Final Project Submission

Please fill out:

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- Student pace: Full time
- Scheduled project review date/time: 12th March 2023
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- Blog post URL:

Movie Genre Trends: An Exploratory Analysis

This project uses data collected from IMDB.

Objective

The purpose of this project is to:

- analyze audience preference
- highlight trends in the industry
- forecast the future trajectory of the industry

The following datasets were used in the project:

- The IMDB databse
- BOM scv file

In [2]:

```
# first we import the relevant packages and connect to the IMDB database:

import sqlite3
import pandas as pd

conn = sqlite3.connect("unzippedData/im.db")
```

In [3]:

```
# the code below shows the tables in the database

df = pd.read_sql("""SELECT name FROM sqlite_master WHERE type = 'table';""", conn
df
```

Out[3]:

	name
0	movie_basics
1	directors
2	known_for
3	movie_akas
4	movie_ratings
5	persons
6	principals
7	writers

In [ ]:

```
```

In [4]:

```
# since we will be using only two tables from the database
# we check of how the movie_basics looks like

movie_basics = pd.read_sql("SELECT * FROM movie_basics;", conn)
movie_basics
```

Out[4]:

	movie_id	primary_title	original_title	start_year	runtime_minutes	ger
0	tt0063540	Sunghursh	Sunghursh	2013	175.0	Action,Crime,Dra
1	tt0066787	One Day Before the Rainy Season	Ashad Ka Ek Din	2019	114.0	Biography,Dra
2	tt0069049	The Other Side of the Wind	The Other Side of the Wind	2018	122.0	Dra
3	tt0069204	Sabse Bada Sukh	Sabse Bada Sukh	2018	NaN	Comedy,Dra
4	tt0100275	The Wandering Soap Opera	La Telenovela Errante	2017	80.0	Comedy,Drama,Fant
...	...	...	...	...	...	
146139	tt9916538	Kuambil Lagi Hatiku	Kuambil Lagi Hatiku	2019	123.0	Dra
146140	tt9916622	Rodolpho Teóphilo - O Legado de um Pioneiro	Rodolpho Teóphilo - O Legado de um Pioneiro	2015	NaN	Documen
146141	tt9916706	Dankyavar Danka	Dankyavar Danka	2013	NaN	Com
146142	tt9916730	6 Gunn	6 Gunn	2017	116.0	N
146143	tt9916754	Chico Albuquerque - Revelações	Chico Albuquerque - Revelações	2013	NaN	Documen

146144 rows × 6 columns

In [5]:

```
movie_basics.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 146144 entries, 0 to 146143
Data columns (total 6 columns):
 #   Column           Non-Null Count   Dtype  
---  ------           --------------   -----  
 0   movie_id         146144 non-null  object 
 1   primary_title    146144 non-null  object 
 2   original_title   146123 non-null  object 
 3   start_year       146144 non-null  int64  
 4   runtime_minutes  114405 non-null  float64
 5   genres           140736 non-null  object 
dtypes: float64(1), int64(1), object(4)
memory usage: 6.7+ MB
```

In [6]:

```
# below is a preview of the ratings table

movie_ratings = pd.read_sql("SELECT * FROM movie_ratings;", conn)
movie_ratings
```

Out[6]:

	movie_id	averagerating	numvotes
0	tt10356526	8.3	31
1	tt10384606	8.9	559
2	tt1042974	6.4	20
3	tt1043726	4.2	50352
4	tt1060240	6.5	21
...	...	...	...
73851	tt9805820	8.1	25
73852	tt9844256	7.5	24
73853	tt9851050	4.7	14
73854	tt9886934	7.0	5
73855	tt9894098	6.3	128

73856 rows × 3 columns

In [7]:

```
movie_ratings.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 73856 entries, 0 to 73855
Data columns (total 3 columns):
 #   Column         Non-Null Count  Dtype  
---  ------         --------------  -----  
 0   movie_id       73856 non-null  object 
 1   averagerating  73856 non-null  float64
 2   numvotes       73856 non-null  int64  
dtypes: float64(1), int64(1), object(1)
memory usage: 1.7+ MB
```

Now that we have a preview of the two tables, we joined the tables to highlight the top 10 rated genres.

