Final Project Submission

Please fill out:

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- Student pace: part time
- Scheduled project review date/time: 07/11/2023
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- Blog post URL:

Business Problem:

Microsoft is interested in venturing in the movie production business but they do not have business analysis to help them make informed decisions as to which movies to produce. We will provide them with the analysis.

I will do several sets of anlysis then combine the results to make informed propositions to Microsoft.

Tasks

1. Find out which is the most produced genre in the industry.
2. Find out the genre with the highest gross revenue.
3. Find out the genre with the least gross revenue.
4. Investigate the revenue performance for the top produced genres
5. Investigate the revenue performance trend for the top revenue generaters over the years.
6. Investigate the relationship between rating and gross revenue.

In [4]:

```
# Import libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
```

In [5]:
```
#load data and preview
movie_titles = pd.read_csv('UnzippedData/title.basics.csv')
movie_titles.head()
```

Out[5]:

	tconst	primary_title	original_title	start_year	runtime_minutes	genres
0	tt0063540	Sunghursh	Sunghursh	2013	175.0	Action,Crime,Drama
1	tt0066787	One Day Before the Rainy Season	Ashad Ka Ek Din	2019	114.0	Biography,Drama
2	tt0069049	The Other Side of the Wind	The Other Side of the Wind	2018	122.0	Drama
3	tt0069204	Sabse Bada Sukh	Sabse Bada Sukh	2018	NaN	Comedy,Drama
4	tt0100275	The Wandering Soap Opera	La Telenovela Errante	2017	80.0	Comedy,Drama,Fantasy

In [6]:
```
#get metadata insights
movie_titles.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 146144 entries, 0 to 146143
Data columns (total 6 columns):
 #   Column           Non-Null Count   Dtype
---  ------           --------------   -----
 0   tconst           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
```

Data clean-up and feature engineering.

We will analyse the data and decide on how to handle nulls

We will look at the data formats for the columns we will be analysing

We will look at the production years and consider the period we'll be analysing

In [73]:
```
# analysis of missing data by computing the percentage of the missing data
from pandas.core.dtypes import missing
def missingdataanalysis(data):
    count_nulls = data.isna().sum()
    nulls_percentage = (data.isna().sum()) / (len(data))
    column_names = pd.DataFrame({'Missing Values':count_nulls, 'Percentage'
    return column_names
```

In [116]:
```
missingdataanalysis(movie_titles)
```

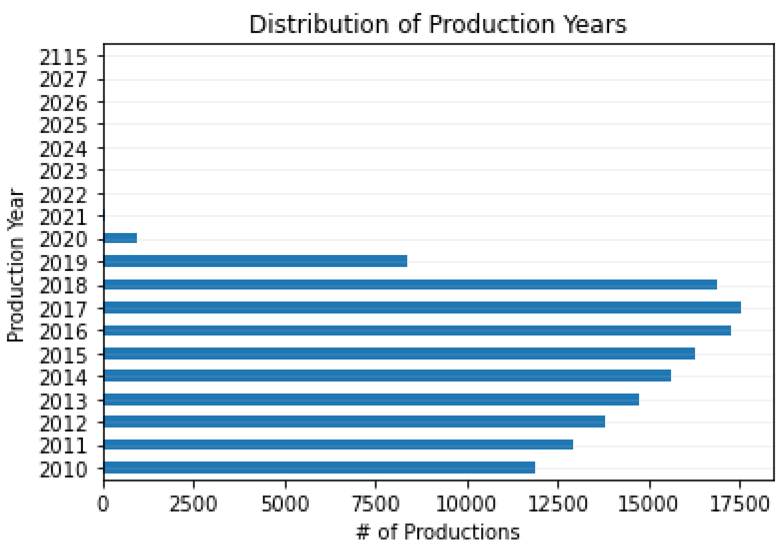
Out[116]:

	Missing Values	Percentage
tconst	0	0.000000
primary_title	0	0.000000
original_title	21	0.000144
start_year	0	0.000000
runtime_minutes	31739	0.217176
genres	5408	0.037005

