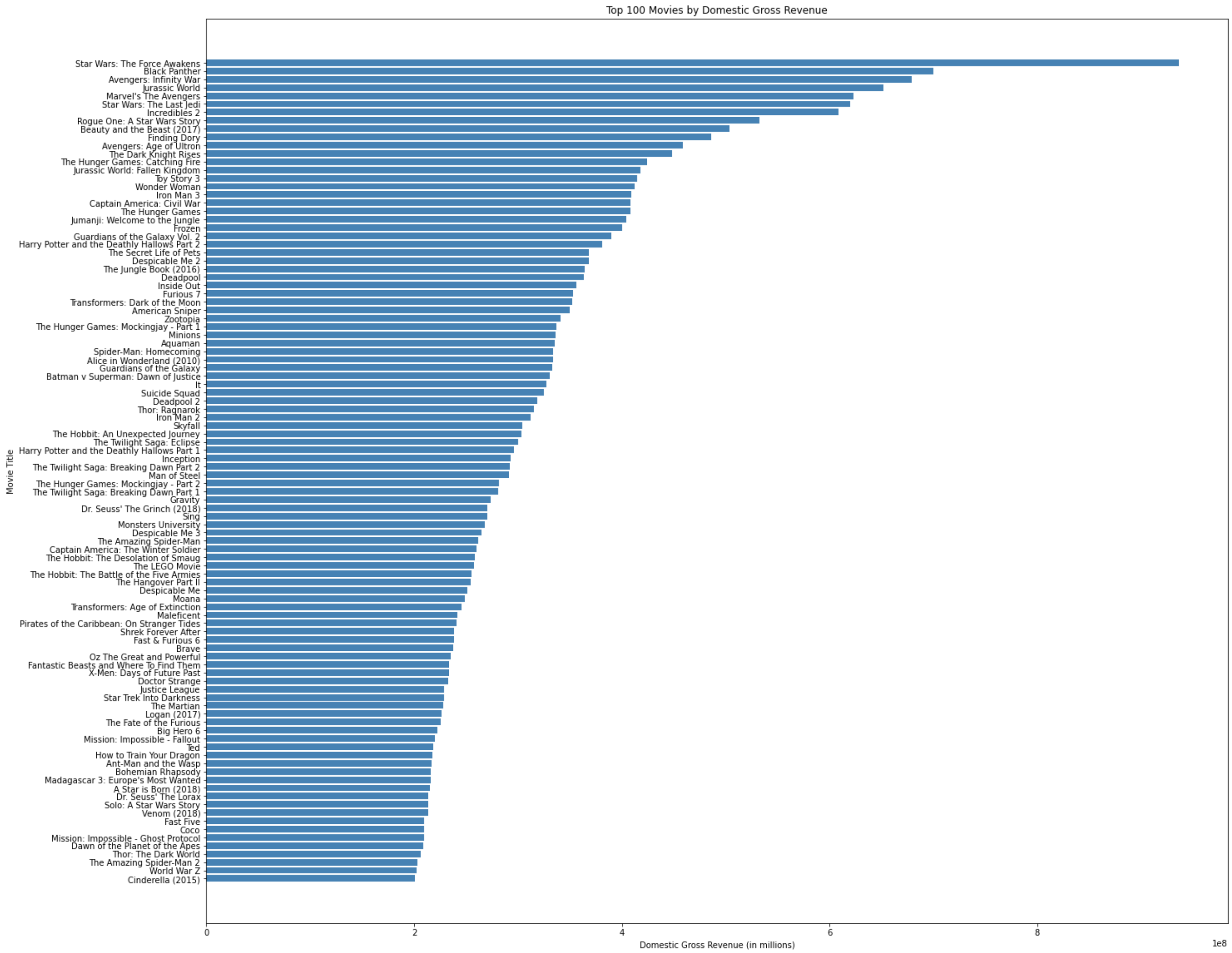
	title	studio	domestic_gross	foreign_gross	year
1872	Star Wars: The Force Awakens	BV	936700000.0	1,131.6	2015
3080	Black Panther	BV	700100000.0	646900000	2018
3079	Avengers: Infinity War	BV	678800000.0	1,369.5	2018
1873	Jurassic World	Uni.	652300000.0	1,019.4	2015
727	Marvel's The Avengers	BV	623400000.0	895500000	2012
2758	Star Wars: The Last Jedi	BV	620200000.0	712400000	2017
3082	Incredibles 2	BV	608600000.0	634200000	2018
2323	Rogue One: A Star Wars Story	BV	532200000.0	523900000	2016
2759	Beauty and the Beast (2017)	BV	504000000.0	759500000	2017
2324	Finding Dory	BV	486300000.0	542300000	2016
1875	Avengers: Age of Ultron	BV	459000000.0	946400000	2015

