Final Project Submission

Student Information

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- Student pace: Part Time
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- Blog post URL: N/A

Business Problem

Microsoft is considering venturing into the movie industry as all the big companies are already creating original video content. It intends to create a successful movie studio and it's major problem is the lack of knowledge in this field. It wants to understand the current trends in the film industry and make informed decisions on the types of movies to create for maximum success.

To help Microsoft solve this problem, i will consider:
1. Which are the years with the highest number of movies produced?
2. What is the relationship between the production budget and the worldwide profits over time?
3. What genre was highly produced?
4. Which genres are the most profitable?
5. What is the general trend of the average profits over the years?
6. What are the highly rated movie genres?
7. What is the relationship between the production budget and profits?
8. What is the relationship between movie ratings and profits?
9. What were the top 10 highly rated movie titles by revenue?

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Introduction

This report is an analysis of IMDB & Box Office Mojo data set containing information about 3017 movies produced between years 2010 and 2019.

Business Understanding

The stated business problem presented by Microsoft is establishing their own movie studio to compete within the movie market, and needing to know what kind of movies will be the most successful.

This analysis aims at solving the stated business problem by determining what kind of movies have been most succesful in terms of - average rating and profits from the year 2000 to 2018. In utilizing three large datasets from movie giants IMDb, The movie database and Box Office Mojo.

Data Sources

In this project, I will analyse movie data from the below sites

- Box Office Mojo
- IMDB
- Rotten Tomatoes
- TheMovieDB.org

The Specific files for analysis are:

- imdb.title.basics.csv.gz
- imdb.title.ratings.csv.gz
- tn_movie_budgets.csv.gz

Data Wrangling

In this section, I merge the above files to come up with a single dataframe that I can now use to perform exploratory data analysis.

In [435]:

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

In [436]:
```
imdb_title_basics_df = pd.read_csv('./zippedData/imdb.title.basics.csv.g
imdb_title_basics_df.head()
```

Out[436]:

	tconst	primary_title	original_title	start_year	runtime_minutes	genı
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

In [437]:
```
imdb_title_basics_df.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
```

In [438]:
```
imdb_title_ratings_df = pd.read_csv('./zippedData/imdb.title.ratings.csv
imdb_title_ratings_df.head()
```

Out[438]:

	tconst	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

In [439]:
```
imdb_title_ratings_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 73856 entries, 0 to 73855
Data columns (total 3 columns):
 #   Column         Non-Null Count  Dtype  
---  ------         --------------  -----  
 0   tconst         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
```

In [440]:
```
# Merging the title_ratings and title basics dfs
new_title_ratings_df = pd.merge(imdb_title_basics_df, imdb_title_rating
new_title_ratings_df.head()
```

Out[440]:

	tconst	primary_title	original_title	start_year	runtime_minutes	geni
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,Fanta

In [441]:
```
new_title_ratings_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 73856 entries, 0 to 73855
Data columns (total 8 columns):
 #   Column           Non-Null Count  Dtype  
---  ------           --------------  -----  
 0   tconst           73856 non-null  object 
 1   primary_title    73856 non-null  object 
 2   original_title   73856 non-null  object 
 3   start_year       73856 non-null  int64  
 4   runtime_minutes  66236 non-null  float64
 5   genres           73052 non-null  object 
 6   averagerating    73856 non-null  float64
 7   numvotes         73856 non-null  int64  
dtypes: float64(2), int64(2), object(4)
memory usage: 5.1+ MB
```

In [443]:

```
# Dropping the columns that are not relevant in answering my problem st
new_title_ratings_df.drop(columns=['original_title', 'runtime_minutes',
new_title_ratings_df.head()
```

Out[443]:

	tconst	title	start_year	genres	averagerating
0	tt0063540	Sunghursh	2013	Action,Crime,Drama	7.0
1	tt0066787	One Day Before the Rainy Season	2019	Biography,Drama	7.2
2	tt0069049	The Other Side of the Wind	2018	Drama	6.9
3	tt0069204	Sabse Bada Sukh	2018	Comedy,Drama	6.1
4	tt0100275	The Wandering Soap Opera	2017	Comedy,Drama,Fantasy	6.5

In [444]:

```
# Renaming the primary_title column to title since the primary title is
new_title_ratings_df.rename(columns={'primary_title': 'title'}, inplace
new_title_ratings_df.head()
```

Out[444]:

	tconst	title	start_year	genres	averagerating
0	tt0063540	Sunghursh	2013	Action,Crime,Drama	7.0
1	tt0066787	One Day Before the Rainy Season	2019	Biography,Drama	7.2
2	tt0069049	The Other Side of the Wind	2018	Drama	6.9
3	tt0069204	Sabse Bada Sukh	2018	Comedy,Drama	6.1
4	tt0100275	The Wandering Soap Opera	2017	Comedy,Drama,Fantasy	6.5

In [445]:

```
new_title_ratings_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 73856 entries, 0 to 73855
Data columns (total 5 columns):
 #   Column         Non-Null Count  Dtype  
---  ------         --------------  -----  
 0   tconst         73856 non-null  object 
 1   title          73856 non-null  object 
 2   start_year     73856 non-null  int64  
 3   genres         73052 non-null  object 
 4   averagerating  73856 non-null  float64
dtypes: float64(1), int64(1), object(3)
memory usage: 3.4+ MB
```

In [446]:

```
# Introducing the movie budgets file to provide us with the production 
tn_movie_budgets_df = pd.read_csv('./zippedData/tn.movie_budgets.csv.gz
tn_movie_budgets_df.head()
```

Out[446]:

	id	release_date	movie	production_budget	domestic_gross	worldwide_gross
0	1	Dec 18, 2009	Avatar	$425,000,000	$760,507,625	$2,776,345,279
1	2	May 20, 2011	Pirates of the Caribbean: On Stranger Tides	$410,600,000	$241,063,875	$1,045,663,875
2	3	Jun 7, 2019	Dark Phoenix	$350,000,000	$42,762,350	$149,762,350
3	4	May 1, 2015	Avengers: Age of Ultron	$330,600,000	$459,005,868	$1,403,013,963
4	5	Dec 15, 2017	Star Wars Ep. VIII: The Last Jedi	$317,000,000	$620,181,382	$1,316,721,747