We now begin data clean-up and feature engineering

In [117]:
```
# Investigate the distribution of production years
unique_years = movie_titles['start_year'].unique()
print({'Years represented in dataset':unique_years})
count_of_years = movie_titles['start_year'].value_counts().sort_index()
count_of_years.plot(kind = 'barh')
plt.xlabel('# of Productions')
plt.ylabel('Production Year')
plt.title('Distribution of Production Years')
plt.grid(axis = 'y', alpha = 0.2)
plt.show()
```

```
{'Years represented in dataset': array([2013, 2019, 2018, 2017, 2012, 201
0, 2011, 2015, 2021, 2016, 2014,
       2020, 2022, 2023, 2024, 2026, 2025, 2115, 2027], dtype=int64)}
```



In [175]:
```python
# Filter dataset to exclude future years. My assumption is that the data is
df = movie_titles[movie_titles['start_year'] <= 2023]
df.head()
```

Out[175]:

	tconst	primary_title	original_title	start_year	runtime_minutes	genres
0	tt0063540	Sunghursh	Sunghursh	2013	175.0	Action,Crime,Drama
1	tt0066787	One Day Before the Rainy Season	Ashad Ka Ek Din	2019	114.0	Biography,Drama
2	tt0069049	The Other Side of the Wind	The Other Side of the Wind	2018	122.0	Drama
3	tt0069204	Sabse Bada Sukh	Sabse Bada Sukh	2018	NaN	Comedy,Drama
4	tt0100275	The Wandering Soap Opera	La Telenovela Errante	2017	80.0	Comedy,Drama,Fantasy

In [176]:
```python
# retain only colums relevant to our analysis.
df = df.drop(['runtime_minutes', 'original_title'], axis = 1)
df.head()
```

Out[176]:

	tconst	primary_title	start_year	genres
0	tt0063540	Sunghursh	2013	Action,Crime,Drama
1	tt0066787	One Day Before the Rainy Season	2019	Biography,Drama
2	tt0069049	The Other Side of the Wind	2018	Drama
3	tt0069204	Sabse Bada Sukh	2018	Comedy,Drama
4	tt0100275	The Wandering Soap Opera	2017	Comedy,Drama,Fantasy

'genre' has 5,408 null values which is equivalent to 3.75% . Due to the nature of our data we cannot impute these values.

We'll drop the null values since dropping nulls which are 3.75% will not significantly affect our dataset.

In [177]:
```python
# Drop genre nulls and confirm drop
df = df.dropna(subset = ['genres'])
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 140731 entries, 0 to 146143
Data columns (total 4 columns):
 #   Column         Non-Null Count   Dtype 
---  ------         --------------   ----- 
 0   tconst         140731 non-null  object
 1   primary_title  140731 non-null  object
 2   start_year     140731 non-null  int64 
 3   genres         140731 non-null  object
dtypes: int64(1), object(3)
memory usage: 5.4+ MB
```

Task One: which is the most produced genre in the industry.

In [131]:
```
# Top 10 produced movie genres
genre_counts = df['genres'].value_counts().sort_values(ascending = False)[:
# genre_counts
df2 = pd.DataFrame(genre_counts)
df2.columns = ['no_of_movies_produced']
df2
```

Out[131]:

	no_of_movies_produced
Documentary	32185
Drama	21485
Comedy	9177
Horror	4372
Comedy,Drama	3519
Thriller	3046
Action	2219
Biography,Documentary	2115
Drama,Romance	2079
Comedy,Drama,Romance	1558

Task One Answer: The most produced genre in the industry is 'Documentary

Now that we know the most produced genre we now know something about the movies in production. This unfortunately is not enough to make recomendations to Microsoft since one metric isn't enough to draw meaningful insights for our case study.

We now move a step further and analyse the relationship between gross revenues and movie genres.

Task Two and Three: Find out the genre with the highest and least gross revenue

Here we will require to combine three data sets in order to achieve our subsequent objectives.

In [7]:
```
# load tables
title_basics = pd.read_csv('UnzippedData/title.basics.csv')
title_ratings = pd.read_csv('UnzippedData/title.ratings.csv')
bom_movies_gross = pd.read_csv('UnzippedData/bom.movie_gross.csv')
```

Merge The Tables

The challenge here is that 'title_ratings' and 'title_basics' have a common column. 'title_basics' and 'bom_movies_gross' have a common column. 'title_ratings' and 'bom_movies_gross' do not have a common column to use in concatenating. In this case we will do the merging in two steps.