729	The Dark Knight Rises	WB	448100000.0	636800000	2012
1131	The Hunger Games: Catching Fire	LGF	424700000.0	440300000	2013
3081	Jurassic World: Fallen Kingdom	Uni.	417700000.0	891800000	2018
0	Toy Story 3	BV	415000000.0	652000000	2010
2767	Wonder Woman	WB	412600000.0	409300000	2017
1128	Iron Man 3	BV	409000000.0	805800000	2013
2322	Captain America: Civil War	BV	408100000.0	745200000	2016
735	The Hunger Games	LGF	408000000.0	286400000	2012
2762	Jumanji: Welcome to the Jungle	Sony	404500000.0	557600000	2017
1127	Frozen	BV	400700000.0	875700000	2013
2765	Guardians of the Galaxy Vol. 2	BV	389800000.0	473900000	2017
328	Harry Potter and the Deathly Hallows Part 2	WB	381000000.0	960500000	2011
2327	The Secret Life of Pets	Uni.	368400000.0	507100000	2016
1129	Despicable Me 2	Uni.	368100000.0	602700000	2013
2326	The Jungle Book (2016)	BV	364000000.0	602500000	2016
2330	Deadpool	Fox	363100000.0	420000000	2016
1878	Inside Out	BV	356500000.0	501100000	2015
1874	Furious 7	Uni.	353000000.0	1,163.0	2015
329	Transformers: Dark of the Moon	P/DW	352400000.0	771400000	2011

the top-performing movies by domestic gross revenue were mostly blockbuster franchise titles.

Data Visualization

In [50]:
```
import pandas as pd
import matplotlib.pyplot as plt

# Sort the data by domestic gross revenue in ascending order
movie_sales_in_ASC_order = df[['title', 'domestic_gross']].sort_values('domestic_gross',

top_100_movies = movie_sales_in_ASC_order[:100]

# Set the size of the plot
plt.figure(figsize=(22,20))

# Create a bar plot
plt.barh(y=top_100_movies['title'], width=top_100_movies['domestic_gross'], color='steel

# Invert the y-axis to display the bars in descending order
plt.gca().invert_yaxis()

# Set the plot title and axis labels
plt.title('Top 100 Movies by Domestic Gross Revenue')
plt.xlabel('Domestic Gross Revenue (in millions)')
plt.ylabel('Movie Title')

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



conclusion

The top-performing movies by domestic gross revenue were mostly blockbuster franchise titles. Out of the top 100 movies, 43% of them were from a franchise, and the remaining 57% were standalone titles. The visualization shows the top 100 movies by domestic gross revenue. As we can see, movies such as "Star Wars: The Force Awakens," "Avatar," and "Black Panther" were some of the highest-grossing movies. This finding suggests that Microsoft's new movie studio could benefit from creating movies that belong to popular franchise titles.

Microsoft should consider acquiring or creating content based on popular franchise titles. Creating movies based on established and popular franchise titles could potentially lead to high box office success.

Analysis of 'tn.movie_budgets.csv' data set to analyze production budgets to determine if the production budget has an effect on how well the movie does in the market in terms of revenue generated.

In [10]:

```
#opening up the file so that we can parse the data
file_path = "C:/Users/ADMIN/dsc-phase-1-project-v2-4/zippedData/tn.movie_budgets.csv.gz"

# Load the gzip compressed CSV file into a pandas dataframe
movie_budget_df = pd.read_csv(file_path, compression='gzip', encoding='ISO-8859-1')

# Display the first few rows of the dataframe
print(movie_budget_df.head())
```

```
   id  release_date                                        movie  \
0   1  Dec 18, 2009                                       Avatar
1   2  May 20, 2011  Pirates of the Caribbean: On Stranger Tides
2   3   Jun 7, 2019                                 Dark Phoenix
3   4   May 1, 2015                      Avengers: Age of Ultron
4   5  Dec 15, 2017            Star Wars Ep. VIII: The Last Jedi

  production_budget domestic_gross worldwide_gross
0      $425,000,000   $760,507,625  $2,776,345,279
1      $410,600,000   $241,063,875  $1,045,663,875
2      $350,000,000    $42,762,350    $149,762,350
3      $330,600,000   $459,005,868  $1,403,013,963
4      $317,000,000   $620,181,382  $1,316,721,747
```

We look at the overview of the data

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

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5782 entries, 0 to 5781
Data columns (total 6 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   id                 5782 non-null   int64
 1   release_date       5782 non-null   object
 2   movie              5782 non-null   object
 3   production_budget  5782 non-null   object
 4   domestic_gross     5782 non-null   object
 5   worldwide_gross    5782 non-null   object
dtypes: int64(1), object(5)
memory usage: 271.2+ KB
```

We will focus the analysis on the " production_budget" ,"domestic_gross" and "worldwide_gross" columns to try and deduce if the budget has an effect on the domestic and worldwide sales.

First we check if we have any missing data in the columns we are going to work with.

In [12]:
```
num_of_missing_values = movie_budget_df[["production_budget","domestic_gross", "worldwid
num_of_missing_values
```

Out[12]:
```
production_budget    0
domestic_gross       0
worldwide_gross      0
dtype: int64
```

We have no missing values .Now, we select the columns we need from the df

In [13]:
```
movie_budget_df1 = movie_budget_df[['production_budget', 'domestic_gross', 'worldwide_gr
movie_budget_df1
```

Out[13]:

	production_budget	domestic_gross	worldwide_gross
0	$425,000,000	$760,507,625	$2,776,345,279
1	$410,600,000	$241,063,875	$1,045,663,875
2	$350,000,000	$42,762,350	$149,762,350
3	$330,600,000	$459,005,868	$1,403,013,963
4	$317,000,000	$620,181,382	$1,316,721,747
...	...	...	...
5777	$7,000	$0	$0

5778	$6,000	$48,482	$240,495
5779	$5,000	$1,338	$1,338
5780	$1,400	$0	$0
5781	$1,100	$181,041	$181,041