In [447]:

```
# Renaming the movie column to title to facilitate inner merging
tn_movie_budgets_df.rename(columns={'movie': 'title'}, inplace=True)
tn_movie_budgets_df.head()
```

Out[447]:

	id	release_date	title	production_budget	domestic_gross	worldwide_gross
0	1	Dec 18, 2009	Avatar	$425,000,000	$760,507,625	$2,776,345,279
1	2	May 20, 2011	Pirates of the Caribbean: On Stranger Tides	$410,600,000	$241,063,875	$1,045,663,875
2	3	Jun 7, 2019	Dark Phoenix	$350,000,000	$42,762,350	$149,762,350
3	4	May 1, 2015	Avengers: Age of Ultron	$330,600,000	$459,005,868	$1,403,013,963
4	5	Dec 15, 2017	Star Wars Ep. VIII: The Last Jedi	$317,000,000	$620,181,382	$1,316,721,747

In [448]:

```
tn_movie_budgets_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   title              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
```

In [449]:

```
# Merging the new_title_ratings with the tn_movie_budgets_df to improve
data = pd.merge(new_title_ratings_df, tn_movie_budgets_df, how='inner',
data.head()
```

Out[449]:

	tconst	title	start_year	genres	averagerating	id	release_
0	tt0249516	Foodfight!	2012	Action,Animation,Comedy	1.9	26	Dec 31, :
1	tt0326592	The Overnight	2010	NaN	7.5	21	Jun 19, :
2	tt3844362	The Overnight	2015	Comedy,Mystery	6.1	21	Jun 19, :
3	tt0337692	On the Road	2012	Adventure,Drama,Romance	6.1	17	Mar 22, :
4	tt4339118	On the Road	2014	Drama	6.0	17	Mar 22, :

In [450]:

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 2875 entries, 0 to 2874
Data columns (total 10 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   tconst             2875 non-null   object 
 1   title              2875 non-null   object 
 2   start_year         2875 non-null   int64  
 3   genres             2867 non-null   object 
 4   averagerating      2875 non-null   float64
 5   id                 2875 non-null   int64  
 6   release_date       2875 non-null   object 
 7   production_budget  2875 non-null   object 
 8   domestic_gross     2875 non-null   object 
 9   worldwide_gross    2875 non-null   object 
dtypes: float64(1), int64(2), object(7)
memory usage: 247.1+ KB
```

Data Cleaning

In [451]:

```
#Dropping the id & tconstruct columns as they are not useful in our ana
data.drop('id', axis=1, inplace=True)
data.drop('tconst', axis=1, inplace=True)
```

In [452]:
```python
# Creating a new column using the release date called release year
data['release_date'] = pd.to_datetime(data['release_date'])
data['release_year'] = data['release_date'].dt.year
data.head()
```

Out[452]:

	title	start_year	genres	averagerating	release_date	productio
0	Foodfight!	2012	Action,Animation,Comedy	1.9	2012-12-31	$4
1	The Overnight	2010	NaN	7.5	2015-06-19	
2	The Overnight	2015	Comedy,Mystery	6.1	2015-06-19	
3	On the Road	2012	Adventure,Drama,Romance	6.1	2013-03-22	$2
4	On the Road	2014	Drama	6.0	2013-03-22	$2

In [453]:
```python
# Converting production_budget, domestic_gross , worldwide_gross to nume

# Remove '$' and convert to numeric for 'production_budget'
data['production_budget'] = pd.to_numeric(data['production_budget'].rep

# Remove '$' and convert to numeric for 'domestic_gross' and 'worldwide_
data['domestic_gross'] = pd.to_numeric(data['domestic_gross'].replace('
data['worldwide_gross'] = pd.to_numeric(data['worldwide_gross'].replace
```

In [454]:
```python
# Creating new columns  domestic profits and worldwide profits
data['domestic_profits'] = data['domestic_gross'] - data['production_bu

# Calculating the worldwide Profits
data['worldwide_profits'] = data['worldwide_gross'] - data['production_
```

In [455]:
```python
data.head()
```

Out[455]:

	title	start_year	genres	averagerating	release_date	productio
0	Foodfight!	2012	Action,Animation,Comedy	1.9	2012-12-31	
1	The Overnight	2010	NaN	7.5	2015-06-19	
2	The Overnight	2015	Comedy,Mystery	6.1	2015-06-19	
3	On the Road	2012	Adventure,Drama,Romance	6.1	2013-03-22	
4	On the Road	2014	Drama	6.0	2013-03-22	

In [456]:

```python
# Since the values for profits and budget are huge, we divide all by 1m
data['domestic_gross_in_mill'] = data['domestic_gross'] / 10**6
data['worldwide_gross_in_mill'] = data['worldwide_gross'] / 10**6
data['production_budget_in_mill'] = data['production_budget'] / 10**6
data['domestic_profits_in_mill'] = data['domestic_profits'] / 10**6
data['worldwide_profits_in_mill'] = data['worldwide_profits']/ 10**6
data.head()
```

Out[456]:

	title	start_year	genres	averagerating	release_date	productic
0	Foodfight!	2012	Action,Animation,Comedy	1.9	2012-12-31	
1	The Overnight	2010	NaN	7.5	2015-06-19	
2	The Overnight	2015	Comedy,Mystery	6.1	2015-06-19	
3	On the Road	2012	Adventure,Drama,Romance	6.1	2013-03-22	
4	On the Road	2014	Drama	6.0	2013-03-22	

In [457]:

```python
# Removing the columns already reproduced.
data.drop(columns=['production_budget', 'domestic_gross', 'worldwide_gr
data.head()
```

Out[457]:

	title	start_year	genres	averagerating	release_date	release_y
0	Foodfight!	2012	Action,Animation,Comedy	1.9	2012-12-31	2
1	The Overnight	2010	NaN	7.5	2015-06-19	2
2	The Overnight	2015	Comedy,Mystery	6.1	2015-06-19	2
3	On the Road	2012	Adventure,Drama,Romance	6.1	2013-03-22	2
4	On the Road	2014	Drama	6.0	2013-03-22	2

In [458]:

```python
# Checking for duplicates
duplicates = data.duplicated()
duplicates
```

Out[458]:

```
0       False
1       False
2       False
3       False
4       False
        ...
2870    False
2871    False
2872    False
2873    False
2874    False
Length: 2875, dtype: bool
```

In [459]:

```python
# To verify whether there are any duplicates in the dataframe
data[data.duplicated(keep=False)]
```

Out[459]:

title	start_year	genres	averagerating	release_date	release_year	domestic_gross_in_

In [460]:

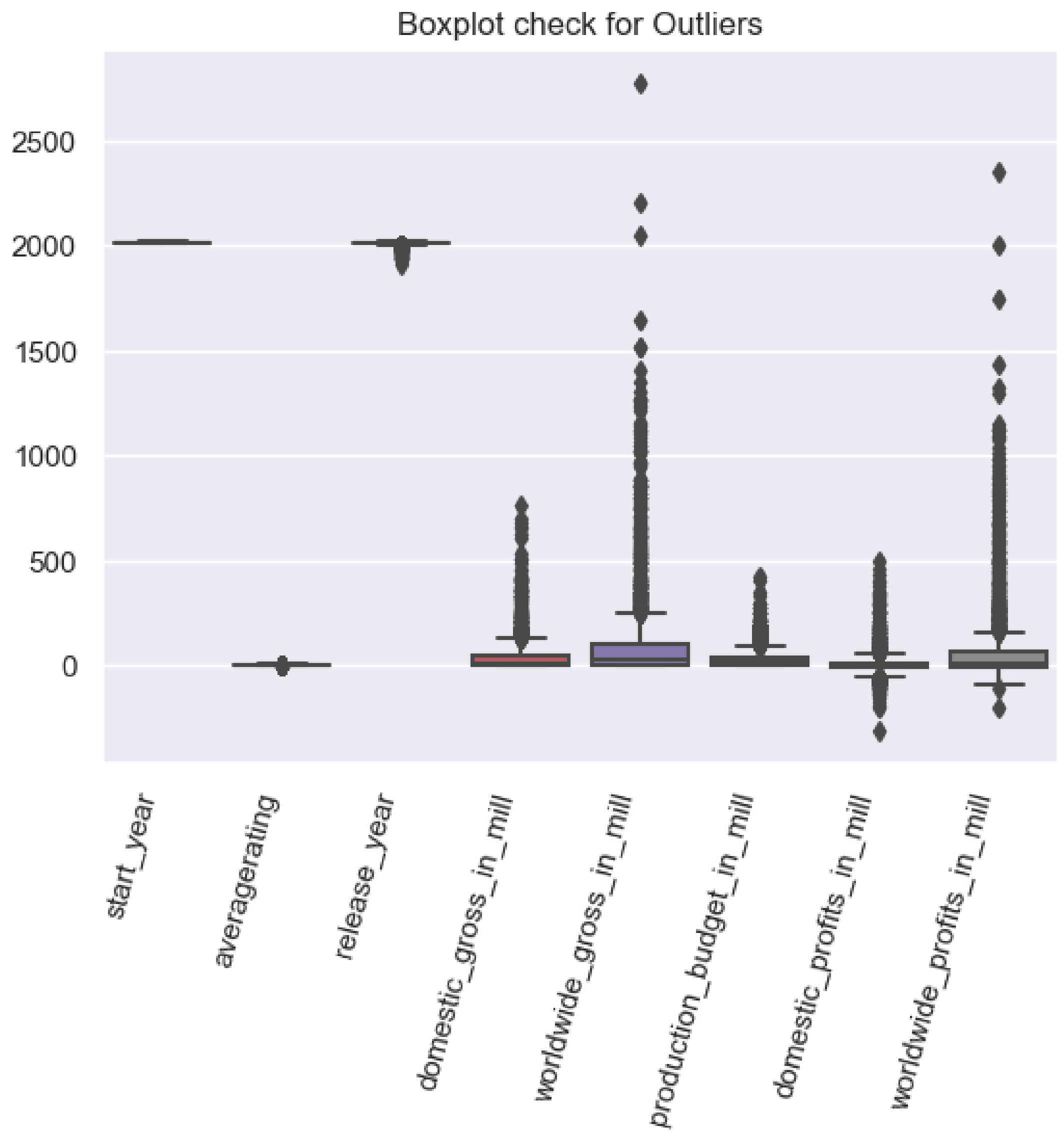
```python
# Checking for null values in each column
data.isna().sum()
```

Out[460]:

```
title                        0
start_year                   0
genres                       8
averagerating                0
release_date                 0
release_year                 0
domestic_gross_in_mill       0
worldwide_gross_in_mill      0
production_budget_in_mill    0
domestic_profits_in_mill     0
worldwide_profits_in_mill    0
dtype: int64
```

In [461]:

```
# Checking for outliers
sns.boxplot(data=data)
sns.set(style="darkgrid")
plt.xticks(rotation=75, ha='right')
plt.title('Boxplot check for Outliers')
plt.show()
```



In [462]:

```
# Checking the release years of our dataset in ascending order
sorted_release_years = data['release_year'].sort_values(ascending=True)
print(sorted_release_years)
```

```
2551    1915
1890    1927
1111    1940
2416    1940
1107    1940
        ...
1998    2019
1346    2019
2489    2019
2025    2019
2611    2019
Name: release_year, Length: 2875, dtype: int64
```

In [463]:
```
# Limiting our data to movies released between 2000 and before 1st Jan 
start_date = '2000-01-01'
end_date = '2019-01-01'
df = data[(data['release_date'] >= start_date) & (data['release_date'] 
```

In [464]:
```
# Double checking to ensure that the data has been sliced between years
sorted_release_years = df['release_year'].sort_values(ascending=True)
print(sorted_release_years)
```

