Movie Market Analysis

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Overview

This notebook contains an analysis of the current trends in the film industry to provide insight and recommendations in relation to the new Microsoft movie studio. Using data from IMDb, Box Office Mojo, and the-numbers.com, actionable recommendations were reached in relation to effective movie budgets, successful movie genres, and the optimal runtime to promote high ratings.

Business Problem

With Microsoft looking to break into the film industry, it is imperative that their investment is well informed. With that in mind, data was explored to provide informed strategy recommendations in regards to ideal investment size, successful movie genres, and effective movie run times to maximize ratings and interest. These strategies have been observed to be effective and profitable business solutions.

The data, methodology, and derived conclusions are detailed in the body of this document.

Data

The data used in this project comes from IMDb, Box Office Mojo, and the-numbers.com. the data is summarized below.

In [1]:
```
# Import standard packages
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
sns.set_style('darkgrid') #setting plotting theme

%matplotlib inline
```

In [2]:
```
bommoviegross_df = pd.read_csv('data/bom.movie_gross.csv.gz') #Box Office Mojo
imdbtitlebasics_df = pd.read_csv('data/imdb.title.basics.csv.gz') #IMDb
imdbtitleratings_df = pd.read_csv('data/imdb.title.ratings.csv.gz') #IMDb
budgets_df = pd.read_csv('data/tn.movie_budgets.csv.gz') #the-numbers
```

DataFrame heads and info lists

In [3]:
```
bommoviegross_df.head(3)
```

Out[3]:

	title	studio	domestic_gross	foreign_gross	year

	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

In [4]:
```
bommoviegross_df.info() #Note: roughly a third of the titles included are missin
```

```
<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
```

In [5]:
```
imdbtitlebasics_df.head(3)
```

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

In [6]:
```
imdbtitlebasics_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 [7]:
```
imdbtitleratings_df.head(3)
```

Out[7]:

	tconst	averagerating	numvotes
0	tt10356526	8.3	31
1	tt10384606	8.9	559
2	tt1042974	6.4	20

In [8]:
```
imdbtitleratings_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 [9]:
```
budgets_df.head(3)
```

Out[9]:

	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

In [10]:
```
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   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
```

---

1. Budget Exploration

The first trends explored involved the rate of return expected from movies in relation to the budget invested. To accomplish this, a combination of the budget table from the-numbers and the data from Box Office Mojo was utilized.

In [11]:
```
#set data index to movie names
bommoviegross_df.set_index('title', inplace = True)
budgets_df.set_index('movie', inplace = True)
```

In [12]:
```
#inner join to avoid NaN values.
#Dropping redundant columns from budgets table

moviebudgets_df = bommoviegross_df.join(budgets_df.drop(columns = ['domestic_gro
moviebudgets_df.head()
```

Out[12]:

	studio	domestic_gross	foreign_gross	year	id	release_date	production_budget
10 Cloverfield Lane	Par.	72100000.0	38100000	2016	54	Mar 11, 2016	$5,000,000
12 Strong	WB	45800000.0	21600000	2018	64	Jan 19, 2018	$35,000,000
12 Years a Slave	FoxS	56700000.0	131100000	2013	18	Oct 18, 2013	$20,000,000
127 Hours	FoxS	18300000.0	42400000	2010	6	Nov 5, 2010	$18,000,000
13 Hours: The Secret Soldiers of Benghazi	Par.	52900000.0	16600000	2016	30	Jan 15, 2016	$50,000,000

Data Cleaning

The tables displayed below reveal some data cleaning that is necessary before any meaningful analysis can be performed.

The production budget values must be converted from strings to integers. This will be accomplished by writing a function and applying it to each row using a .map(lambda x) function.

Because the foreign gross column has enough missing data to strongly affect any algorythms, the scope of this analysis will focus on domestic analysis. Because there are only two missing domestic gross values, those rows will just be dropped from calculations.

In [13]:

```
moviebudgets_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 1247 entries, 10 Cloverfield Lane to mother!
Data columns (total 7 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   studio             1246 non-null   object 
 1   domestic_gross     1245 non-null   float64
 2   foreign_gross      1086 non-null   object 
 3   year               1247 non-null   int64  
 4   id                 1247 non-null   int64  
 5   release_date       1247 non-null   object 
 6   production_budget  1247 non-null   object 
dtypes: float64(1), int64(2), object(4)
memory usage: 77.9+ KB
```

In [14]:

```
moviebudgets_df.isna().sum()
```

Out[14]:

```
studio                 1
domestic_gross         2
foreign_gross        161
year                   0
id                     0
release_date           0
production_budget      0
dtype: int64
```

In [15]:

```
#money string to integer function ($000,000,000)->(000000000)
def moneystr(str):
```

```
    no_dollar = str[1:]
    cleanstr = ''
    for i in range(len(no_dollar)):
        if no_dollar[i] != ',':
            cleanstr += no_dollar[i]
    return int(cleanstr)
```

In [16]:
```
#convert production budget to integer
moviebudgets_df['production_budget'] = moviebudgets_df['production_budget'].map(
```

In [17]:
```
#Drop rows with missing domestic gross data
moviebudgets_df.dropna(subset=['domestic_gross'], inplace=True)
```

Before continuing, the columns above must be checked to see if their updated values reflect the adjustments desired.