In [8]:
```
title_basics_df1 = pd.DataFrame(title_basics)
title_ratings_df = pd.DataFrame(title_ratings)
bom_movies_gross_df = pd.DataFrame(bom_movies_gross)

# combine first level(two tables)
combined_t1 = pd.merge(title_basics_df1, title_ratings_df, on = 'tconst', h
combined_t1.sample(20)

# Combine second level (combined table and the third table)

combined_t2 = pd.merge(combined_t1, bom_movies_gross_df, left_on='primary_t
combined_t2.sample(10)
```

Out[8]:

	tconst	primary_title	original_title	start_year	runtime_minutes	
136896	tt8748882	24/25 Il fotogramma in più	24/25 Il fotogramma in più	2018	50.0	Docu
38531	tt2382596	John Wesley: The Man and His Mission	John Wesley: The Man and His Mission	2012	55.0	Docu
20970	tt1867539	El Limpiapiscinas	El Limpiapiscinas	2011	92.0	
12541	tt1664813	Rasa Yatra	Rasa Yatra	2012	50.0	Documentar
126492	tt7725692	Murdery Christmas	Murdery Christmas	2018	NaN	Horro
49023	tt2917742	El hijo de Hernández	El hijo de Hernández	2013	77.0	Adventure,Comed
88971	tt5144202	And on the Seventh Day...	And on the Seventh Day...	2015	62.0	
120994	tt7287896	Descending Roads	Descending Roads	2015	NaN	Dram
120861	tt7279144	Jeerjimbe	Jeerjimbe	2016	126.0	Dram
37188	tt2352422	Briefe aus der Deportation, Französischer Wide...	Briefe aus der Deportation, Französischer Wide...	2012	60.0	Docu

Start data clean up and feature engineering

In [392]:

```
# get metadata insights
combined_t2.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 146146 entries, 0 to 146145
Data columns (total 13 columns):
 #   Column           Non-Null Count   Dtype  
---  ------           --------------   -----  
 0   tconst           146146 non-null  object 
 1   primary_title    146146 non-null  object 
 2   original_title   146125 non-null  object 
 3   start_year       146146 non-null  int64  
 4   runtime_minutes  114407 non-null  float64
 5   genres           140738 non-null  object 
 6   averagerating    73858 non-null   float64
 7   numvotes         73858 non-null   float64
 8   title            3366 non-null    object 
 9   studio           3363 non-null    object 
 10  domestic_gross   3342 non-null    float64
 11  foreign_gross    2043 non-null    object 
 12  year             3366 non-null    float64
dtypes: float64(5), int64(1), object(7)
memory usage: 15.6+ MB
```

In 'domestic_gross', there are nulls and non nulls in 'foreign_gross' in the same row and the same is true for 'foreign_gross'.

We will assume that 'domestic_gross' and 'foreign_gross' are gross revenues and so we will add them to get the total gross revenue.

To accomplish this task we will convert the data type of foreign_gross from object to float64 and also remove the commas that seperate the values.

We'll then create a column 'Total_gross_revenue'. Where there is a null in one of the columns we are adding, we'll take the non null value else we'll add the two values.

I take this approach instead of imputing with zeros because doing so will be challenging in dealing with null gross values.

In [9]:

```

#convert the data type of foreign_gross from object to float64 and remove c
combined_t2['foreign_gross'] = combined_t2['foreign_gross'].str.replace(','
# add the domestic_gross revenue and foreign_gross revenue so as to obtain 
combined_t2['Total_gross_revenue'] = np.where((combined_t2['domestic_gross'
                                               (combined_t2['foreign_gross']
                                              np.where((combined_t2['domesti
                                               (combined_t2['foreign_gross']
                                              np.where((combined_t2['domesti
                                               (combined_t2['foreign_gross']
                                                      combined_t2['foreign_g
combined_t2['Total_gross_revenue']=combined_t2['Total_gross_revenue'].astyp
```