This will give an insight to see which movie genres have the highest ratings over the years

In [8]:

```
avrate = """SELECT DISTINCT m.genres AS Genre, r.averagerating AS Rating
FROM movie_basics m
INNER JOIN movie_ratings r
ON m.movie_id = r.movie_id
ORDER BY Rating DESC;"""
pd.read_sql(avrate, conn).head(10)
```

Out[8]:

	Genre	Rating
0	Documentary	10.0
1	Comedy,Drama	10.0
2	Crime,Documentary	10.0
3	Drama	10.0
4	Documentary,History	10.0
5	Adventure,Comedy	10.0
6	Drama	9.9
7	Documentary	9.9
8	Documentary	9.8
9	Action	9.8

Next we will check which movie genres were the highest rated in a period of 10 years.

This information will help us undersand the change of trend with time

In [9]:

```
gen_trend = """SELECT m.start_year AS Year, m.genres AS Genre, MAX(r.averageratin
FROM movie_basics m
INNER JOIN movie_ratings r
ON m.movie_id = r.movie_id
GROUP BY Year
ORDER BY Year DESC, Rating DESC;
"""

pd.read_sql(gen_trend, conn)
```

Out[9]:

	Year	Genre	Rating
0	2019	Documentary	10.0
1	2018	Documentary	10.0
2	2017	Drama	10.0
3	2016	Documentary	10.0
4	2015	Documentary	10.0
5	2014	Biography,Documentary,Drama	9.8
6	2013	Biography,Documentary,Music	9.8
7	2012	Documentary	10.0
8	2011	Comedy,Documentary,Drama	9.4
9	2010	Crime,Documentary	10.0

Now that we have data for the most rated movie genre in each year, we visualized the data by creating a stacked bar chart where each bar represents a year, and the height of each segment in the bar represents the average rating for that genre in that year.

The legend shows which color corresponds to which genre.

In [10]:

```
import matplotlib.pyplot as plt

dfg = pd.read_sql(gen_trend, conn)

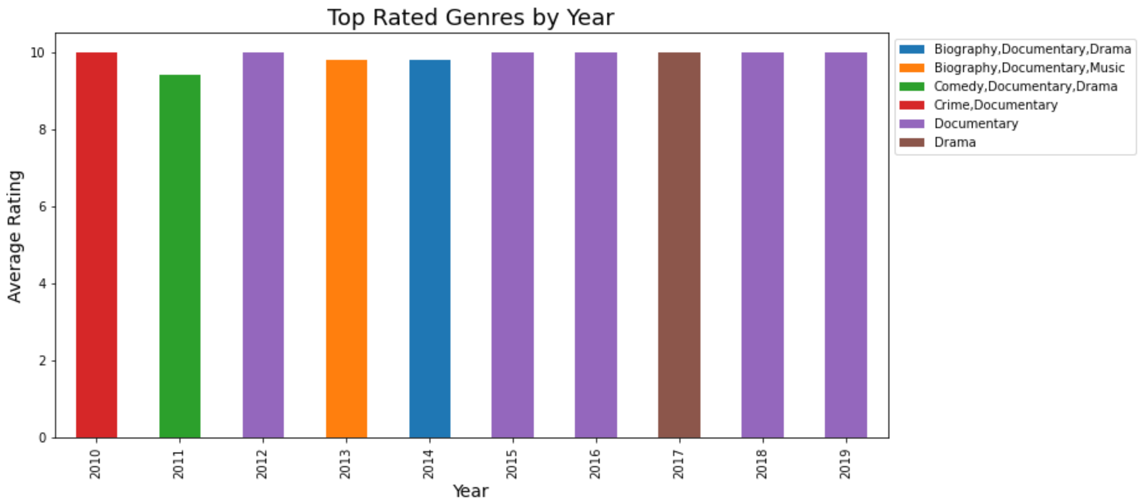
# Pivot the data to create a matrix with genres as columns and years as rows
df_pivot = dfg.pivot(index='Year', columns='Genre', values='Rating')

# Create a stacked bar chart with one bar for each year
ax = df_pivot.plot(kind='bar', stacked=True, figsize=(12, 6))

# Set the title and axis labels
ax.set_title('Top Rated Genres by Year', fontsize=18)
ax.set_xlabel('Year', fontsize=14)
ax.set_ylabel('Average Rating', fontsize=14)

# Add a legend and adjust its position
ax.legend(loc='upper left', bbox_to_anchor=(1, 1))

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



Next, we created a category for the movies.

The following rating levels determined where each movie was categorized

- Rating of 0 - 3.99 = Poor
- Rating of 4 - 6.99 = Good
- Rating of 7 - 10 = Top-Rated

In [11]:

```
cate_rate = """SELECT m.primary_title as Title, start_year as Year, r.averagerati
CASE
    WHEN r.averagerating BETWEEN 0 AND 3.99 THEN 'Poor'
    WHEN r.averagerating BETWEEN 4 AND 6.99 THEN 'Good'
    WHEN r.averagerating BETWEEN 7 AND 10 THEN 'Top-Rated'
END AS Category
FROM movie_basics m JOIN movie_ratings r
ON m.movie_id = r.movie_id;
"""
pd.read_sql(cate_rate, conn)
```

Out[11]:

	Title	Year	Rating	Category
0	Sunghursh	2013	7.0	Top-Rated
1	One Day Before the Rainy Season	2019	7.2	Top-Rated
2	The Other Side of the Wind	2018	6.9	Good
3	Sabse Bada Sukh	2018	6.1	Good
4	The Wandering Soap Opera	2017	6.5	Good
...	...	...	...	...
73851	Diabolik sono io	2019	6.2	Good
73852	Sokagin Çocuklari	2019	8.7	Top-Rated
73853	Albatross	2017	8.5	Top-Rated
73854	La vida sense la Sara Amat	2019	6.6	Good
73855	Drømmeland	2019	6.5	Good

73856 rows × 4 columns

Using the above data, we created a bar chart that shows the count of movies in each category for each year.

In [12]:

```
import numpy as np
df_cat = pd.read_sql(cate_rate, conn)

# Create a pivot table with the count of movies in each category for each year
table = pd.pivot_table(df_cat, values='Title', index='Year', columns='Category',

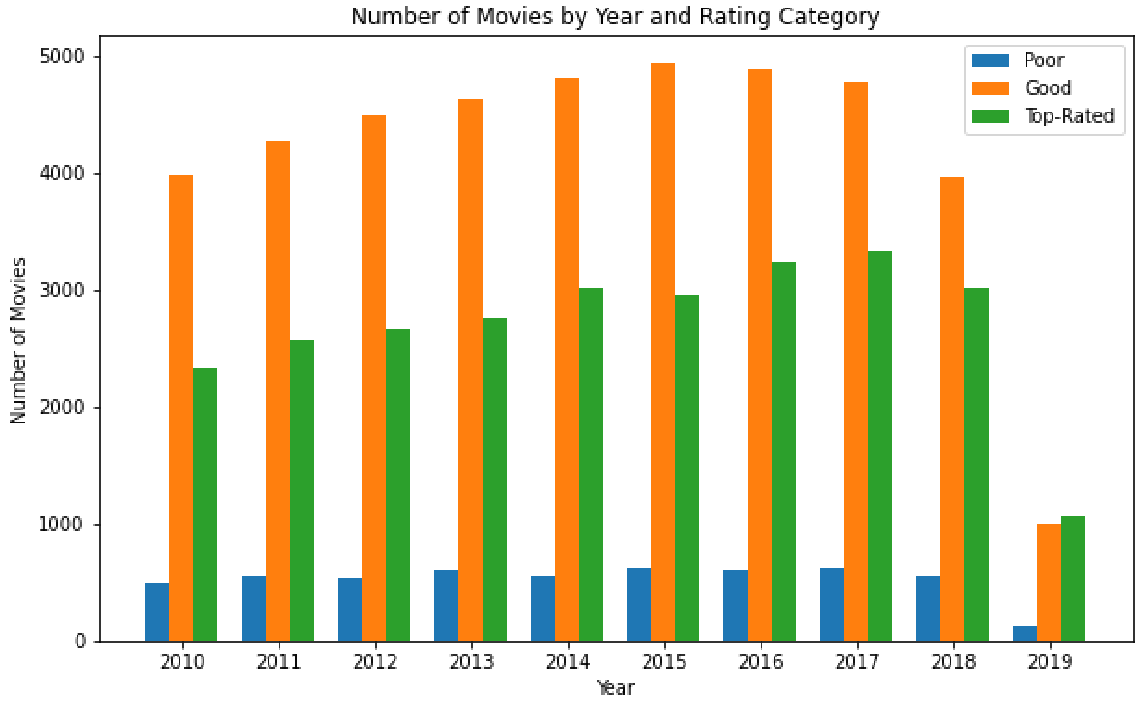
# Create the grouped bar chart
fig, ax = plt.subplots(figsize=(10, 6))
width = 0.25
years = table.index
x1 = np.arange(len(years))
x2 = [x + width for x in x1]
x3 = [x + width for x in x2]