In [18]:
```
moviebudgets_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 1245 entries, 10 Cloverfield Lane to mother!
Data columns (total 7 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   studio             1244 non-null   object 
 1   domestic_gross     1245 non-null   float64
 2   foreign_gross      1084 non-null   object 
 3   year               1245 non-null   int64  
 4   id                 1245 non-null   int64  
 5   release_date       1245 non-null   object 
 6   production_budget  1245 non-null   int64  
dtypes: float64(1), int64(3), object(3)
memory usage: 77.8+ KB
```

In [19]:
```
moviebudgets_df.isna().sum()
```

Out[19]:
```
studio                 1
domestic_gross         0
foreign_gross        161
year                   0
id                     0
release_date           0
production_budget      0
dtype: int64
```

Profit Margins

To analyze profit against budget invested, a domestic profit and percent profit columns will be created.

Percent profit is useful because it is unitless so it is not affected by inflation.

In [20]:
```
moviebudgets_df['domestic_profit'] = moviebudgets_df['domestic_gross'] - moviebu
moviebudgets_df['profit_percentage'] = moviebudgets_df['domestic_profit']*100/mo
moviebudgets_df.head()
```

Out[20]:

	studio	domestic_gross	foreign_gross	year	id	release_date	production_budget	do

	studio	domestic_gross	foreign_gross	year	id	release_date	production_budget	do
10 Cloverfield Lane	Par.	72100000.0	38100000	2016	54	Mar 11, 2016	5000000	
12 Strong	WB	45800000.0	21600000	2018	64	Jan 19, 2018	35000000	
12 Years a Slave	FoxS	56700000.0	131100000	2013	18	Oct 18, 2013	20000000	
127 Hours	FoxS	18300000.0	42400000	2010	6	Nov 5, 2010	18000000	
13 Hours: The Secret Soldiers of Benghazi	Par.	52900000.0	16600000	2016	30	Jan 15, 2016	50000000	

In order to better emmulate established studios with the most movie making experience, the profit margins of the studios that have produced the most work will be analyzed.