In [10]:
```
# remove nulls in the column 'Total_gross_revenue'
filter_sample1 = combined_t2[combined_t2['Total_gross_revenue'].notna()]

# remove nulls in the column 'genres'
filter_sample2 = filter_sample1[filter_sample1['genres'].notna()]

# remove future dates assuming the data was collected in 2023'
filter_sample= filter_sample2[filter_sample2['start_year'] <= 2023]
filter_sample.head()
```

Out[10]:

	tconst	primary_title	original_title	start_year	runtime_minutes	genı
38	tt0315642	Wazir	Wazir	2016	103.0	Action,Crime,Drai
48	tt0337692	On the Road	On the Road	2012	124.0	Adventure,Drama,Romar
54	tt0359950	The Secret Life of Walter Mitty	The Secret Life of Walter Mitty	2013	114.0	Adventure,Comedy,Drai
58	tt0365907	A Walk Among the Tombstones	A Walk Among the Tombstones	2014	114.0	Action,Crime,Drai
60	tt0369610	Jurassic World	Jurassic World	2015	124.0	Action,Adventure,Sci

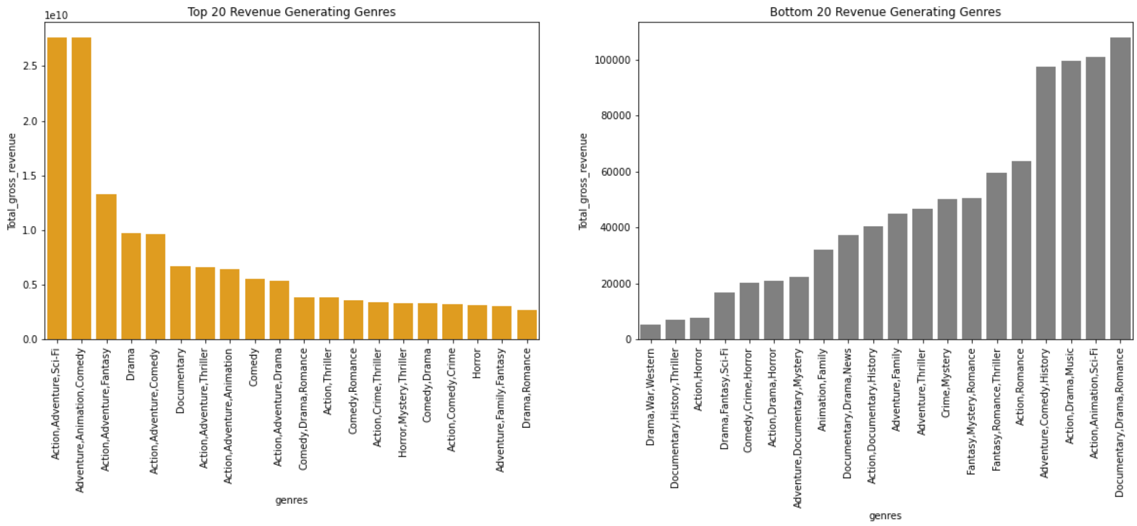
In [289]:
```
# confirm nulls have been removed.
filter_sample.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 3326 entries, 38 to 146080
Data columns (total 14 columns):
 #   Column               Non-Null Count  Dtype  
---  ------               --------------  -----  
 0   tconst               3326 non-null   object 
 1   primary_title        3326 non-null   object 
 2   original_title       3326 non-null   object 
 3   start_year           3326 non-null   int64  
 4   runtime_minutes      3185 non-null   float64
 5   genres               3326 non-null   object 
 6   averagerating        3020 non-null   float64
 7   numvotes             3020 non-null   float64
 8   title                3326 non-null   object 
 9   studio               3323 non-null   object 
 10  domestic_gross       3302 non-null   float64
 11  foreign_gross        2016 non-null   float64
 12  year                 3326 non-null   float64
 13  Total_gross_revenue  3326 non-null   float64
dtypes: float64(7), int64(1), object(6)
memory usage: 389.8+ KB
```

Let us now have a view of the top performing genres in compared to the total gross revenue and the bottom performers as well.

This will give Microsoft a quick glance of where to venture and where not to in terms of revenue generation.