5782 rows × 3 columns

In [14]:
```
#characteristics of the columns
movie_budget_df1.describe()
```

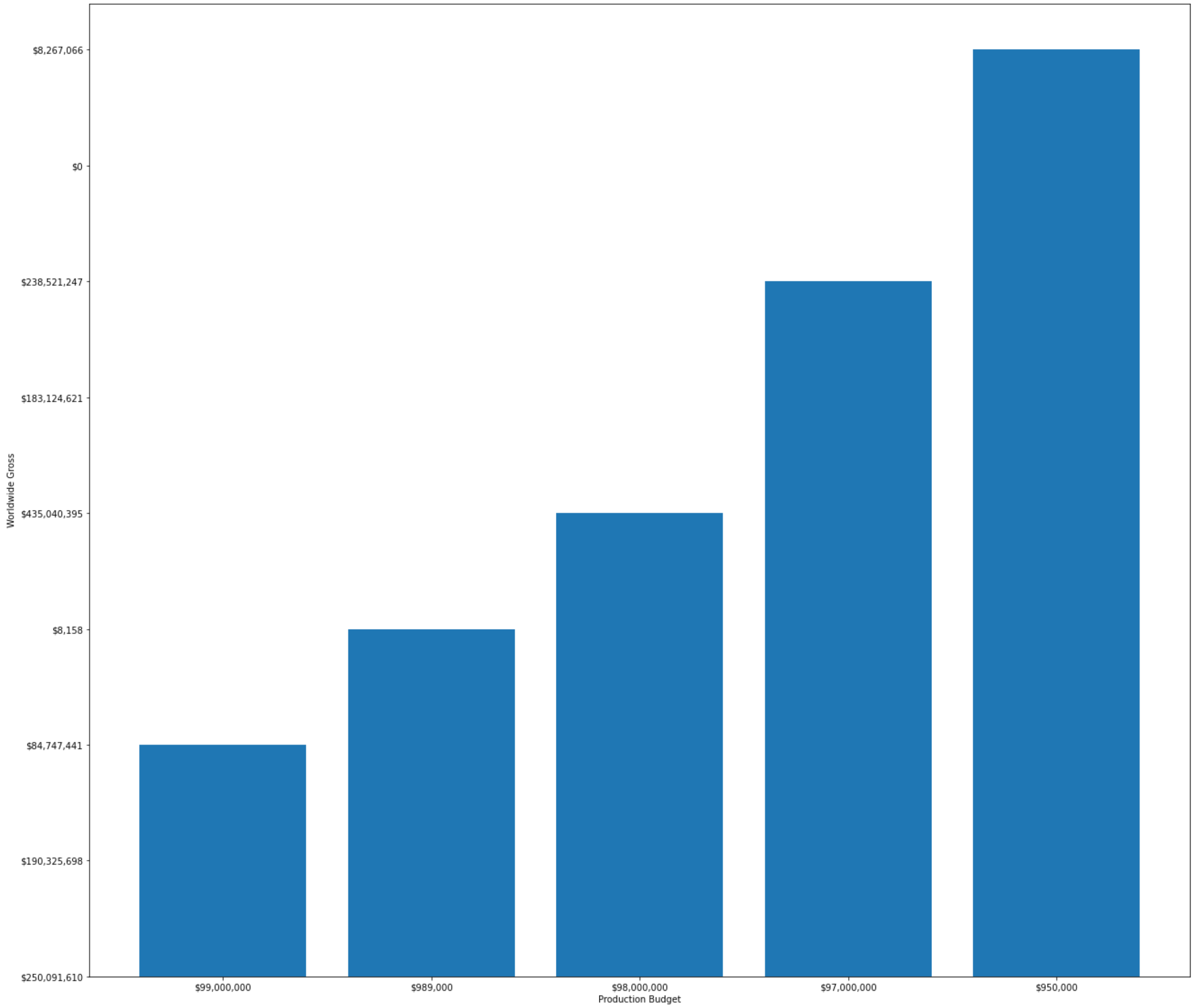
Out[14]:

	production_budget	domestic_gross	worldwide_gross
count	5782	5782	5782
unique	509	5164	5356
top	$20,000,000	$0	$0
freq	231	548	367

These deductions indicate that there is a wide range of values for production_budget, domestic_gross, and worldwide_gross, suggesting that there is a large variation in the amount spent on producing movies and the revenue generated from them. However, the high frequency of $0 for domestic_gross and worldwide_gross indicates that a significant number of movies did not generate any revenue despite having a production budget.

Data visualization visualization of production budget against domestic and worldwide gross.