```
2874    2000
548     2000
549     2000
1542    2000
2543    2000
        ...
2693    2018
426     2018
1823    2018
959     2018
1899    2018
Name: release_year, Length: 2553, dtype: int64
```

In [ ]:
```
# Converting release_year to string datatype
df['release_year'] = df['release_year'].astype(str)
```

In [468]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 2553 entries, 0 to 2874
Data columns (total 11 columns):
 #   Column                   Non-Null Count  Dtype
---  ------                   --------------  -----
 0   title                    2553 non-null   object
 1   start_year               2553 non-null   int64
 2   genres                   2545 non-null   object
 3   averagerating            2553 non-null   float64
 4   release_date             2553 non-null   datetime64[ns]
 5   release_year             2553 non-null   object
 6   domestic_gross_in_mill   2553 non-null   float64
 7   worldwide_gross_in_mill  2553 non-null   float64
 8   production_budget_in_mill 2553 non-null  float64
 9   domestic_profits_in_mill  2553 non-null  float64
 10  worldwide_profits_in_mill 2553 non-null  float64
dtypes: datetime64[ns](1), float64(6), int64(1), object(3)
memory usage: 239.3+ KB
```

Exploratory Data Analysis

In [470]:

```python
# Getting a summary to understand the data
df.describe()
```

Out[470]:

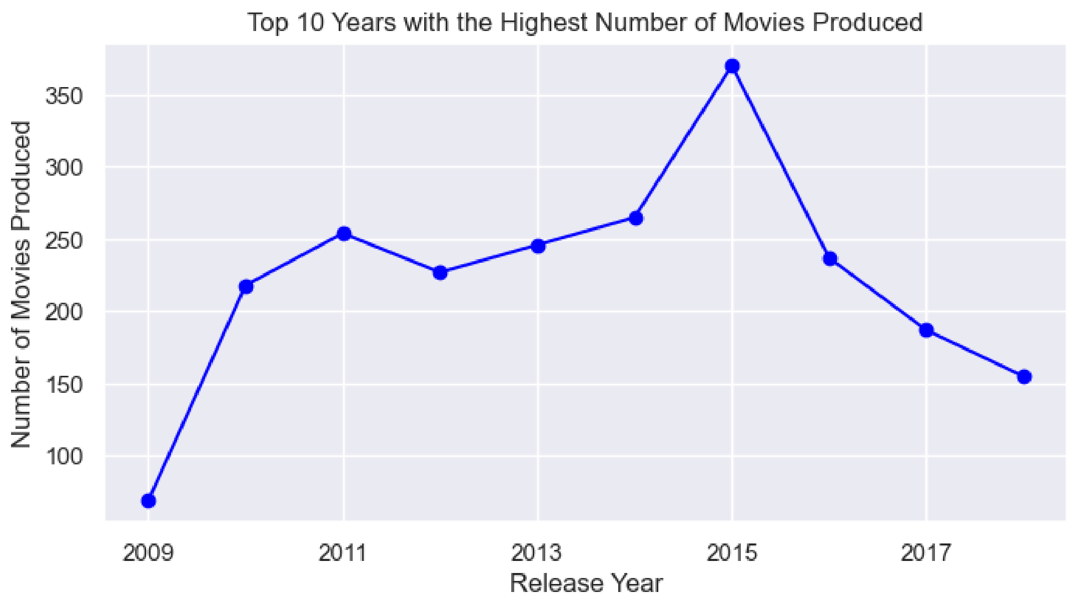
	start_year	averagerating	domestic_gross_in_mill	worldwide_gross_in_mill	pro
count	2553.000000	2553.000000	2553.000000	2553.000000	
mean	2013.809244	6.254524	42.849598	105.165461	
std	2.491215	1.175536	75.455290	207.079844	
min	2010.000000	1.600000	0.000000	0.000000	
25%	2012.000000	5.600000	0.307631	1.642939	
50%	2014.000000	6.400000	14.677674	30.063805	
75%	2016.000000	7.100000	51.100486	101.379287	
max	2019.000000	9.300000	760.507625	2776.345279	

In [471]:

```python
# 1. Which are the years with the highest number of movies produced?
# The top 10 years with the highest number of movies produced
top_10_years = df['release_year'].value_counts().nlargest(10)
print(top_10_years)
```

```
2015    370
2014    265
2011    254
2013    246
2016    237
2012    227
2010    218
2017    187
2018    155
2009     69
Name: release_year, dtype: int64
```

In [472]:
```
plt.figure(figsize=(8, 4))
top_10_years.sort_index().plot(kind='line', marker='o', color='blue')
plt.title('Top 10 Years with the Highest Number of Movies Produced')
plt.xlabel('Release Year')
plt.ylabel('Number of Movies Produced')
plt.show()
```



In [473]:
```
df.columns
```

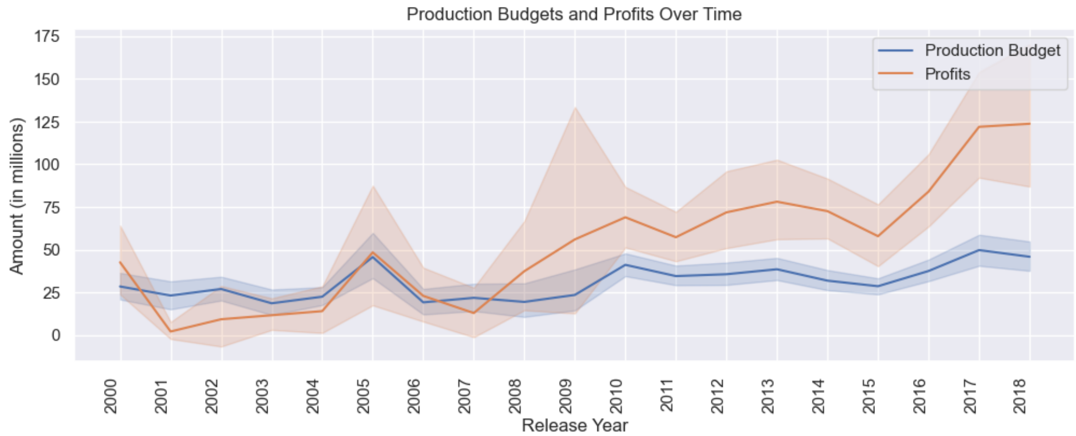
Out[473]:
```
Index(['title', 'start_year', 'genres', 'averagerating', 'release_dat
e',
       'release_year', 'domestic_gross_in_mill', 'worldwide_gross_in_m
ill',
       'production_budget_in_mill', 'domestic_profits_in_mill',
       'worldwide_profits_in_mill'],
      dtype='object')
```