In [11]:
```
# Gross revenue vs Genre

# calculate the total revenue generated by each genre
grouped_genres = filter_sample.groupby('genres')['Total_gross_revenue'].sum

# Sort by total gross revenue and select the top 20 and bottom 20 genres in
top_revenue_generators = grouped_genres.nlargest(20, 'Total_gross_revenue')
least_revenue_generators = grouped_genres.nsmallest(20, 'Total_gross_revenu

fig, axes = plt.subplots(1, 2, figsize = (20, 6))

# plot top revenue generaters
sns.barplot(data=top_revenue_generators, x='genres', y='Total_gross_revenue
axes[0].set_xticklabels(axes[0].get_xticklabels(), rotation=90)
axes[0].set_title('Top 20 Revenue Generating Genres')

# plot bottom revenue generaters
sns.barplot(data=least_revenue_generators, x='genres', y='Total_gross_reven
axes[1].set_xticklabels(axes[1].get_xticklabels(), rotation = 90)
axes[1].set_title('Bottom 20 Revenue Generating Genres')
plt.show()
```



Task Two Answer: The genre with the highest gross revenue is 'Action,Adventure,Sci-Fi'

Task Three Answer: The genre with the least gross revenue is 'Drama,War,Western'

In [12]:
```
grouped_genres.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 331 entries, 0 to 330
Data columns (total 2 columns):
 #   Column               Non-Null Count  Dtype  
---  ------               --------------  -----  
 0   genres               331 non-null    object 
 1   Total_gross_revenue  331 non-null    float64
dtypes: float64(1), object(1)
memory usage: 5.3+ KB
```

Let's look at the performance of the top produced genres and compare them with the gross

Task Four: Investigate the performance for the top produced genres in relation to the associated gross revenue.

In [13]:

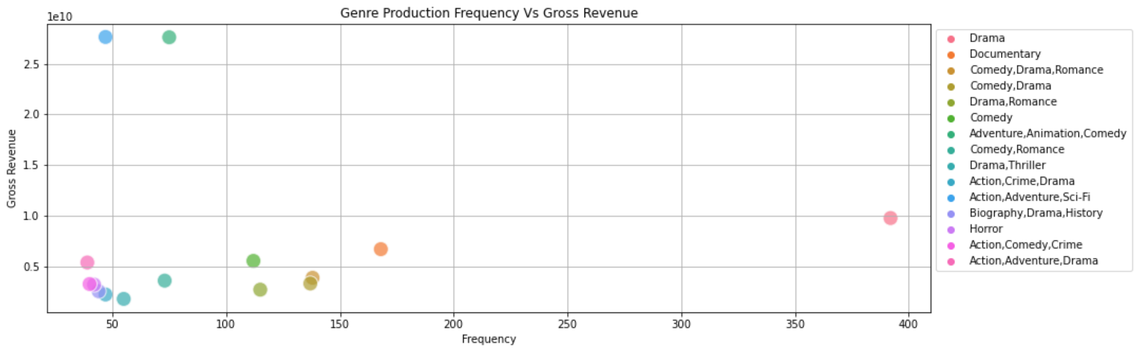
```
# create a table for counting the genre frequency
genre_counts = filter_sample['genres'].value_counts().reset_index()
genre_counts.columns = ['genres', 'frequency']
# create a table for adding the gross revenue per genre
genre_revenue = filter_sample.groupby('genres')['Total_gross_revenue'].sum(
# merge the two tables and return the top 20 produced genres
top_produced_genre = pd.merge(genre_counts, genre_revenue, on='genres').sor
top_produced_genre[:30]
```

Out[13]:

	genres	frequency	Total_gross_revenue
0	Drama	392	9.750485e+09
1	Documentary	168	6.675822e+09
2	Comedy,Drama,Romance	138	3.848966e+09
3	Comedy,Drama	137	3.285812e+09
4	Drama,Romance	115	2.676497e+09
5	Comedy	112	5.517496e+09
6	Adventure,Animation,Comedy	75	2.760733e+10
7	Comedy,Romance	73	3.566841e+09
8	Drama,Thriller	55	1.762643e+09
10	Action,Crime,Drama	47	2.197532e+09
9	Action,Adventure,Sci-Fi	47	2.763610e+10
11	Biography,Drama,History	44	2.520359e+09
12	Horror	42	3.171984e+09
13	Action,Comedy,Crime	40	3.234542e+09
14	Action,Adventure,Drama	39	5.360137e+09
15	Crime,Drama,Thriller	39	1.011223e+09
16	Biography,Drama	38	1.334131e+09
17	Thriller	38	1.475258e+09
18	Horror,Mystery,Thriller	37	3.320993e+09
19	Action,Crime,Thriller	36	3.386371e+09
20	Crime,Drama	34	1.831095e+09
21	Action,Thriller	33	3.813461e+09
22	Horror,Thriller	33	1.778974e+09
23	Action,Adventure,Comedy	32	9.666672e+09
24	Action,Adventure,Fantasy	31	1.331489e+10
25	Action,Drama,Thriller	30	2.605212e+09
26	Biography,Comedy,Drama	27	1.125084e+09
29	Crime,Drama,Mystery	25	6.236270e+08
28	Biography,Documentary	25	2.392266e+08
27	Comedy,Crime,Drama	25	5.289667e+08

Let's plot the visual representation for the top 15 produced genres below

In [350]:
```
plt.figure(figsize=(15, 5))
sns.scatterplot(data=top_produced_genre[:15], x= 'frequency', y='Total_gros
plt.title('Genre Production Frequency Vs Gross Revenue')
plt.xlabel('Frequency')
plt.ylabel('Gross Revenue')
plt.grid(True)
plt.legend(bbox_to_anchor=(1, 1), loc='upper left')
plt.show()
```



Task Four Answer: 'Drama has the highest frequency'

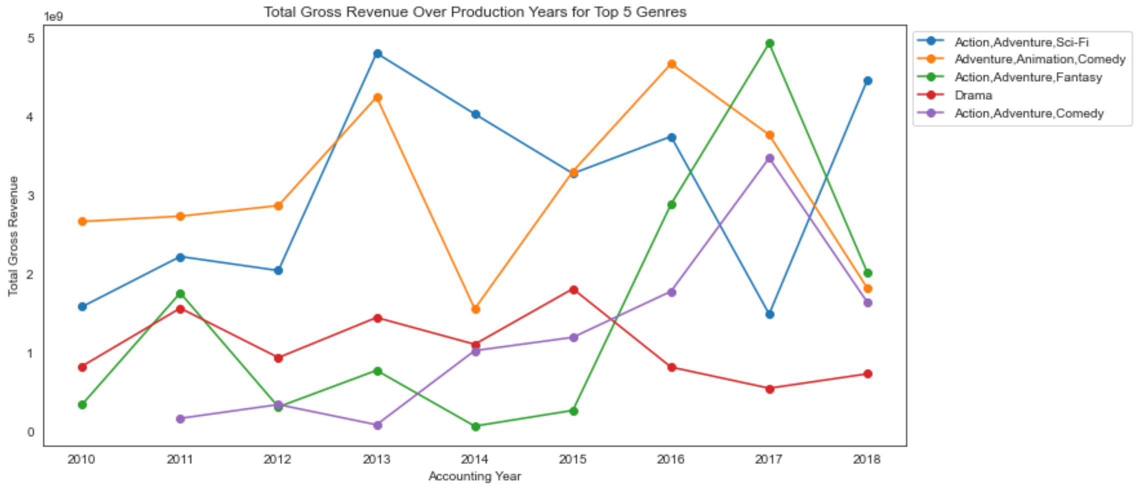
It is quite interesting to note that the genre with the highest gross revenue which is 'Action,Adventure,Sci-Fi' isn't the most produced genre. Infact it is number ten in the frequency ranking.

'Drama' which is the most produced ranks 4th in the top 20 revenue generating genres.

Task Five: Investigate the performance trend for the top revenue generaters over the years.