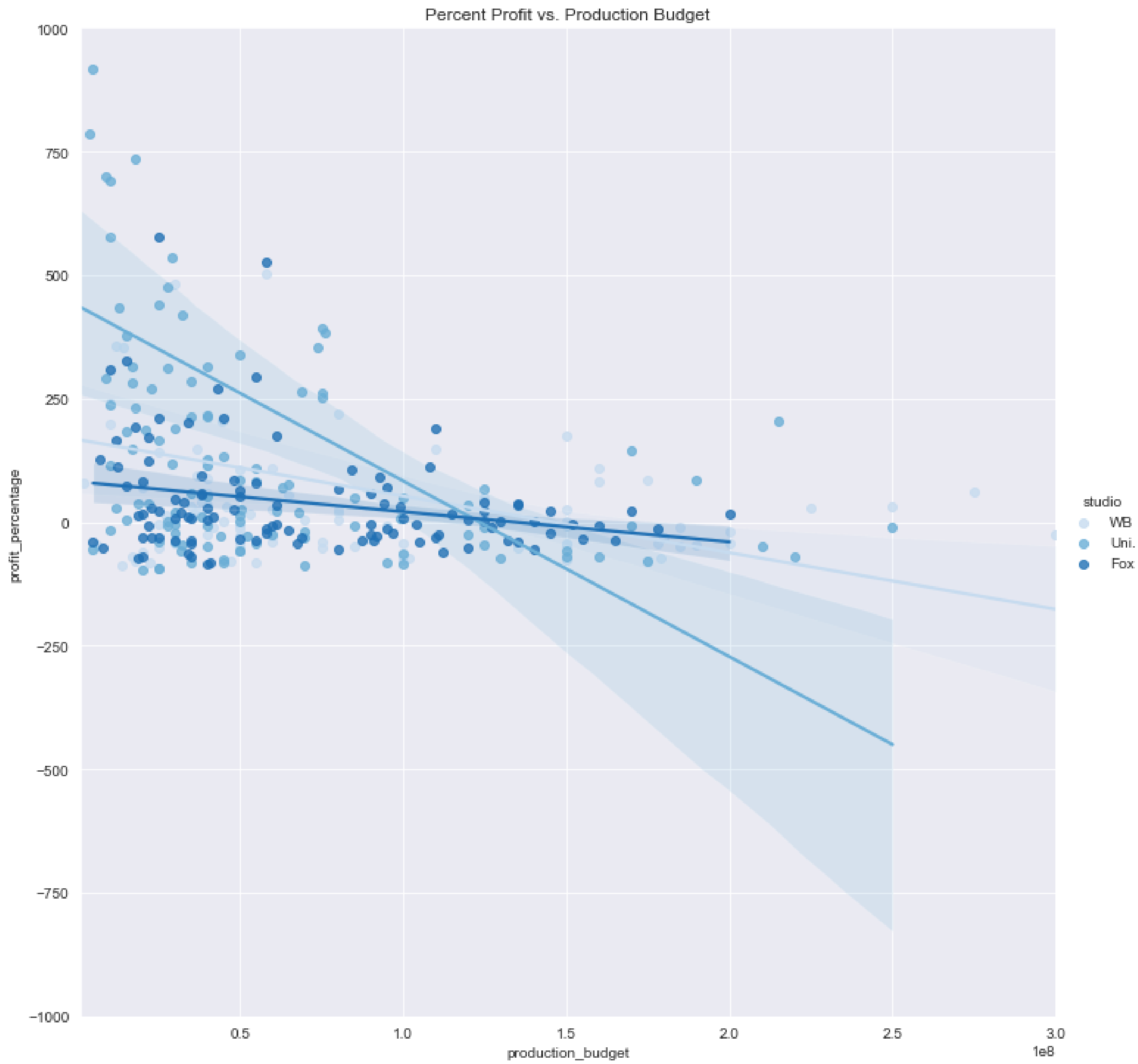
In [21]:
```
#most productive studios
moviebudgets_df.studio.value_counts().head()
```

Out[21]:
```
Uni.    117
Fox     110
WB      102
Par.     74
Sony     74
Name: studio, dtype: int64
```

Lastly, a new dataframe of movies exclusively from the top three highest producing studios and a visualization of the resulting data will be created.

In [22]:
```
high_output_studios = moviebudgets_df[(moviebudgets_df['studio']=='Uni.')
                                      |(moviebudgets_df['studio']=='Fox')
                                      |(moviebudgets_df['studio']=='WB')]
```

In [23]:
```
profit_plot = sns.lmplot(x='production_budget', y='profit_percentage',
           hue='studio',palette='Blues', height=10,
           data=high_output_studios).set(title = 'Percent Profit vs. Production
profit_plot.set(ylim=(-1000, 1000));
```



Insight:

From the top three studios' data, it can be shown that percent profit tends to shrink as the budget increases. More money can be made with higher budgets, but that positive rate of return slowly diminishes until budgets reach roughly $120,000,000. This is the budget statistically most likely to break even.

---

2. Genre Exploration

The second trends explored were in an effort to discover the best movie genres to pursue. To accomplish this, a combination of data from IMDb was used.

Data Cleaning

Any missing values in the genre column will be filled with 'UNKNOWN'

In [24]:
```
# replace NaN genres with 'UNKNOWN'
imdbtitlebasics_df['genres'].fillna('UNKNOWN', inplace=True)
```

Next, the genres values will be made into itterable lists instead of strings

In [25]:
```
imdbtitlebasics_df['genrelist']=imdbtitlebasics_df['genres'].map(lambda x: x.spl
imdbtitlebasics_df.head()
```

Out[25]:

	tconst	primary_title	original_title	start_year	runtime_minutes	genres	ge
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	[Biog [
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	[Co [
4	tt0100275	The Wandering Soap Opera	La Telenovela Errante	2017	80.0	Comedy,Drama,Fantasy	[Co [Fa

For a future calculation, it will be easier to also break up the genre list into separate columns. First check max length of genre list then make genre columns to fit that max number. Any row with less than three columns will fill the empty columns with 'NONE'

In [26]:
```
imdbtitlebasics_df['genrelist'].map(lambda x: len(x)).max()
```

Out[26]: 3

In [27]:
```
imdbtitlebasics_df['genre1']=imdbtitlebasics_df['genrelist'].map(lambda x: x[0])
imdbtitlebasics_df['genre2']=imdbtitlebasics_df['genrelist'].map(lambda x: x[1]
imdbtitlebasics_df['genre3']=imdbtitlebasics_df['genrelist'].map(lambda x: x[2]
```