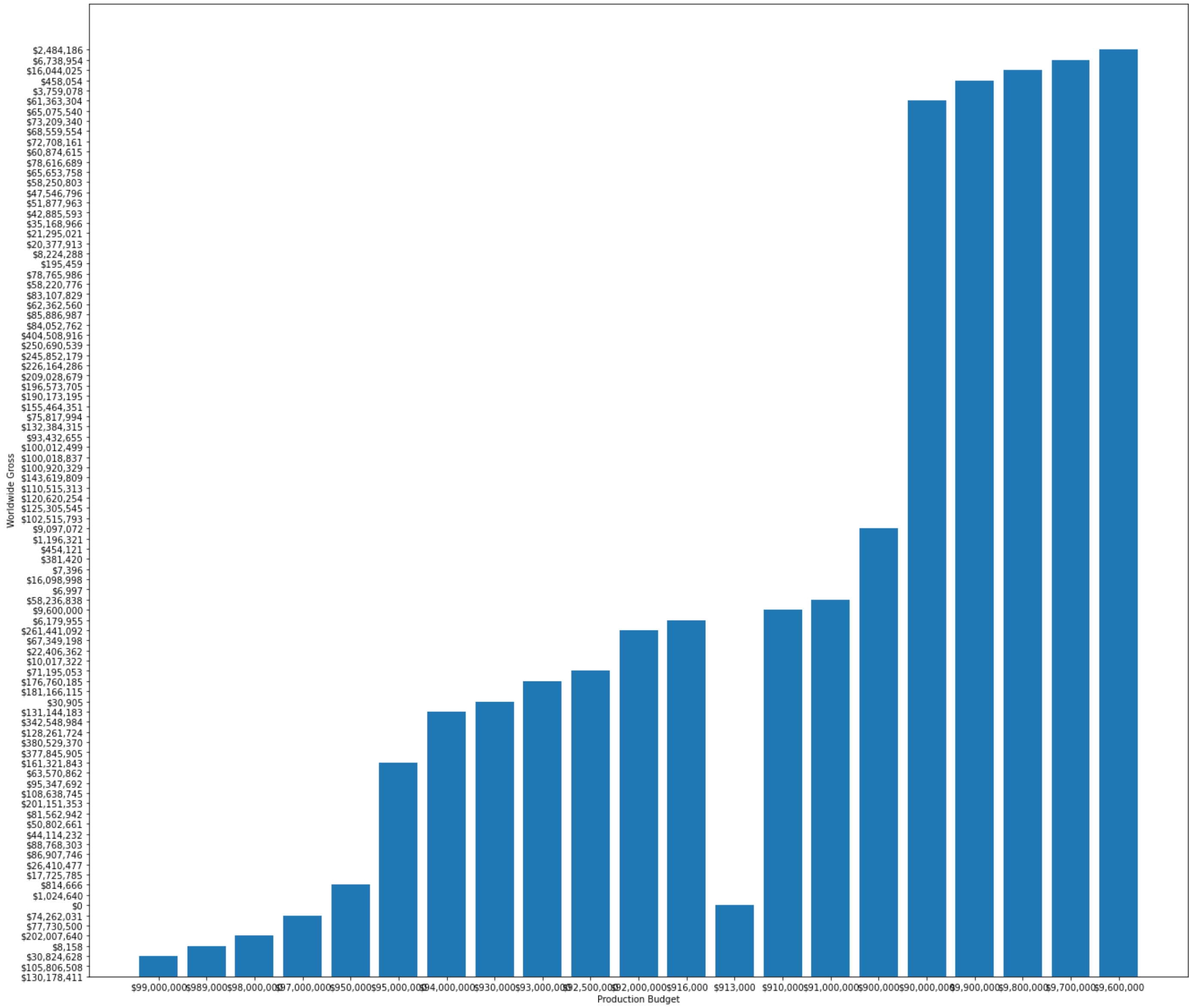
In [15]:
```
#plotting production budget vs worldwide gross
import pandas as pd
import matplotlib.pyplot as plt

#Sort the data by production budget revenue in ascending order
prod_budget_in_ASC_order = movie_budget_df[['production_budget','domestic_gross','worldw

top_100_movies = prod_budget_in_ASC_order[:10]


data = top_100_movies

#Set the size of the plot
plt.figure(figsize=(22,20))


plt.bar(data['production_budget'], data['worldwide_gross'])
plt.xlabel('Production Budget')
plt.ylabel('Worldwide Gross')
plt.show()
```



The plot shows the relationship between the production budget and worldwide gross revenue for the top 100 movies sorted by production budget in ascending order. It appears that there is a positive correlation between the two variables, as higher production budgets tend to result in higher worldwide gross revenue. However, there are some outliers where the production budget is high but the worldwide gross revenue is relatively low, indicating that other factors may also play a role in a movie's success

In [16]:
```
#plotting production budget vs domestic  gross
import pandas as pd
import matplotlib.pyplot as plt

#Sort the data by production budget revenue in ascending order
prod_budget_in_ASC_order = movie_budget_df[['production_budget', 'domestic_gross', 'worl

top_100_movies = prod_budget_in_ASC_order[:100]


data = top_100_movies

#Set the size of the plot
plt.figure(figsize=(22,20))


plt.bar(data['production_budget'], data['domestic_gross'])
plt.xlabel('Production Budget')
```

```
plt.ylabel('Worldwide Gross')
plt.show()
```



From the plot, we can see that there is a positive correlation between the production budget and the domestic gross, which means that as the production budget of a movie increases, the domestic gross also increases. However, in this data set too there are some outliers where the production budget is high but the worldwide gross revenue is relatively low, indicating that other factors may also play a role in a movie's success.

conclusion

The production budget is a key matrix to consider when producing a film. The analysis indicates that a bigger budget increases the probability of a movie doing well in both the domestic and foreign markets. We can asssume that a bigger budget will hire the best available cast, produce better quality movies and cater for good marketing for the movie, hence the likelyhood of better perfomance in the market.

Analysis of 'tmdb.movies.csv' to analyze genres and their popularity to determine if a genre is key in determining how popular a movie is.