In [416]:

```
top_5_performers = top_revenue_generators[:5]
top_5_genres = top_5_performers['genres']
filter_data_years = filter_sample[filter_sample['genres'].isin(top_5_genres
filter_data_years['year'] = filter_data_years['year'].astype(int)
grouped_data = filter_data_years.groupby(['year', 'genres'])['Total_gross_r
plt.figure(figsize=(12, 6))
for genre in top_5_genres:
    genre_data = grouped_data[grouped_data['genres'] == genre]
    plt.plot(genre_data['year'], genre_data['Total_gross_revenue'], marker=

plt.xlabel('Accounting Year')
plt.ylabel('Total Gross Revenue')
plt.title('Total Gross Revenue Over Production Years for Top 5 Genres')
plt.legend(bbox_to_anchor=(1, 1), loc='upper left');
plt.show()
```



Task Six: Investigate the relationship between rating and gross revenue.

From the 'filter_sample' data, we have 306 nulls which we will drop.

In [418]:

```python
filter_sample.dropna(subset =['averagerating'],inplace = True )
# confirm nulls dropped
filter_sample.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 3020 entries, 38 to 146080
Data columns (total 14 columns):
 #   Column               Non-Null Count  Dtype  
---  ------               --------------  -----  
 0   tconst               3020 non-null   object 
 1   primary_title        3020 non-null   object 
 2   original_title       3020 non-null   object 
 3   start_year           3020 non-null   int64  
 4   runtime_minutes      2975 non-null   float64
 5   genres               3020 non-null   object 
 6   averagerating        3020 non-null   float64
 7   numvotes             3020 non-null   float64
 8   title                3020 non-null   object 
 9   studio               3017 non-null   object 
 10  domestic_gross       2998 non-null   float64
 11  foreign_gross        1825 non-null   float64
 12  year                 3020 non-null   float64
 13  Total_gross_revenue  3020 non-null   float64
dtypes: float64(7), int64(1), object(6)
memory usage: 353.9+ KB
```

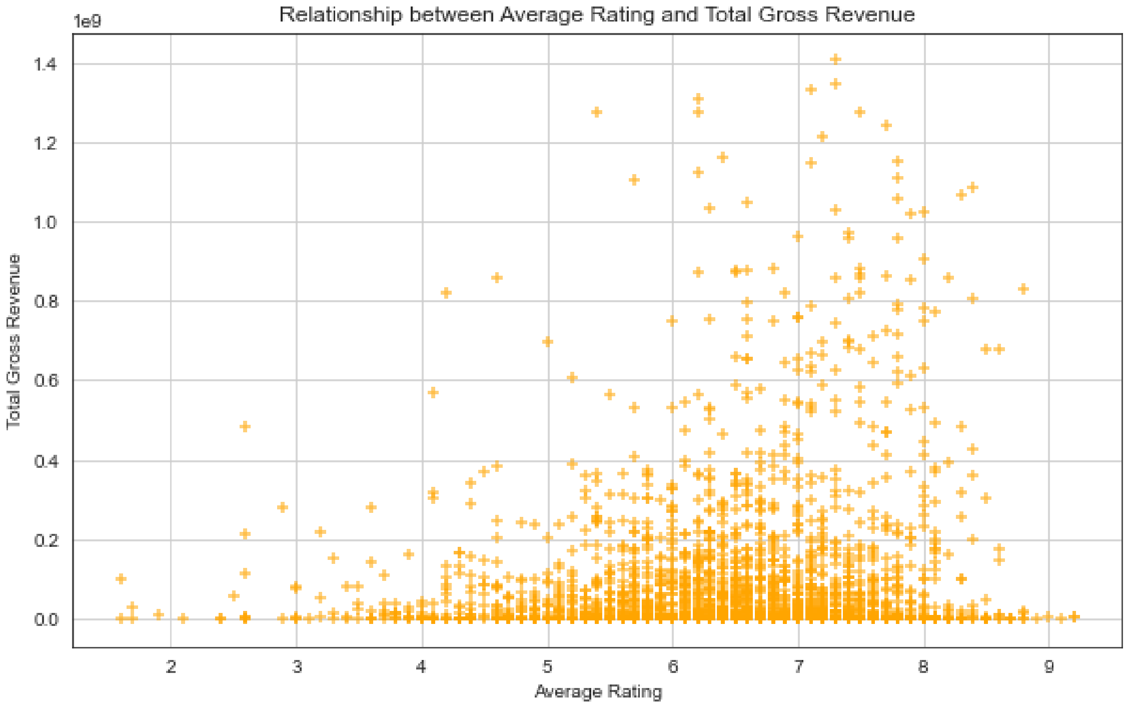
In [427]:

```python
filter_sample.describe()
```