In [28]:
```
imdbtitlebasics_df.head()
```

Out[28]:

	tconst	primary_title	original_title	start_year	runtime_minutes	genres	ge
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	[Biog [
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	[Co [

	tconst	primary_title	original_title	start_year	runtime_minutes	genres	ge
4	tt0100275	The Wandering Soap Opera	La Telenovela Errante	2017	80.0	Comedy,Drama,Fantasy	[Cc I Fa

Next, set the titlebasics and titleratings indeces to 'tconst' to be ready for joining. Using inner join to avoid missing data

In [29]:
```
imdbtitlebasics_df.set_index('tconst', inplace=True)
imdbtitleratings_df.set_index('tconst', inplace=True)
```

In [30]:
```
genreandrating_df = imdbtitlebasics_df.join(imdbtitleratings_df, how='inner')
genreandrating_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 73856 entries, tt0063540 to tt9916160
Data columns (total 11 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   primary_title    73856 non-null  object
 1   original_title   73856 non-null  object
 2   start_year       73856 non-null  int64
 3   runtime_minutes  66236 non-null  float64
 4   genres           73856 non-null  object
 5   genrelist        73856 non-null  object
 6   genre1           73856 non-null  object
 7   genre2           73856 non-null  object
 8   genre3           73856 non-null  object
 9   averagerating    73856 non-null  float64
 10  numvotes         73856 non-null  int64
dtypes: float64(2), int64(2), object(7)
memory usage: 6.8+ MB
```

In [31]:
```
genreandrating_df.head()
```

Out[31]:

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

Best Performing Genres

From the joined dataframe above, the genres that performed best can be found.

The ratings of every movie in the dataframe that are associated with each genre are averaged and the resulting average rating is stored in a dictionary. {'genre': rating}

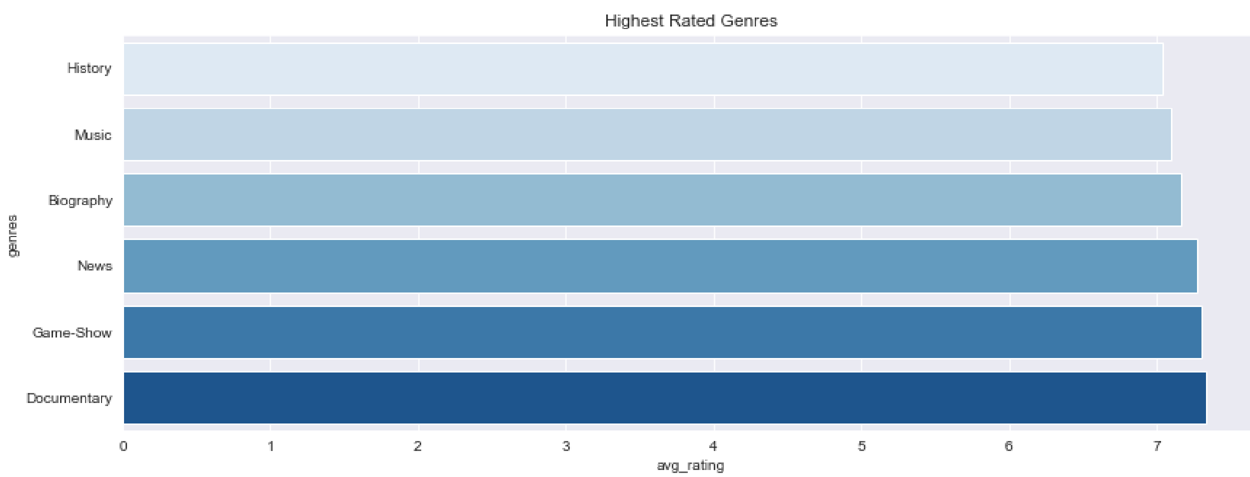
In [32]:
```
# itterate through every movie and be sure every unique genre is accounted for i
genremean1 = genreandrating_df.groupby('genre1').mean()
```

In [33]:
```
genres_list = list(genremean1.index)
genre_avg_rating = {}
for genre in genres_list:
    rate_sum = 0
    rate_len = 0
    for i in range(len(genreandrating_df)):
        if genre in genreandrating_df.iloc[i]['genrelist']:
            rate_sum += genreandrating_df.iloc[i]['averagerating']
            rate_len += 1
    genre_avg_rating[genre] = rate_sum/rate_len
```

With this dictionary of data, a new dataframe is created for plotting.