In [17]:
```
#importing and opening the data set

import pandas as pd
```

```
# opening up the file so that we can parse the data
file_path = "C:/Users/ADMIN/dsc-phase-1-project-v2-4/zippedData/tmdb.movies.csv.gz"

# Load the CSV file into a pandas dataframe
movies_df = pd.read_csv(file_path, encoding='ISO-8859-1', delimiter=',')

# Display the first few rows of the dataframe
print(movies_df.head())
```

```
   Unnamed: 0             genre_ids     id original_language  \
0           0       [12, 14, 10751]  12444                en   
1           1   [14, 12, 16, 10751]  10191                en   
2           2         [12, 28, 878]  10138                en   
3           3       [16, 35, 10751]    862                en   
4           4         [28, 878, 12]  27205                en   

                               original_title  popularity release_date  \
0  Harry Potter and the Deathly Hallows: Part 1      33.533   2010-11-19   
1                     How to Train Your Dragon      28.734   2010-03-26   
2                                  Iron Man 2      28.515   2010-05-07   
3                                   Toy Story      28.005   1995-11-22   
4                                   Inception      27.920   2010-07-16   

                                        title  vote_average  vote_count  
0  Harry Potter and the Deathly Hallows: Part 1           7.7       10788  
1                     How to Train Your Dragon           7.7        7610  
2                                  Iron Man 2           6.8       12368  
3                                   Toy Story           7.9       10174  
4                                   Inception           8.3       22186  
```

The genre_ids are in codes that are not understable to many people who are not in the movie business.I am going to use API method to extract the genre names associted with the codes from the tmdb website. I will keep referring back to this codes to figure which code stands for which genre.

In [38]:
```
import requests

# Make a request to get the list of genres
response = requests.get('https://api.themoviedb.org/3/genre/movie/list?api_key=731656d01
genres = response.json()['genres']

# Create a dictionary mapping genre IDs to their names
genre_map = {genre['id']: genre['name'] for genre in genres}
print(genre_map )
```

```
{28: 'Action', 12: 'Adventure', 16: 'Animation', 35: 'Comedy', 80: 'Crime', 99: 'Documen
tary', 18: 'Drama', 10751: 'Family', 14: 'Fantasy', 36: 'History', 27: 'Horror', 10402:
'Music', 9648: 'Mystery', 10749: 'Romance', 878: 'Science Fiction', 10770: 'TV Movie', 5
3: 'Thriller', 10752: 'War', 37: 'Western'}
```

now we have a look at the overview of the data

In [3]:
```
movies_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 26517 entries, 0 to 26516
Data columns (total 10 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   Unnamed: 0         26517 non-null  int64  
 1   genre_ids          26517 non-null  object 
 2   id                 26517 non-null  int64  
 3   original_language  26517 non-null  object 
 4   original_title     26517 non-null  object 
 5   popularity         26517 non-null  float64
```

```
 6   release_date        26517 non-null  object 
 7   title               26517 non-null  object 
 8   vote_average        26517 non-null  float64
 9   vote_count          26517 non-null  int64  
dtypes: float64(2), int64(3), object(5)
memory usage: 2.0+ MB
```

From the over view,we get the outline of the columns of data contained in the data set. For this analysis,i am going to focus on the genre_id and popularity columns,to see if there is a correlation between the two.First i check if there is any misssing data in the two columns.

In [18]:
```
print(movies_df['genre_ids'].isnull().sum())
print(movies_df['popularity'].isnull().sum())
```

```
0
0
```

Further analysis on the data by exploding the genre_ids to create a new row for each genre.Then we group them by their popularity mean, to get the popularity for each genre.

In [20]:
```
# Split the genre_ids column into a list of genres
movies_df['genres'] = movies_df['genre_ids'].apply(lambda x: [int(i) for i in str(x).rep

# Create a new dataframe with a row for each genre associated with a movie
genres_df = movies_df.explode('genres')
genres_df
```

Out[20]:

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

26517 rows × 11 columns

The we sort the genres in order of descending popularity, selecting the top 100 genres

In [21]:
```
# Calculate the average popularity for each genre
popularity_by_genre = genres_df.groupby('genres')['popularity'].mean().sort_values(ascen
popularity_by_genre
```

Out[21]:
```
genres
28       6.625442
12       6.479233
80       4.998628
10752    4.391825
14       4.373590
878      4.032484
16       4.013293
9648     3.974254
18       3.719678
53       3.714827
10749    3.472112
35       3.367115
36       3.236016
27       3.046198
10751    2.981259
37       2.742321
10770    2.506381
99       1.331823
10402    1.258976
Name: popularity, dtype: float64
```

Next, we find out the most popular and least popular genres

In [22]:
```
most_popular_genre = popularity_by_genre.idxmax(5)
most_popular_genre
```

Out[22]:
```
28
```

In [23]:
```
least_popular_genre = popularity_by_genre.idxmin()
least_popular_genre
```

Out[23]:
```
10402
```

Top 5 in each category

In [22]:
```
# Find the top 5 genres by average popularity
top_5_genres = genres_df.groupby('genres')['popularity'].mean().sort_values(ascending=Fa

# Find the least popular genre
least_5popular_genre = genres_df.groupby('genres')['popularity'].mean().sort_values(asce
print(top_5_genres),(least_5popular_genre)
```

```
genres
28       6.625442
12       6.479233
80       4.998628
10752    4.391825
14       4.373590
Name: popularity, dtype: float64
```