In [474]:

```
# 2. What is the relationship between the production budget and the wor

df_sorted = df.sort_values('release_year')

plt.figure(figsize=(12, 4))
sns.lineplot(x='release_year', y='production_budget_in_mill', data=df_s
sns.lineplot(x='release_year', y='worldwide_profits_in_mill', data=df_s
plt.title('Production Budgets and Profits Over Time')
plt.xlabel('Release Year')
plt.ylabel('Amount (in millions)')
plt.xticks(rotation=90, ha='right')
plt.legend()
plt.show()
```



In [475]:

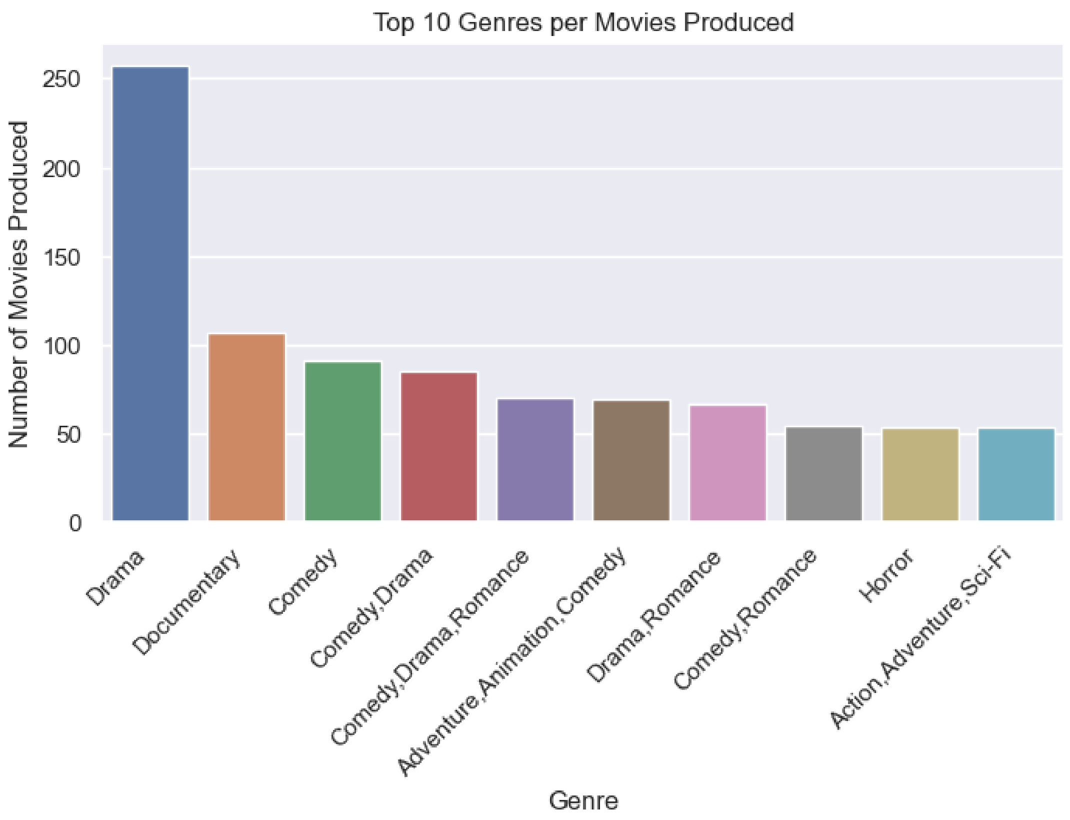
```
# 3.What genre was highly produced.
genre_counts = df['genres'].value_counts().sort_values(ascending=False)
genre_counts.head(10)
```

Out[475]:

```
Drama                        257
Documentary                  107
Comedy                        91
Comedy,Drama                  85
Comedy,Drama,Romance          70
Adventure,Animation,Comedy    69
Drama,Romance                 66
Comedy,Romance                54
Action,Adventure,Sci-Fi       53
Horror                        53
Name: genres, dtype: int64
```

In [476]:
```
top_genres = df['genres'].value_counts().nlargest(10)

plt.figure(figsize=(8, 4))
sns.barplot(x=top_genres.index, y=top_genres.values,)
plt.title('Top 10 Genres per Movies Produced')
plt.xlabel('Genre')
plt.ylabel('Number of Movies Produced')
plt.xticks(rotation=45, ha='right')
plt.show()
```



In [477]:
```
df.columns
```

Out[477]:
```
Index(['title', 'start_year', 'genres', 'averagerating', 'release_dat
e',
       'release_year', 'domestic_gross_in_mill', 'worldwide_gross_in_m
ill',
       'production_budget_in_mill', 'domestic_profits_in_mill',
       'worldwide_profits_in_mill'],
      dtype='object')
```

In [478]:

```python
# 4. Which genres are the most profitable
top_10_profitable_genres = df.groupby('genres')['worldwide_profits_in_mi
top_10_profitable_genres
```