In [34]:
```
avg_rating_df = pd.DataFrame.from_dict({'genres': list(genre_avg_rating.keys()),
                                        'avg_rating': list(genre_avg_rating.valu
```

In [35]:
```
plt.figure(figsize=(14,5))
plt.title("Highest Rated Genres")
sns.barplot(x='avg_rating', y='genres',
            palette = 'Blues', data=avg_rating_df.sort_values('avg_rating').tail
```



This plot shows that documentaries are the highest rated movies on average!

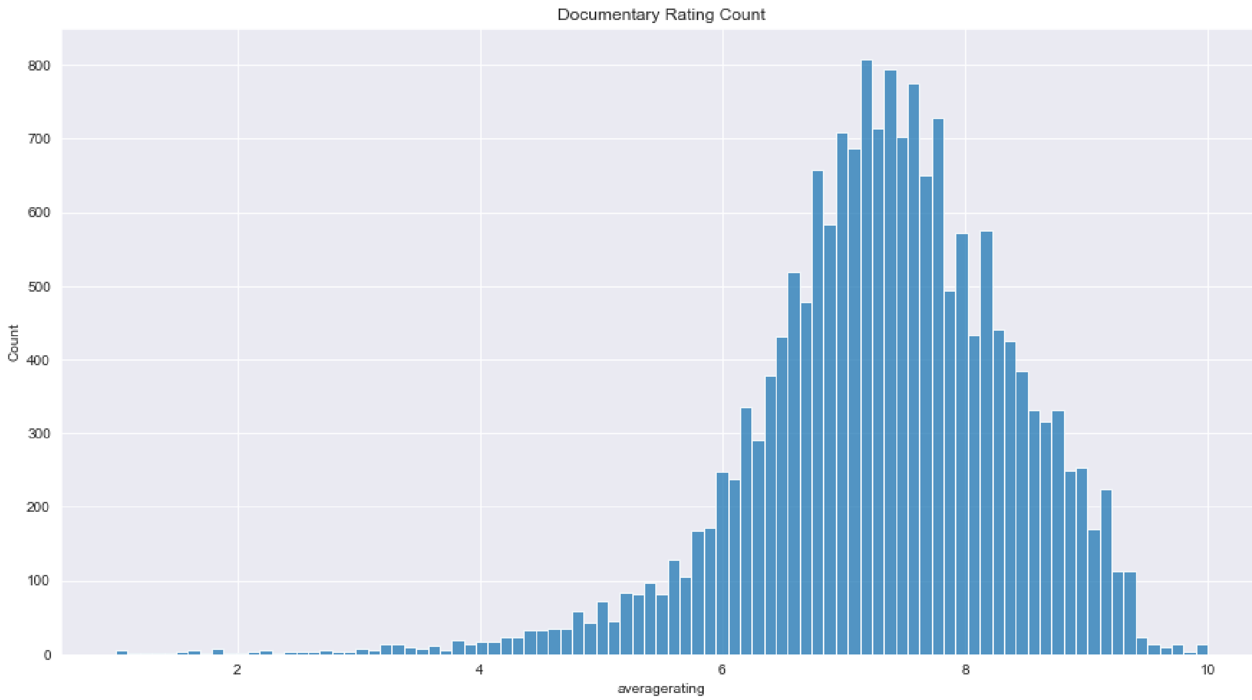
To double check that the distribution of these movie ratings is consistent with these findings, a function is created that returns a dataframe of all movies with a selected genre. This function is used to plot histograms of movie ratings.

In [36]:
```
def genreselector(data, genre):
    temp_df = data[(data['genre1']==genre)
                                    |(data['genre2']==genre)
                                    |(data['genre3']==genre)]
    return temp_df
```