p1 = ax.bar(x1, table['Poor'], width, label='Poor')
p2 = ax.bar(x2, table['Good'], width, label='Good')
p3 = ax.bar(x3, table['Top-Rated'], width, label='Top-Rated')

ax.set_ylabel('Number of Movies')
ax.set_xlabel('Year')
ax.set_title('Number of Movies by Year and Rating Category')
ax.set_xticks(x2)
ax.set_xticklabels(years)
ax.legend()
```

Out[12]:

```
<matplotlib.legend.Legend at 0x7f76067728b0>
```



According to the bar graph above we can conclude that over the years most movies are rated as above average wherelse few

movies are rated as 'poor'

View Count

Now, assuming that the vote count represents the percentage of watched movies, we can say that the movies with the least

vote count have the lowest views while movies with highest vote count has the most views

Now we will get data of vote_count (views) and use that data

In [13]:

```
views = """SELECT m.primary_title as Title, m.start_year as Year, m.genres as Gen
FROM movie_basics m
JOIN movie_ratings r ON m.movie_id = r.movie_id
ORDER BY Votes DESC


;"""

df_views = pd.read_sql(views, conn)
df_views.drop_duplicates(inplace=True)

df_views
```

Out[13]:

	Title	Year	Genre	Votes
0	Inception	2010	Action,Adventure,Sci-Fi	1841066
1	The Dark Knight Rises	2012	Action,Thriller	1387769
2	Interstellar	2014	Adventure,Drama,Sci-Fi	1299334
3	Django Unchained	2012	Drama,Western	1211405
4	The Avengers	2012	Action,Adventure,Sci-Fi	1183655
...	...	...	...	...
73851	Columbus	2018	Comedy	5
73852	BADMEN with a good behavior	2018	Comedy,Horror	5
73853	July Kaatril	2019	Romance	5
73854	Swarm Season	2019	Documentary	5
73855	La vida sense la Sara Amat	2019	None	5

73855 rows × 4 columns

With that information, we can get the top 10 most viewed movies, the top five most viewed movies each year and most viewd

genre cummulatively.

Below is a list of the top 10 most viewed movies

Top 10 Most Watched Movies

In [14]:

```
df_views.index = df_views.index + 1
df_views.head(10)
```

Out[14]:

	Title	Year	Genre	Votes
1	Inception	2010	Action,Adventure,Sci-Fi	1841066
2	The Dark Knight Rises	2012	Action,Thriller	1387769
3	Interstellar	2014	Adventure,Drama,Sci-Fi	1299334
4	Django Unchained	2012	Drama,Western	1211405
5	The Avengers	2012	Action,Adventure,Sci-Fi	1183655
6	The Wolf of Wall Street	2013	Biography,Crime,Drama	1035358
7	Shutter Island	2010	Mystery,Thriller	1005960
8	Guardians of the Galaxy	2014	Action,Adventure,Comedy	948394
9	Deadpool	2016	Action,Adventure,Comedy	820847
10	The Hunger Games	2012	Action,Adventure,Sci-Fi	795227

Top 10 Watched Movies Yearly

The code below prompts the user to input year between 2010 and 2019.

The results are the top 10 movies for that year

In [15]:

```
#below is a function that returns top 5 movies for a given year

def top_five(year):
    year_df = df_views[df_views['Year'] == year]
    top_movies = year_df.sort_values('Votes', ascending = False).head(10)
    return top_movies