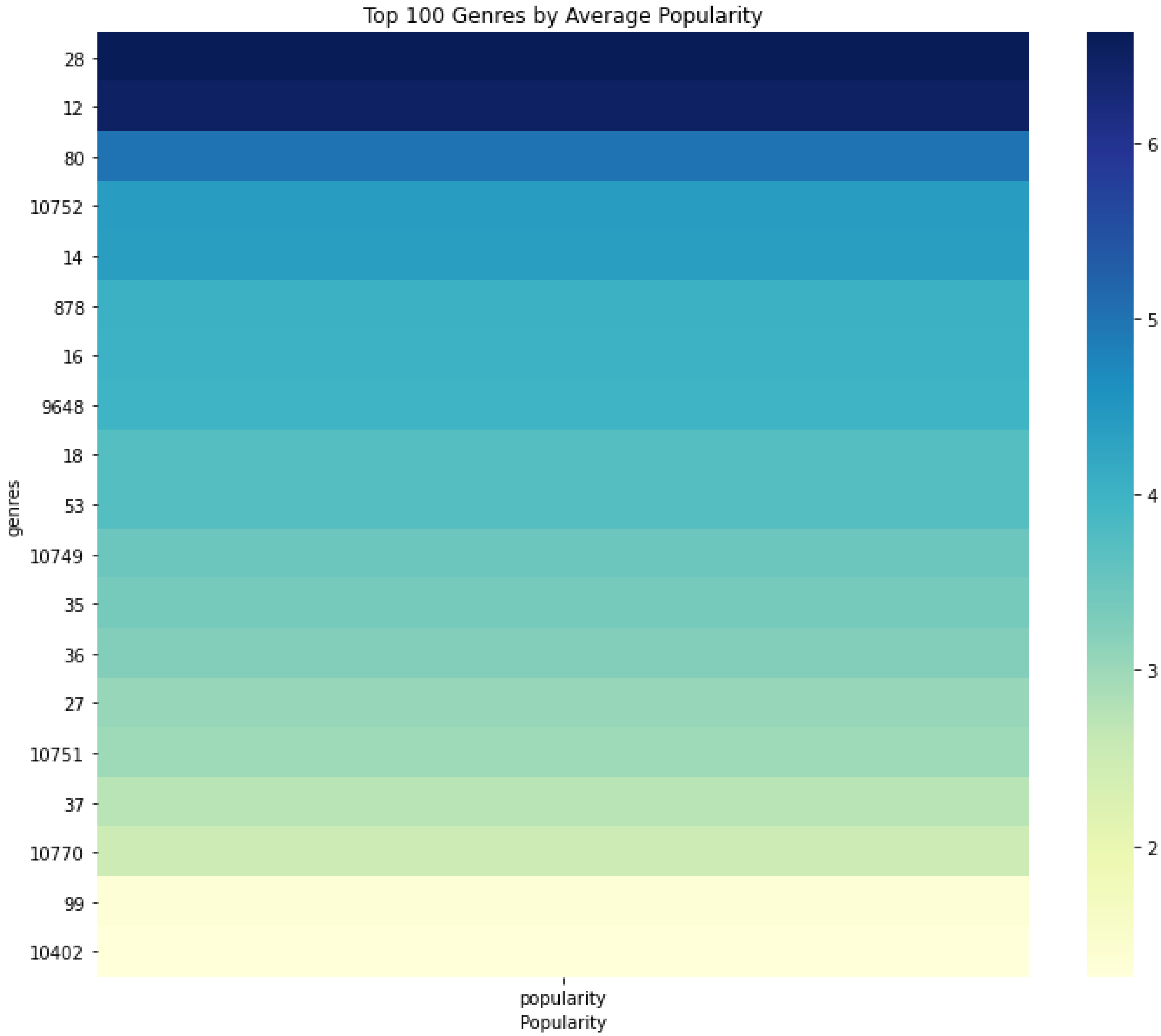
Out[22]:
```
(None,
 genres
 10402    1.258976
 99       1.331823
 10770    2.506381
 37       2.742321
 10751    2.981259
 Name: popularity, dtype: float64)
```

From the above analysis, we can conclude that Action,adventure,crime, war and fantasy are the most popular.Music,Documentaries,TV movie ,Western and Family being the least popular genres.

Data Visualization

In [27]:

```
import seaborn as sns
import matplotlib.pyplot as plt

# group by genre and calculate the mean popularity
popularity_by_genre = genres_df.groupby('genres')['popularity'].mean()

# sort by popularity in descending order and select top 100 genres
top_popular_genres = popularity_by_genre.sort_values(ascending=False)[:100]

# create a pivot table of genre vs popularity
genre_popularity_pivot = genres_df.pivot_table(index='genres', values='popularity')

# filter to only include top 100 genres
genre_popularity_pivot = genre_popularity_pivot.loc[top_popular_genres.index]

# plot the heatmap
plt.figure(figsize=(12, 10))
sns.heatmap(genre_popularity_pivot, cmap='YlGnBu')
plt.title('Top 100 Genres by Average Popularity')
plt.xlabel('Popularity')
plt.show()
```



The above plot,-6 is the most popular and -2 is the least popular genre.

From the plot, we can deduce that the Action genre has the highest popularity among the top 100 most popular genres, followed by Adventure and crime .Least popular is music,documentary and TV movie.

Conclusion

From the analysis,Microsoft new production company can identify the most popular genres and create more content around the most popular genres like action and adventure.The more popular a genre is, the more it will resonate with a bigger audience,hence do well in the market.