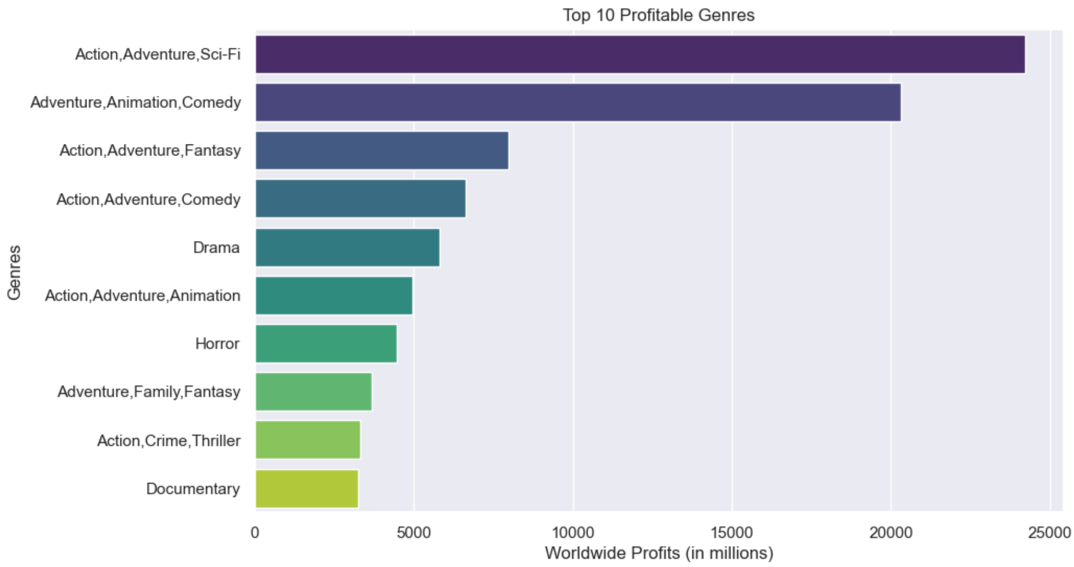
Out[478]:

```
genres
Action,Adventure,Sci-Fi       24213.766663
Adventure,Animation,Comedy    20321.014565
Action,Adventure,Fantasy       7986.155783
Action,Adventure,Comedy        6635.558760
Drama                          5818.192862
Action,Adventure,Animation     4973.873272
Horror                         4477.882968
Adventure,Family,Fantasy       3666.994251
Action,Crime,Thriller          3334.094820
Documentary                    3268.306807
Name: worldwide_profits_in_mill, dtype: float64
```

In [479]:

```python
plt.figure(figsize=(10, 6))
sns.barplot(x=top_10_profitable_genres.values, y=top_10_profitable_genr
plt.title('Top 10 Profitable Genres')
plt.xlabel('Worldwide Profits (in millions)')
plt.ylabel('Genres')

plt.show()
```



In [480]:

```python
df.columns
```

Out[480]:

```
Index(['title', 'start_year', 'genres', 'averagerating', 'release_dat
e',
       'release_year', 'domestic_gross_in_mill', 'worldwide_gross_in_m
ill',
       'production_budget_in_mill', 'domestic_profits_in_mill',
       'worldwide_profits_in_mill'],
      dtype='object')
```

In [400]:

```
# 5. What is the general trend of the average profits over the years
average_gross_by_year = df.groupby('release_year')['worldwide_profits_i
average_gross_by_year
```

```
2001      2.030446
2002      9.213339
2003     11.572078
2004     13.972990
2005     48.396859
2006     22.922621
2007     12.854817
2008     37.357367
2009     55.980328
2010     68.903208
2011     57.263991
2012     71.822146
2013     78.083481
2014     72.534761
2015     57.790808
2016     84.268362
2017    121.941726
2018    124.631442
Name: worldwide_profits_in_mill, dtype: float64
```

In [481]:

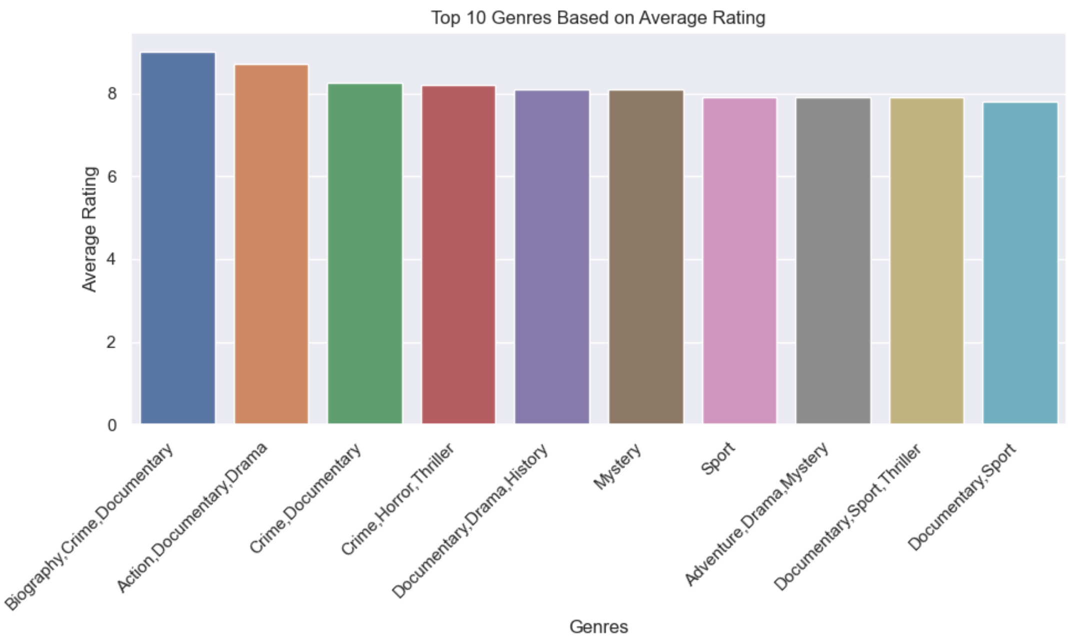
```
plt.figure(figsize=(12, 4))
sns.lineplot(x=average_gross_by_year.index, y=average_gross_by_year.valu
plt.title('Average Worlwide Profits Over the Years')
plt.xlabel('Release Year')
plt.ylabel('worldwide_profits_in_mill')
plt.show()
```