# Prompt the user to enter a year from 2010 to 2019
year = int(input("Enter a year between 2010 and 2019: "))

if year < 2010 or year > 2019:
    print("Invalid year.")
else:
    top_movies = top_five(year)
    print(f"The top 10 most watched movies in {year} are:")
    for i, row in enumerate(top_movies.iterrows()):
        print(f"{i+1}. {row[1]['Title']}")
```

```
The top 10 most watched movies in 2018 are:
1. Avengers: Infinity War
2. Black Panther
3. Deadpool 2
4. Bohemian Rhapsody
5. A Quiet Place
6. Ready Player One
7. Venom
8. Aquaman
9. A Star Is Born
10. Ant-Man and the Wasp
```

Relationship Between Movie Sale, Reviews and Watch Count

In this section we will check how movie ratings and watch count can affect sales.

This relationship will help us understand how movie ratings affects domestic and foreign gross

In [16]:

```
#merge bom.movie dataset with the IMDB database

imdb = """SELECT *
FROM movie_basics m
JOIN movie_ratings r ON m.movie_id = r.movie_id;"""

imdb_df = pd.read_sql(imdb, conn)

bom_df = pd.read_csv('unzippedData/bom.movie_gross.csv')

bom_df
```

Out[16]:

	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

In [17]:

```
gross_df = pd.merge(imdb_df, bom_df, left_on='primary_title', right_on='title', h

#change foreign gross to float
gross_df["foreign_gross"] = gross_df["foreign_gross"].str.replace(',', '').astype



gross_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 3027 entries, 0 to 3026
Data columns (total 14 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   movie_id         3027 non-null   object
 1   primary_title    3027 non-null   object
 2   original_title   3027 non-null   object
 3   start_year       3027 non-null   int64
 4   runtime_minutes  2980 non-null   float64
 5   genres           3020 non-null   object
 6   movie_id         3027 non-null   object
 7   averagerating    3027 non-null   float64
 8   numvotes         3027 non-null   int64
 9   title            3027 non-null   object
 10  studio           3024 non-null   object
 11  domestic_gross   3005 non-null   float64
 12  foreign_gross    1832 non-null   float64
 13  year             3027 non-null   int64
dtypes: float64(4), int64(3), object(7)
memory usage: 354.7+ KB
```

In [18]:

```
gross_df = gross_df.loc[:, ['primary_title', 'genres', 'averagerating', 'numvotes
# replace missing values with 0
gross_df['domestic_gross'].fillna(0, inplace=True)
gross_df['foreign_gross'].fillna(0, inplace=True)

#group movies by title and get average of the rating and numvotes

gross_df = gross_df.groupby('primary_title').agg({'genres': 'first', 'averagerati


gross_df
```

Out[18]:

	primary_title	genres	averagerating	numvotes	studio	domestic_gr
0	'71	Action,Drama,Thriller	7.2	46103.0	RAtt.	13000
1	1,000 Times Good Night	Drama,War	7.1	6848.0	FM	539
2	10 Cloverfield Lane	Drama,Horror,Mystery	7.2	260383.0	Par.	721000
3	10 Years	Comedy,Drama,Romance	6.1	22484.0	Anch.	2030
4	1001 Grams	Drama	6.3	1301.0	KL	110
...	...	...	...	...	...	
2593	Zindagi Na Milegi Dobara	Comedy,Drama	8.1	58912.0	Eros	31000
2594	Zombeavers	Action,Adventure,Comedy	4.8	14825.0	Free	149
2595	Zookeeper	Comedy,Family,Romance	5.2	52396.0	Sony	804000
2596	Zoolander 2	Comedy	4.7	59914.0	Par.	288000
2597	Zootopia	Adventure,Animation,Comedy	8.0	383446.0	BV	3413000

2598 rows × 8 columns

Now that we have all the data we need, we can highlight the relationship between ratings and foreign gross

In [19]:

```
rate_effect = gross_df.loc[:,['averagerating', 'domestic_gross', 'foreign_gross']

rate_effect
```

Out[19]:

	averagerating	domestic_gross	foreign_gross
0	7.2	1300000.0	355000.0
1	7.1	53900.0	0.0
2	7.2	72100000.0	38100000.0
3	6.1	203000.0	0.0
4	6.3	11000.0	0.0
...	...	...	...
2593	8.1	3100000.0	0.0
2594	4.8	14900.0	0.0
2595	5.2	80400000.0	89500000.0
2596	4.7	28800000.0	27900000.0
2597	8.0	341300000.0	682500000.0

2598 rows × 3 columns

Relationship Between Average Rating and Domestic Gross

In [20]:

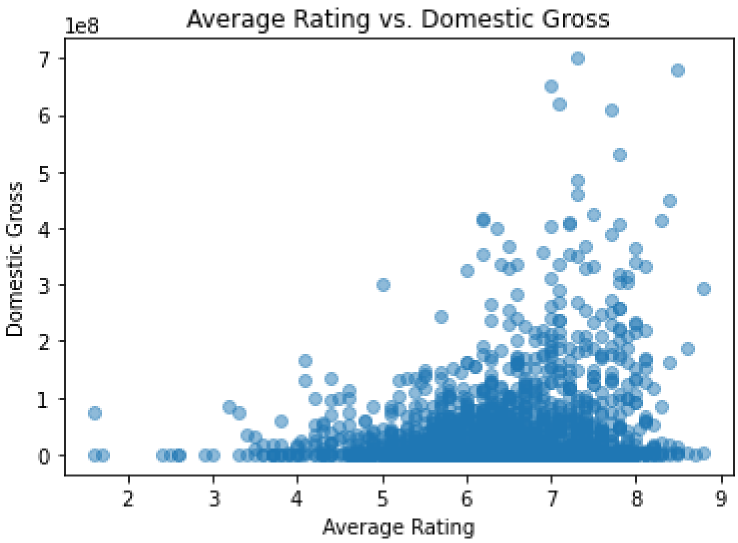
```
import matplotlib.pyplot as plt

# Create a scatter plot of averagerating vs. domestic_gross
plt.scatter(gross_df['averagerating'], gross_df['domestic_gross'], alpha=0.5)

# Set the plot title and axis labels
plt.title('Average Rating vs. Domestic Gross')
plt.xlabel('Average Rating')
plt.ylabel('Domestic Gross')
```

Out[20]:

```
Text(0, 0.5, 'Domestic Gross')
```



Relationship Between Average Rating and Foreign Gross

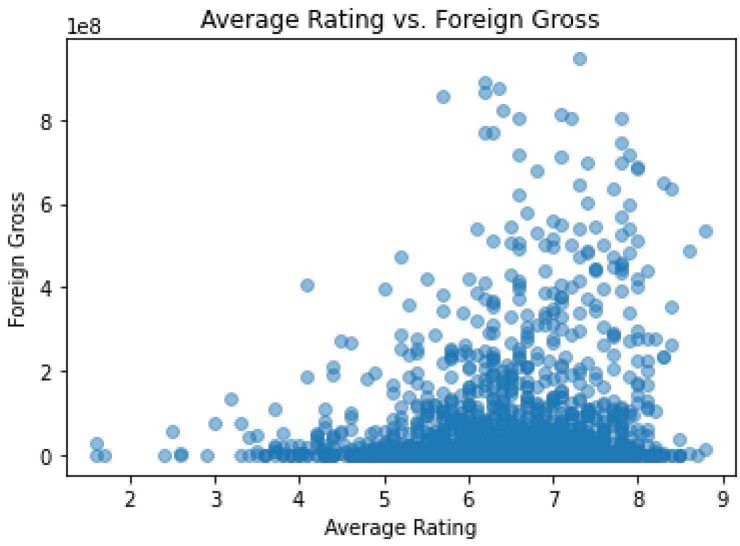
In [21]:

```
import matplotlib.pyplot as plt

# Create a scatter plot of averagerating vs. foreign_gross
plt.scatter(gross_df['averagerating'], gross_df['foreign_gross'], alpha=0.5)

# Set the plot title and axis labels
plt.title('Average Rating vs. Foreign Gross')
plt.xlabel('Average Rating')
plt.ylabel('Foreign Gross')

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



Results

According to the above representations, we concluded that the higher a movie is rated, the better it sells.