Analysis of 'tmdb.movies.csv' to analyze genres and their vote count to determine if a genre is key in determining how a movie is rated

In [351…

```
#importing and opening the data set

import pandas as pd
```

```
# opening up the file so that we can parse the data
file_path = "C:/Users/ADMIN/dsc-phase-1-project-v2-4/zippedData/tmdb.movies.csv.gz"

# Load the CSV file into a pandas dataframe
movies_df = pd.read_csv(file_path, encoding='ISO-8859-1', delimiter=',')

# Display the first few rows of the dataframe
print(movies_df.head())
```

```
   Unnamed: 0            genre_ids     id original_language  \
0           0      [12, 14, 10751]  12444                en
1           1  [14, 12, 16, 10751]  10191                en
2           2        [12, 28, 878]  10138                en
3           3      [16, 35, 10751]    862                en
4           4        [28, 878, 12]  27205                en

                                 original_title  popularity release_date  \
0  Harry Potter and the Deathly Hallows: Part 1      33.533   2010-11-19
1                      How to Train Your Dragon      28.734   2010-03-26
2                                    Iron Man 2      28.515   2010-05-07
3                                     Toy Story      28.005   1995-11-22
4                                     Inception      27.920   2010-07-16

                                          title  vote_average  vote_count
0  Harry Potter and the Deathly Hallows: Part 1           7.7       10788
1                      How to Train Your Dragon           7.7        7610
2                                    Iron Man 2           6.8       12368
3                                     Toy Story           7.9       10174
4                                     Inception           8.3       22186
```

From the over view,we get the outline of the columns of data contained in the data set. For this analysis,we are going to focus on the genre_id and vote_count columns,to see if there is a correlation between the two.First we check if there is any misssing data in the two columns.

In [367…

```
print(movies_df['genre_ids'].isnull().sum())
print(movies_df['vote_count'].isnull().sum())
```

```
0
0
```

Further analysis on the data by exploding the genre_ids to create a new row for each genre.Then we group them by their vote_count mean, to get the engagement for for each genre.

In [29]:

```
# Split the genre_ids column into a list of genres
movies_df['genres'] = movies_df['genre_ids'].apply(lambda x: [int(i) for i in str(x).rep

# Create a new dataframe with a row for each genre associated with a movie
genres_df = movies_df.explode('genres')
genres_df
```

Out[29]:

	Unnamed: 0	genre_ids	id	original_language	original_title	popularity	release_date	title
0	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	1	[14, 12, 16, 10751]	10191	en	How to Train Your Dragon	28.734	2010-03-26	How to Train Your Dragon
2	2	[12, 28, 878]	10138	en	Iron Man 2	28.515	2010-05-07	Iron Man 2
3	3	[16, 35,	862	en	Toy Story	28.005	1995-11-22	Toy Story

		10751]						
4	4	[28, 878, 12]	27205	en	Inception	27.920	2010-07-16	Inception
...	...	...	...	...	...	...	...	...
26512	26512	[27, 18]	488143	en	Laboratory Conditions	0.600	2018-10-13	Laboratory Conditions
26513	26513	[18, 53]	485975	en	_EXHIBIT_84xxx_	0.600	2018-05-01	_EXHIBIT_84xxx_
26514	26514	[14, 28, 12]	381231	en	The Last One	0.600	2018-10-01	The Last One
26515	26515	[10751, 12, 28]	366854	en	Trailer Made	0.600	2018-06-22	Trailer Made
26516	26516	[53, 27]	309885	en	The Church	0.600	2018-10-05	The Church

26517 rows × 11 columns

The we sort the genres in order of descending vote_count, selecting the top 100 genres

In [31]:
```
# Calculate the average popularity for each genre
votecount_by_genre = genres_df.groupby('genres')['vote_count'].mean().sort_values(ascend
votecount_by_genre
```

Out[31]:
```
genres
12       867.827523
28       792.004240
10752    401.912621
14       396.198738
80       390.533457
878      360.680070
37       295.024691
16       288.848419
9648     229.059233
36       211.488189
18       209.772903
10749    185.386167
10751    174.886710
53       160.469015
35       156.143722
27       123.183794
10770     25.643836
10402     14.920354
99        12.157931
Name: vote_count, dtype: float64
```

Next, we find out the most popular and least popular genres

In [33]:
```
most_votecount_genre = votecount_by_genre.idxmax(5)
most_votecount_genre
```

Out[33]:
```
12
```

In [35]:
```
least_votecount_genre = votecount_by_genre.idxmin(5)
least_votecount_genre
```

Out[35]:
```
99
```

Top 5 genres by average vote count

In [36]:
```
# Find the top 5 genres by average votecount
top_5_genres = genres_df.groupby('genres')['vote_count'].mean().sort_values(ascending=Fa

# Find the least popular genre
least_5popular_genre = genres_df.groupby('genres')['vote_count'].mean().sort_values(asce
print(top_5_genres),(least_5popular_genre)
```

```
genres
12       867.827523
28       792.004240
10752    401.912621
14       396.198738
80       390.533457
Name: vote_count, dtype: float64
```