In [37]:
```
plt.figure(figsize=(15,8))
```

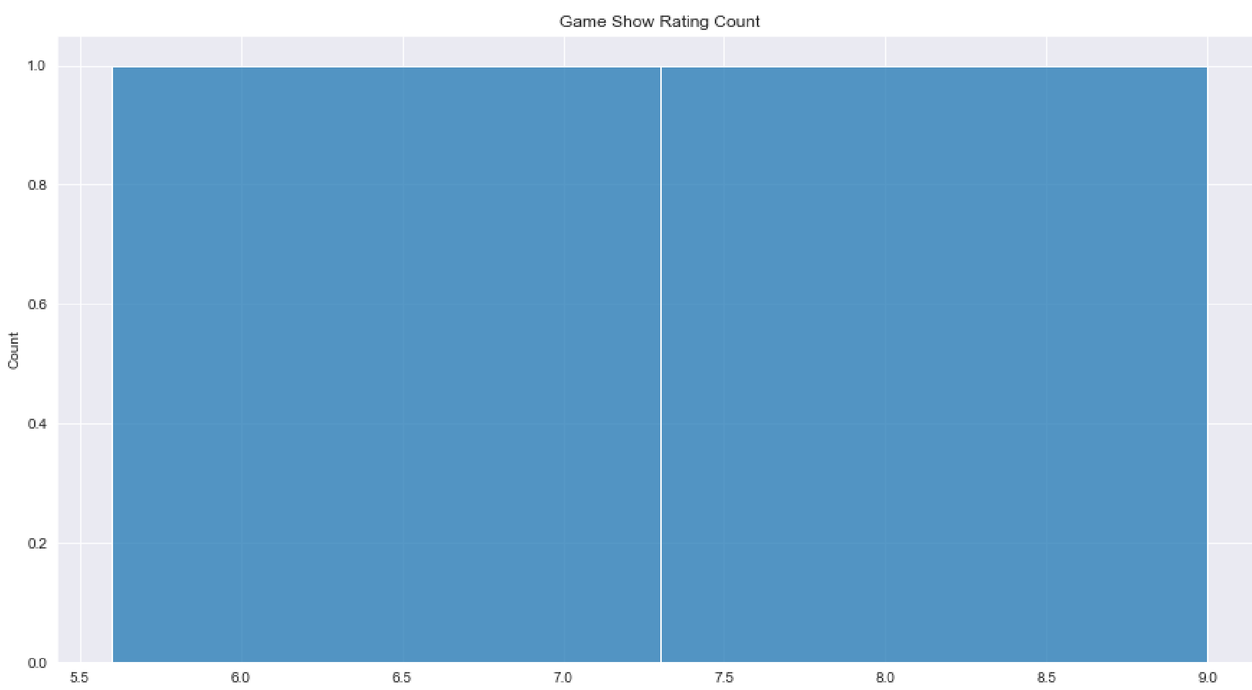
```
sns.histplot(x = 'averagerating', palette = 'Blues', data = genreselector(genrea
plt.title('Documentary Rating Count')
```

Out[37]: Text(0.5, 1.0, 'Documentary Rating Count')



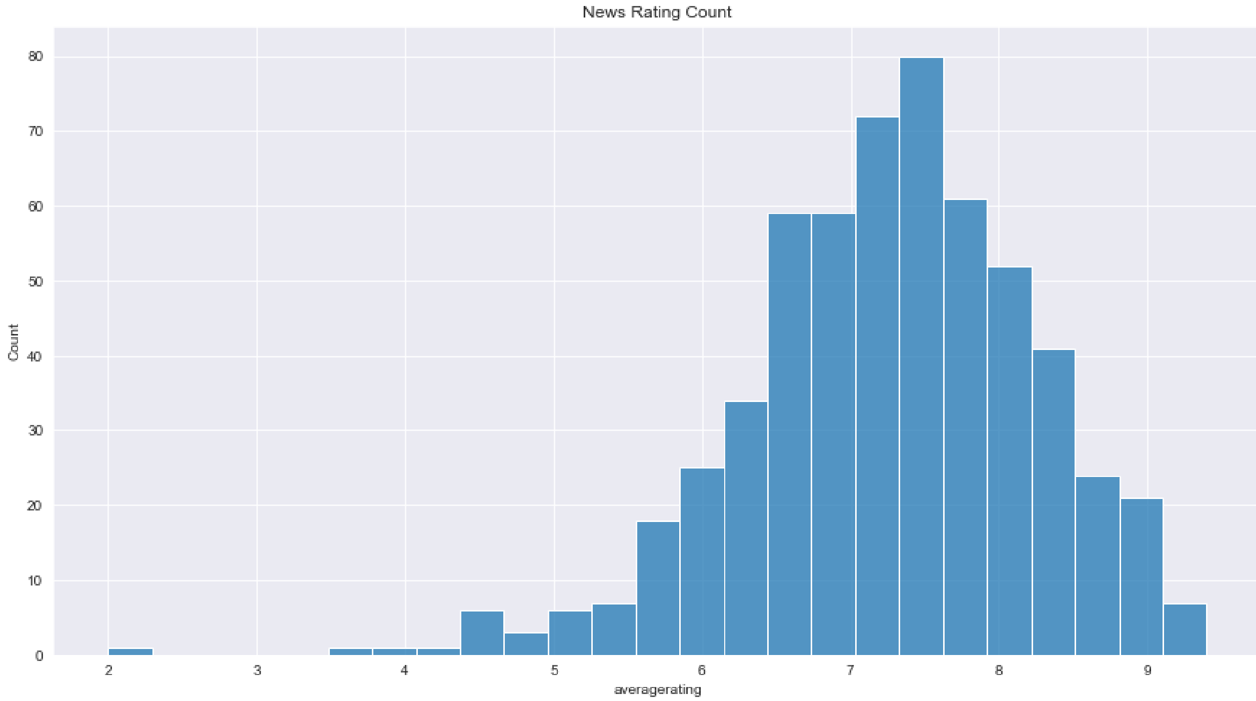
In [38]:
```
plt.figure(figsize=(15,8))
sns.histplot(x = 'averagerating', palette = 'Blues', data = genreselector(genrea
plt.title('Game Show Rating Count')
```