This shows that people tend to buy/stream highly rated movies more.

Rating will affect how a movie sells both locally and internationally

Next, we looked at how engagements (represented by vote count as it shows how many people have engaged with the movie)

affects or relates to the sale of the movie.

In [22]:

```
watch_effect = gross_df.loc[:,['numvotes', 'domestic_gross', 'foreign_gross']]

watch_effect
```

Out[22]:

	numvotes	domestic_gross	foreign_gross
0	46103.0	1300000.0	355000.0
1	6848.0	53900.0	0.0
2	260383.0	72100000.0	38100000.0
3	22484.0	203000.0	0.0
4	1301.0	11000.0	0.0
...	...	...	...
2593	58912.0	3100000.0	0.0
2594	14825.0	14900.0	0.0
2595	52396.0	80400000.0	89500000.0
2596	59914.0	28800000.0	27900000.0
2597	383446.0	341300000.0	682500000.0

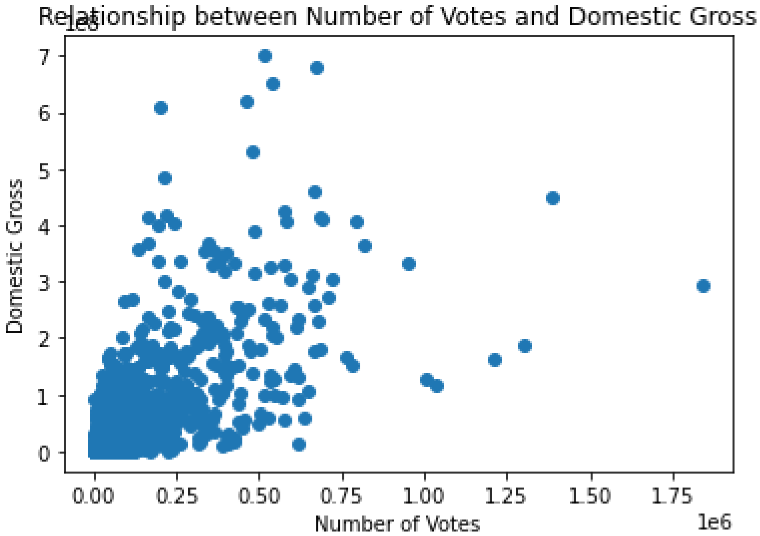
2598 rows × 3 columns

Relationship Between Vote Count and Domestic Gross

In [23]:

```
# Scatter plot for numvotes vs domestic_gross

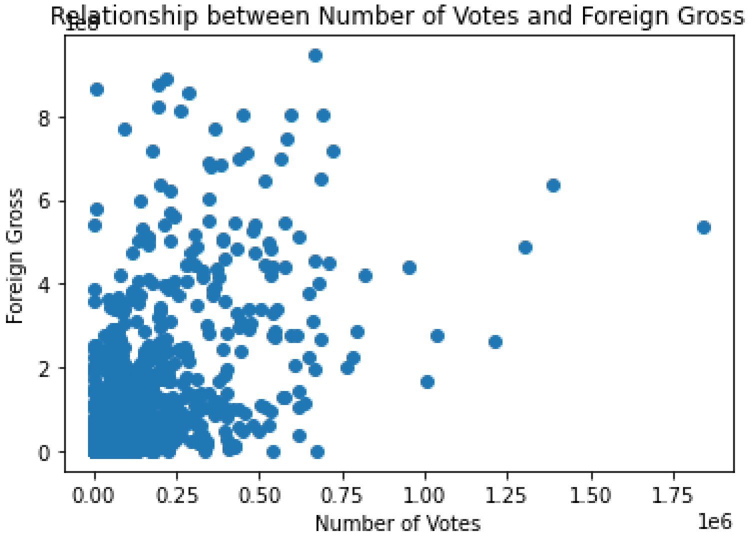
plt.scatter(watch_effect['numvotes'], watch_effect['domestic_gross'])
plt.xlabel('Number of Votes')
plt.ylabel('Domestic Gross')
plt.title('Relationship between Number of Votes and Domestic Gross')
plt.show()
```



Relationship Between Vote Count and Foreign Gross

In [24]:

```
# Scatter plot for numvotes vs foreign_gross
plt.scatter(watch_effect['numvotes'], watch_effect['foreign_gross'])
plt.xlabel('Number of Votes')
plt.ylabel('Foreign Gross')
plt.title('Relationship between Number of Votes and Foreign Gross')
plt.show()
```



Results

According to the representations above, we concluded that there is no signficant efect between viewrs engagement and movie sales.

What really matters is the average rating that the movie will get.

Relationship Between Movie Genres and Gross Sales

In this part, we analyzed the sales variation of different genres. This analysis will show whether some genres sell more than others.

The analysis will help study the market and show where consumers are willing to pay more. The analysis will also highlight which genres sold more in the past years.

The analysis studies consumer behaviour over a preiod of 10 years (2010-2019)

In [25]:

```
#get relevant datafram

genre_vs_sales_df = gross_df.loc[:,['genres', 'domestic_gross', 'foreign_gross']]

genre_vs_sales_df
```

Out[25]:

	genres	domestic_gross	foreign_gross
0	Action,Drama,Thriller	1300000.0	355000.0
1	Drama,War	53900.0	0.0
2	Drama,Horror,Mystery	72100000.0	38100000.0
3	Comedy,Drama,Romance	203000.0	0.0
4	Drama	11000.0	0.0
...	...	...	...
2593	Comedy,Drama	3100000.0	0.0
2594	Action,Adventure,Comedy	14900.0	0.0
2595	Comedy,Family,Romance	80400000.0	89500000.0
2596	Comedy	28800000.0	27900000.0
2597	Adventure,Animation,Comedy	341300000.0	682500000.0

2598 rows × 3 columns

From that dataset, we can find the top 10 genres with the most sales. To do that we summed domestic gross and foreign gross

and then selected the top 10 with the highest sum

In [29]:

```
genre_vs_sales_df = gross_df.loc[:,['genres', 'domestic_gross', 'foreign_gross']]

genre_vs_sales_df['total_gross'] = genre_vs_sales_df['domestic_gross'] + genre_vs

genre_gross = genre_vs_sales_df.groupby('genres')['total_gross'].sum().reset_inde

genre_gross = genre_gross.sort_values('total_gross', ascending=False).reset_index

top_10_genres = genre_gross.head(10)['genres'].tolist()

top_10_genres
```

Out[29]:

```
['Action,Adventure,Sci-Fi',
 'Adventure,Animation,Comedy',
 'Action,Adventure,Fantasy',
 'Action,Adventure,Comedy',
 'Action,Adventure,Animation',
 'Action,Adventure,Thriller',
 'Action,Adventure,Drama',
 'Comedy',
 'Action,Thriller',
 'Action,Crime,Thriller']
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According to our findings we have seen that the top 10 genres with the highest sales are

1. Action,Adventure,Sci-Fi
2. Adventure,Animation,Comedy
3. Action,Adventure,Fantasy
4. Action,Adventure,Comedy
5. Action,Adventure,Animation
6. Action,Adventure,Thriller
7. Action,Adventure,Drama
8. Comedy
9. Action,Thriller
10. Action,Crime,Thriller

Conclusion

According to the annalysis done on movie genre trends, we concluded that various factors affect viewres behaviour when it comes to buying and watching movies.

Some of these factors are:

- Movie rating
- Genre
- Year of release
- Movie reviews

Recommendation

Based on our analysis of movie genre trends, we found that the genre of a movie plays a significant role in its success.

Action and adventure movies have consistently performed well in both domestic and foreign markets, while comedies and dramas

have been less consistent in their performance.

Our analysis also showed that viewers tend to prefer movies with higher ratings and positive reviews. Therefore, we recommend

that movie producers focus on producing high-quality movies and investing in effective marketing strategies that highlight

positive ratings and reviews.

Additionally, our analysis suggests that movie producers should pay attention to the year of release, as viewers tend to

prefer more recent movies. Producers should, therefore, strive to keep their content fresh and relevant to current trends.

Overall, the key to success in the movie industry is to produce high-quality movies that appeal to viewers' preferences and

to effectively market those movies to a wider audience. By considering these factors, movie producers can increase their

chances of producing successful movies and building a loyal fan base.