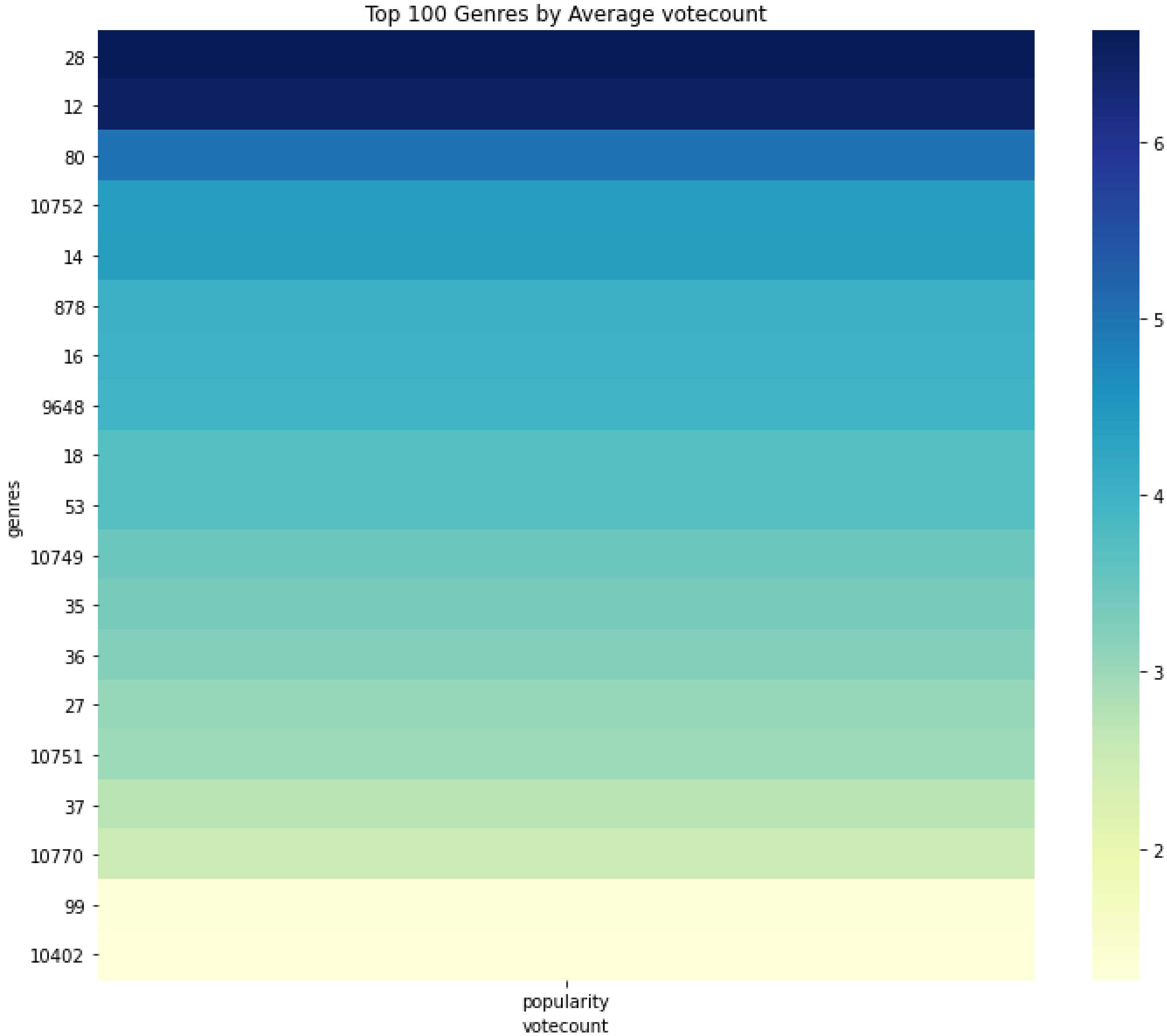
Out[36]:
```
(None,
 genres
 99        12.157931
 10402     14.920354
 10770     25.643836
 27       123.183794
 35       156.143722
 Name: vote_count, dtype: float64)
```

From the above analysis, we can conclude that Action,adventure and crime have the highest vote count ie engagement with viewers. Music and Documentaries have some of the lowest engagements.

Next we plot genre against the vote count to visualize the data.

Data visualization

In [37]:
```
import seaborn as sns
import matplotlib.pyplot as plt

# group by genre and calculate the mean popularity
popularity_by_genre = genres_df.groupby('genres')['vote_count'].mean()

# sort by popularity in descending order and select top 100 genres
top_popular_genres = votecount_by_genre.sort_values(ascending=False)[:100]

# create a pivot table of genre vs popularity
genre_votecount_pivot = genres_df.pivot_table(index='genres', values='vote_count')

# filter to only include top 100 genres
genre_votecount_pivot = genre_votecount_pivot.loc[top_popular_genres.index]

# plot the heatmap
plt.figure(figsize=(12, 10))
sns.heatmap(genre_popularity_pivot, cmap='YlGnBu')
plt.title('Top 100 Genres by Average votecount')
plt.xlabel('votecount')
plt.show()
```



Again, the graph shows that Action and Adventure have the highest vote counts ie engagement/ratings with viewrs audience. However,a low vote count doesn't necessarily indicate that a movie performed poorly in the market. It could mean that the movie is not popular among the audience or it could be due to other factors such as marketing or release strategy. Additionally, some movies with a low vote count may have a cult following or may have been overlooked at the time of their release, but gained popularity later on. However,

Conclusion

vote count usually refers to the number of votes a movie has received on a particular platform, such as IMDb or Rotten Tomatoes. These votes are often used to calculate the movie's rating, with the assumption that a larger number of votes provides a more accurate representation of the movie's overall quality or popularity. In general, a higher vote count indicates that more people have watched and rated the movie, which could suggest that the genre is more popular or well-known. From the analysis, genres such as Science Action tend to have more engagement hence more vote counts. Microsoft should consider producing movie genres that have a higher likelyhood of having high vote counts such as Action and Adventure.