Out[38]: Text(0.5, 1.0, 'Game Show Rating Count')



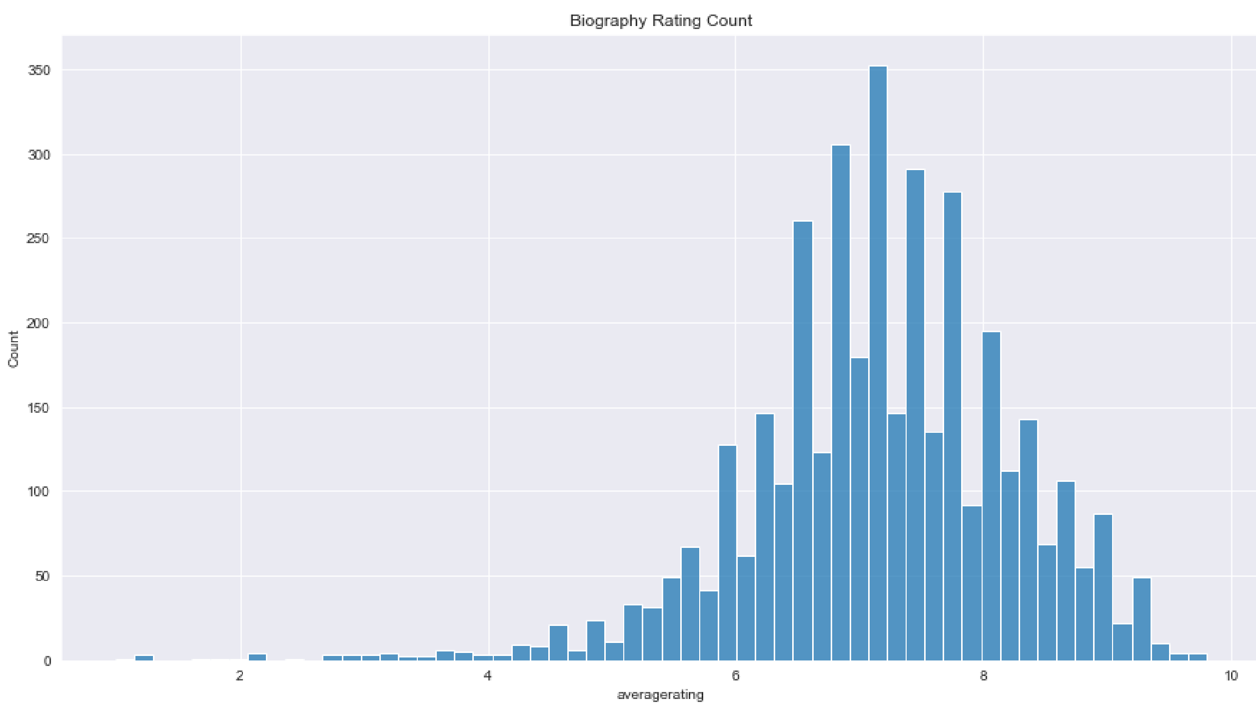
In [39]:
```
plt.figure(figsize=(15,8))
sns.histplot(x = 'averagerating', palette = 'Blues', data = genreselector(genrea
plt.title('News Rating Count')
```

Out[39]: Text(0.5, 1.0, 'News Rating Count')



In [40]:
```
plt.figure(figsize=(15,8))
sns.histplot(x = 'averagerating', palette = 'Blues', data = genreselector(genrea
plt.title('Biography Rating Count')
```

Out[40]: Text(0.5, 1.0, 'Biography Rating Count')



Insight:

the game show genre might have too few data points to be helpful in this analysis, but the top three genres excluding game shows have potential to be successful directions for the new Microsoft Studio.

3. Documentary Length

If Microsoft moves into the field of documentary production, is it more beneficial to produce short documentaries or feature length+ documentaries? Using the genreselector function from insight 2, documentary length can be explored for valuable trends.

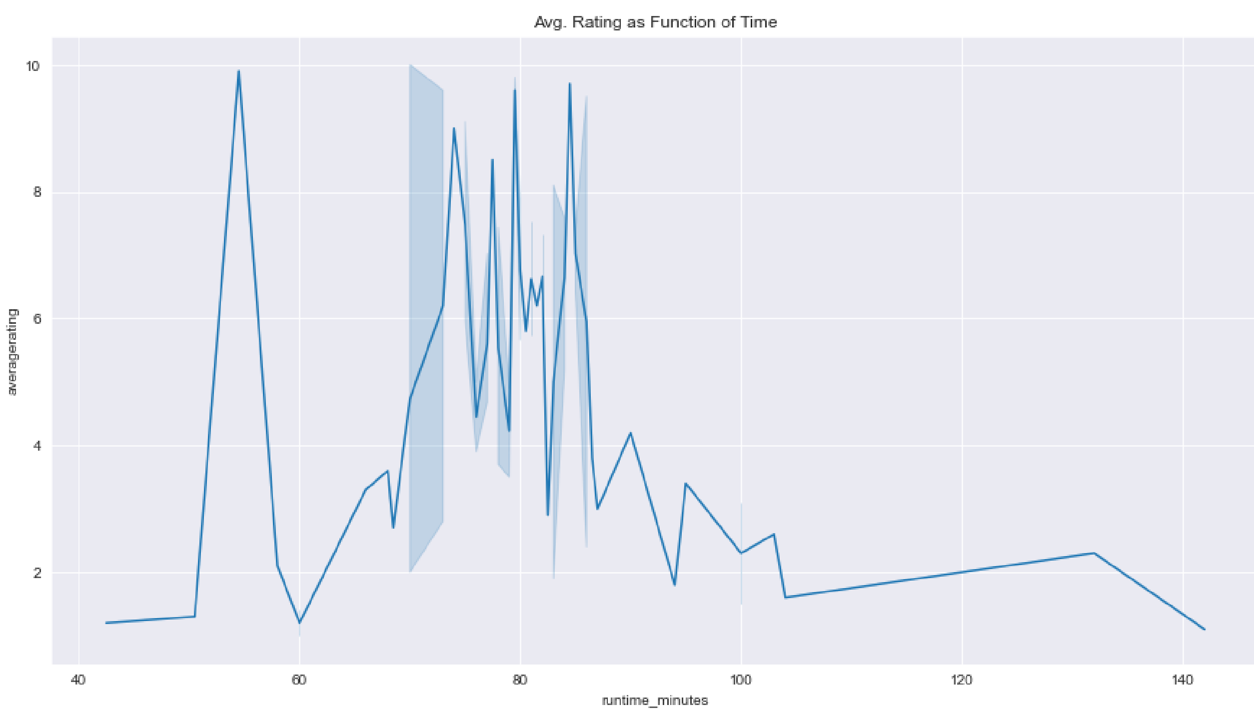
In [41]:
```
documentaries = genreselector(genreandrating_df,'Documentary')
runtime_ratings = documentaries.groupby('averagerating').median().reset_index()
runtime_ratings.head()
```

Out[41]:

	averagerating	start_year	runtime_minutes	numvotes
0	1.0	2012.0	60.0	8.0
1	1.1	2012.0	142.0	55.0
2	1.2	2012.0	42.5	199.0
3	1.3	2016.5	50.5	1631.0
4	1.4	2016.0	60.0	23.0

In [42]:
```
plt.figure(figsize=(15,8))
sns.lineplot(y='averagerating', x = 'runtime_minutes', data = runtime_ratings)
plt.title('Avg. Rating as Function of Time')
```

Out[42]: `Text(0.5, 1.0, 'Avg. Rating as Function of Time')`



Insight:

From the line graph relating average rating to runtime in minutes, there are definite peaks just below 60 minutes and between 70 and 90 minutes. This suggests that somewhat short documentaries meant for television slots or streaming are very highly rated, as well as more detailed documentaries that are no longer than 90 minutes.

Conclusions

A very effective direction for the newly established Microsoft Studio would be to produce hour to hour and a half long documentaries with budgets that do not exceed $120M.

Documentaries are an extremely popular film genre that pretty consistently earns good reviews. With Microsoft's branding aimed for the, "tech savvy, working, and educated," it is safe to assume that a large part of Microsoft's existing users and audience also enjoys documentaries.

If documentaries and other educational genres like news and biography films make up the beginning of the Microsoft Studios catalog, they may provide the flexibility to enter other genre markets with experience and an existing reputation of success.

Future Work

Continuing this work, there are a handful of details that could prove useful in refining results.

One factor ommitted in the analysis was review counts. When aggragating the average reviews to find the highest rated genres, It could prove insightful to weigh average reviews differently depending on review count. Lower review counts increase the risk of a sample not properly representing a full population.

Another future analysis might include budget v. profit analysis for individual genres rather than all movies as a whole. Different genres may behave differently from one another.