In [482]:
```python
# 6. What are the highly rated movie genres?
genre_ratings = df.groupby('genres')['averagerating'].mean()
sorted_genres = genre_ratings.sort_values(ascending=False)
top_10_genres = sorted_genres.head(10)
top_10_genres
```

Out[482]:
```
genres
Biography,Crime,Documentary    9.00
Action,Documentary,Drama       8.70
Crime,Documentary              8.25
Crime,Horror,Thriller          8.20
Documentary,Drama,History      8.10
Mystery                        8.10
Sport                          7.90
Adventure,Drama,Mystery        7.90
Documentary,Sport,Thriller     7.90
Documentary,Sport              7.80
Name: averagerating, dtype: float64
```

In [483]:
```python
df_top_10_genres = top_10_genres.reset_index(name='average_rating')

plt.figure(figsize=(10, 6))
sns.barplot(x='genres', y='average_rating', data=df_top_10_genres)
plt.title('Top 10 Genres Based on Average Rating')
plt.xlabel('Genres')
plt.ylabel('Average Rating')
plt.xticks(rotation=45, ha='right')
plt.tight_layout()
plt.show()
```



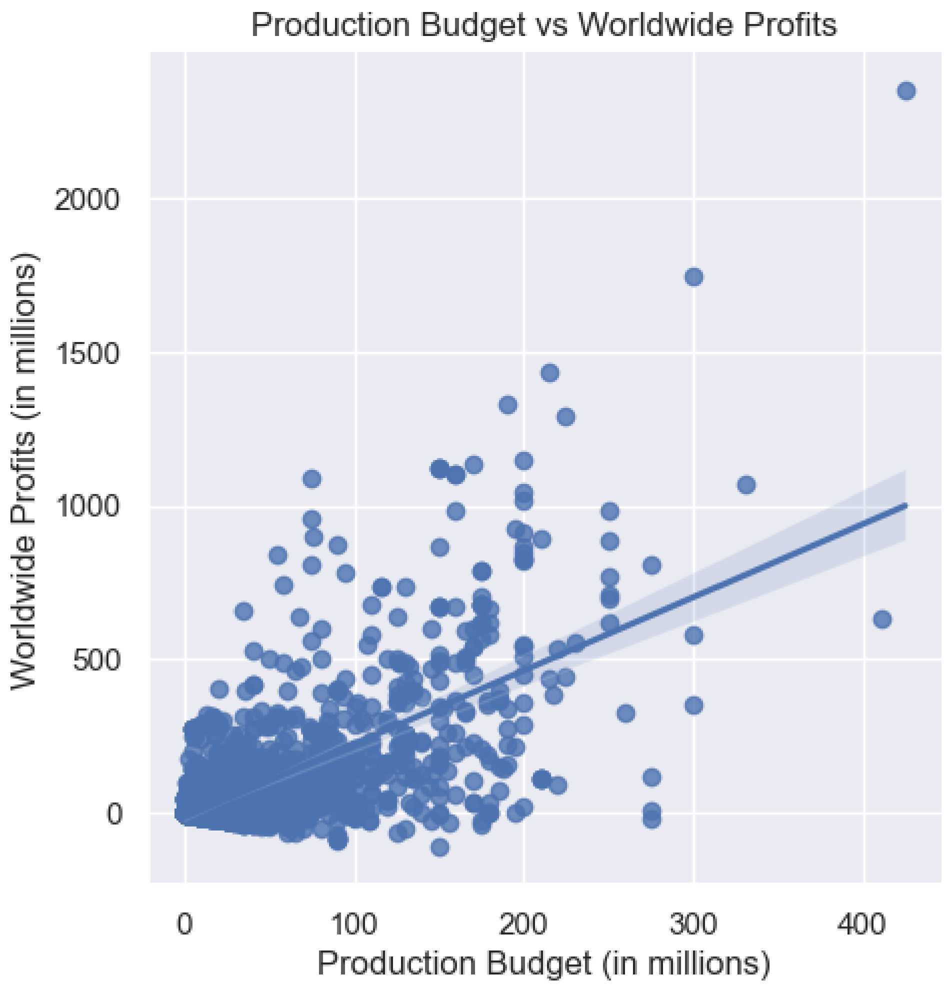
In [484]:
```python
df.columns
```

Out[484]:
```
Index(['title', 'start_year', 'genres', 'averagerating', 'release_dat
e',
       'release_year', 'domestic_gross_in_mill', 'worldwide_gross_in_m
ill',
       'production_budget_in_mill', 'domestic_profits_in_mill',
       'worldwide_profits_in_mill'],
      dtype='object')
```

In [485]:

```python
# 7. What is the relationship between the production budget and profits

sns.lmplot(x='production_budget_in_mill', y='worldwide_profits_in_mill'
plt.title('Production Budget vs Worldwide Profits')
plt.xlabel('Production Budget (in millions)')
plt.ylabel('Worldwide Profits (in millions)')
plt.show()
```



In [486]:

```
# 8. What is the relationship between movie ratings and profits

sns.lmplot(x='worldwide_profits_in_mill', y='averagerating', data=df)
plt.title('Worldwide Profits vs Average Rating')
plt.xlabel('Worldwide Profits (in millions)')
plt.ylabel('Average Rating')
plt.show()
```

In [487]:

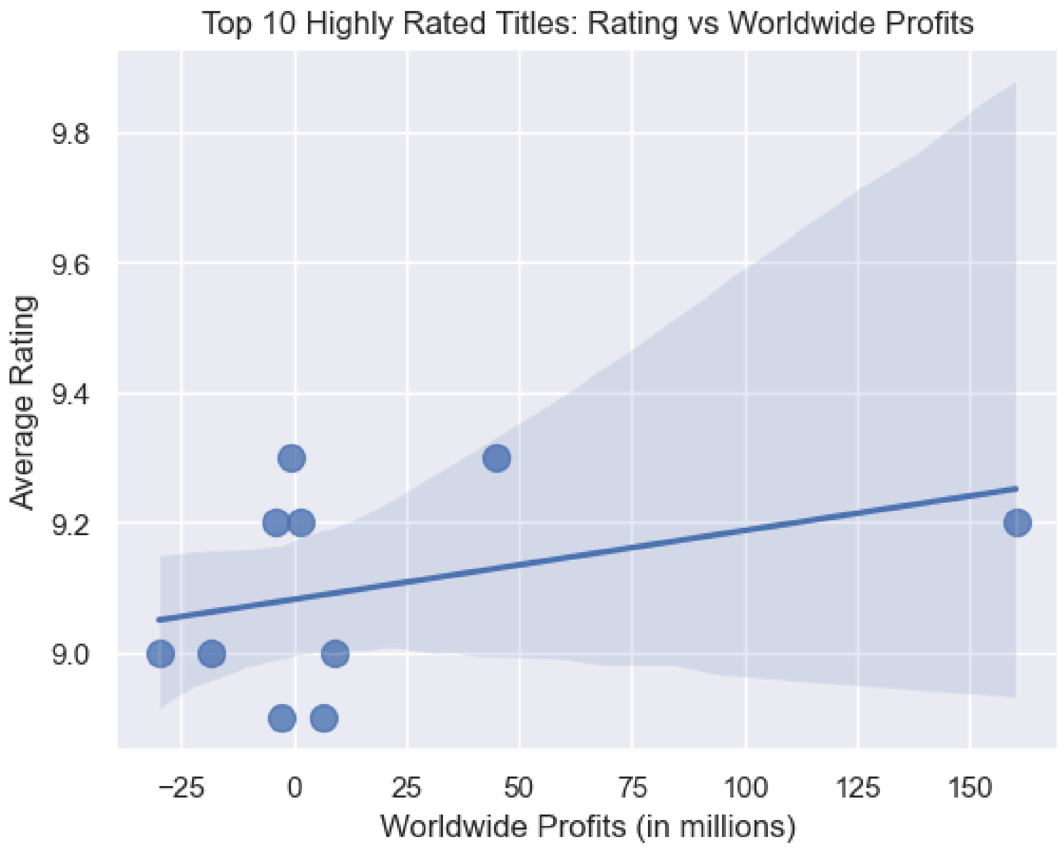
```
# 9. What were the top 10 highly rated movie titles by revenue?
top_10_highly_rated = df.nlargest(10, 'averagerating')[['title', 'world
print("Top 10 Highly Rated Titles by Average Rating and Worldwide Profi
print(top_10_highly_rated)
```

```
Top 10 Highly Rated Titles by Average Rating and Worldwide Profits:
             title  worldwide_profits_in_mill
1393    Crossroads                  45.000000
1394    Crossroads                  -0.500000
193   The Runaways                  -4.221368
684       The Wall                   1.495262
1343       Traffic                 160.300000
1804      Survivor                 -18.296719
1921       Frailty                   8.947280
2065     Dragonfly                 -29.936195
1505     Dark Blue                  -2.737935
2614         Bobby                   6.597806
```

In [488]:

```
top_10_highly_rated = df.nlargest(10, 'averagerating')

# Regression plot
sns.regplot(x='worldwide_profits_in_mill', y='averagerating', data=top_1
plt.title('Top 10 Highly Rated Titles: Rating vs Worldwide Profits')
plt.xlabel('Worldwide Profits (in millions)')
plt.ylabel('Average Rating')
plt.show()
```



Results

The stated business problem presented by Microsoft is establishing their own movie studio to compete within the movie market, and needing to know what kind of movies will be the most successful.

This analysis aims at solving the stated business problem by determining what kind of movies have been most succesful in terms of - average rating and profits from the year 2000 to 2018. In utilizing three large datasets from movie giants IMDb, The movie database and Box Office Mojo, the data is credible.

The analysis of movies from the year 2000 to 2018 shows the following:

1. Number of Movies produced have been declining over time.
   Movie production had been on an upward trajectory in terms of films produced annually until it peaked in the year 2015. However, there has been a steep reduction in the number of movies released from 2015 onwards.
2. The correlation between production budget and profits have been positive. There was a negative correlation between production budget and profits between the year 2000 and 2007. Since then, there has been a positive correlation

3. The highly produced genre is Drama (257) followed by Documentary (107), Comedy and Drama.
4. The most profitable genres on average are Action, Adventure, Sci-fi. Adventure, Animation, Comedy all averaging more than 20 billion dollars.
5. The average profits generated from the movie business has been on a steady growth from 2007 to 2018.
6. The highly audience rated movie genres are Biography, Crime, Documentary followed by Action, Documentary, Drama. Crime, Horror, Thriller also rank in the top 5.
7. There is a high positive correlation between movie ratings and profits.
8. There is a low positive correlation between movie ratings and profits when looking at the highly rated movie title.

Conclusions & Recommendations

This analysis leads to three recommendations of what movies to produce for Microsoft's new Movie studio.

1. To start by producing Action, Adventure, SCi-Fi and Adventure, Animation and Comedy movies to assured sustained profits across the globe. These genres have demonstrated success over 18 years.
2. The profits generated by movie producing companies over the 18 years have been on a steady growth. This means that the movie producing business is a business that is worth the investment
3. The number of movies produced have been declining over time. This means that the movie producing companies have started diversifying to movie streaming sites and therefore Microsoft will have to include a movie streaming website in their budget.

The Next Steps

Further analysis could yield additional insights that would better inform Microsoft in their decision making:

1. Analyze streaming data - The dataset used in this analysis was from the tradition theatre released movies and therefore there is need to analyze data on profits and ratings from streaming websites to better inform the investment decision
2. Movies like Black Panther hit the top charts in the year 2018 as it appealed to a certain demographic. So there is need to study which demographic in terms of gender, race, and language a certain genre appeal to. So Microsoft can tailor its studio to production of movies appealing to diverse groups of people
3. Analyze the most recent data from the year 2019 to 2023. This can bring alot of insight on the trend of movie production revenue given that there was Covid-19 pandemic that likely influenced production of movies and also the consumer behavior.