Out[427]:

	start_year	runtime_minutes	averagerating	numvotes	domestic_gross	foreign_g
count	3020.000000	2975.000000	3020.000000	3.020000e+03	2.998000e+03	1.82500
mean	2013.784437	107.257815	6.458543	6.184327e+04	3.059426e+07	7.82998
std	2.464499	20.048405	1.011853	1.256234e+05	6.676743e+07	1.38795
min	2010.000000	3.000000	1.600000	5.000000e+00	1.000000e+02	6.00000
25%	2012.000000	94.000000	5.900000	2.199000e+03	1.380000e+05	4.60000
50%	2014.000000	105.000000	6.600000	1.324900e+04	2.000000e+06	2.11000
75%	2016.000000	118.000000	7.100000	6.319075e+04	3.240000e+07	8.16000
max	2019.000000	272.000000	9.200000	1.841066e+06	7.001000e+08	9.46400

```
In [420]: plt.figure(figsize=(10, 6))
          plt.scatter(filter_sample['averagerating'], filter_sample['Total_gross_reve
          plt.xlabel('Average Rating')
          plt.ylabel('Total Gross Revenue')
          plt.title('Relationship between Average Rating and Total Gross Revenue')
          plt.grid(True)
          plt.show()
```



We can observe that most of the top ranking genres in relation to total gross revenue are within the averagerating mean of 6.458543

Let's further investigate the average rating for our top 5 performing genres which were based on total gross revenue

In [425]:
```
merge_data = top_revenue_generators.merge(filter_sample, on= 'genres', how=

average_genre_rating = merge_data.groupby('genres')['averagerating'].mean()
average_genre_rating = average_genre_rating.rename(columns= {'averagerating
average_genre_rating
```

Out[425]:

	genres	meanrating
0	Action,Adventure,Animation	7.354545
1	Action,Adventure,Comedy	6.271875
2	Action,Adventure,Drama	6.112821
3	Action,Adventure,Fantasy	6.287097
4	Action,Adventure,Sci-Fi	6.776596
5	Action,Adventure,Thriller	6.476471
6	Action,Comedy,Crime	5.985000
7	Action,Crime,Thriller	6.413889
8	Action,Thriller	6.106452
9	Adventure,Animation,Comedy	6.438667
10	Adventure,Family,Fantasy	6.112500
11	Comedy	5.793684
12	Comedy,Drama	6.588722
13	Comedy,Drama,Romance	6.350000
14	Comedy,Romance	6.080556
15	Documentary	7.214545
16	Drama	6.672871
17	Drama,Romance	6.641071
18	Horror	5.030000
19	Horror,Mystery,Thriller	5.517647

Task Six Findings: The averagerating mean is 6.458543 This indicates that our top revenue generators have a mean around the group averagerating mean.

1. Action,Adventure,Sci-Fi with a mean rating of 7.354545
2. Adventure,Animation,Comedy with a mean rating of 6.438667
3. Action,Adventure,Fantasy with a mean rating of 6.287097
4. Drama with a mean rating of 6.672871
5. Action,Adventure,Comedy with a mean rating 6.271875

Conclusion:

Microsoft should consider the following when making a decision:

1. Based on industry trends:

Produce 'Drama' movies.
It is the most produced genre and has an average rating of 6.672871 which is above the group average rating of 6.672871.
It is also important to note that 'Drama' is not the genre with the highest revenue generator, it is ranked 9th.

2. Based on total gross revenue:

Produce 'Action,Adventure,Sci-Fi'
This is the genre that is generating the highest gross revenue in the industry. It has a mean of 6.776596 which intrestingly is below the group average rating mean.

3. Based on total rating:

Produce 'Action,Adventure,Animation'.
This genre has the highest average rating mean of 7.354545.
This is genre ranked 8th in the total gross revenue rating.

4. Based on gross revenue trends over the accounting period:

Produce 'Action,Adventure,Sci-Fi'.
Although all genres project a sawtooth pattern on the line graph, the genre seems to exhibit

In [ ]: