Final Project Submission

Please fill out:

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- Student pace: Part time
- Scheduled project review date/time: Not scheduled
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- Blog post URL: NA

Movies Data Analysis

Overview

This project analyzes movies data to come up with a recommendation on the best film genre for Microsoft's new movie studio. It takes into account film genres, ratings, runtime, cost of production and revenue to come up with the most ideal film genres for production. Our Analysis dataset contains movie data between the years 2010 and 2019 from IMDb movies and The Numbers.

Business Problem

Microsoft

Microsoft sees all the big companies creating original video content and they want to get in on the fun. They have decided to create a new movie studio, but they don’t know anything about creating movies. You are charged with exploring what types of films are currently doing the best at the box office. You must then translate those findings into actionable insights that the head of Microsoft's new movie studio can use to help decide what type of films to create.

Data

We are using imdb.title.basics and imdb.title.ratings data sets from IMDB Movies and tn.movie.budgets data from The Numbers to study the relatationship between film genres, ratings and return on investment.

Data Preparation

Let us import the libraries that we will be using for data cleaning, analysis and visualization

In [2]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
plt.style.available
import seaborn as sns
```

Next, we shall load the data sets that we will need. For this project, we shall be using the data sets; imdb.title.basics as df1, imdb.title.ratings as df2, tn.movies.budgets as df3,

In [3]:
```
df1= pd.read_csv('./zippedData/imdb.title.basics.csv.gz')
df1.head()
```

Out[3]:

	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 [4]:
```
df1.shape
```

Out[4]:
```
(146144, 6)
```

The data set has 146,144 records with 6 atributes. Lets view more information on the attributes use .info() method

In [5]:
```
df1.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 [6]:
```
df1.isna().sum()
```

Out[6]:
```
tconst                 0
primary_title          0
original_title        21
start_year             0
runtime_minutes    31739
genres              5408
dtype: int64
```

In [7]:
```
df1.describe()
```

Out[7]:

	start_year	runtime_minutes
count	146144.000000	114405.000000
mean	2014.621798	86.187247
std	2.733583	166.360590
min	2010.000000	1.000000
25%	2012.000000	70.000000
50%	2015.000000	87.000000
75%	2017.000000	99.000000
max	2115.000000	51420.000000

In [8]:
```
#Q3 = 95
#Q1 = 75
#IQR = Q3 - Q1
#IQR
#20
```

In [9]:
```
#print(Q1 - IQR*1.5) #45
#print(Q3 + IQR*1.5) #125
```

In [10]:
```
len(df1[df1['runtime_minutes'] <15])
```

Out[10]: 2089

In [11]:
```
len(df1[df1['runtime_minutes'] >1500])
```

Out[11]: 18

The minimum runtime is 1, whereas the maximum runtime is 51420. These values appear unreleastic, and could probably be placeholders or typos. There are 5891/140729 which is 4.18% of the data (values less than 45 mins)outliers in the dataset. For the purposes of this analysis, we will only drop rows with less than 15 minutes runtime (seems more unrealistic in realworld), as outliers might represent natural variations in the popuation. We shall also drop rows with runtime values greater than 1500 minutes.

In [12]:
```
df1 = df1[(df1['runtime_minutes'] >=15) & (df1['runtime_minutes']<=1500)]
df1.head()
```

Out[12]:

	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
4	tt0100275	The Wandering Soap Opera	La Telenovela Errante	2017	80.0	Comedy,Drama,Fantasy
5	tt0111414	A Thin Life	A Thin Life	2018	75.0	Comedy

In [13]:
```
df1.describe()
```

Out[13]:

	start_year	runtime_minutes
count	112298.000000	112298.000000
mean	2014.384121	86.582450
std	2.641270	30.760859
min	2010.000000	15.000000
25%	2012.000000	71.000000
50%	2014.000000	87.000000
75%	2017.000000	100.000000
max	2022.000000	1440.000000

In [14]:
```
len(df1[df1['start_year'] == 2019])
```
Out[14]:
```
4443
```

The data set contains columns with missing values. We shall replace runtime with mean then drop missing values in 'original_title' and 'genres' columns since they are an insignificant number (0.01% & 3% respectively).

In [15]:
```
#first, lets fill the runtime_minutes column
df1['runtime_minutes'].fillna(df1['runtime_minutes'].mean(), inplace = Tru
```

In [16]:
```
#Next, lets drop rows with null values.
df1.dropna(inplace = True)
df1.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 110130 entries, 0 to 146139
Data columns (total 6 columns):
 #   Column           Non-Null Count   Dtype  
---  ------           --------------   -----  
 0   tconst           110130 non-null  object 
 1   primary_title    110130 non-null  object 
 2   original_title   110130 non-null  object 
 3   start_year       110130 non-null  int64  
 4   runtime_minutes  110130 non-null  float64
 5   genres           110130 non-null  object 
dtypes: float64(1), int64(1), object(4)
memory usage: 5.9+ MB
```

In [17]:
```
df1.isna().sum()
```
Out[17]:
```
tconst             0
primary_title      0
original_title     0
start_year         0
runtime_minutes    0
genres             0
dtype: int64
```

In [18]:
```
#Lets check if there is any start year greater than current year
len(df1[df1['start_year'] >2023])
```
Out[18]:
```
0
```

In [19]:
```
df1.describe(include = 'all')
```

Out[19]:

	tconst	primary_title	original_title	start_year	runtime_minutes	genres
count	110130	110130	110130	110130.000000	110130.000000	110130
unique	110130	103643	105047	NaN	NaN	1033
top	tt4312624	Home	Broken	NaN	NaN	Documentary
freq	1	18	14	NaN	NaN	23824
mean	NaN	NaN	NaN	2014.389394	86.662281	NaN
std	NaN	NaN	NaN	2.643005	30.696081	NaN
min	NaN	NaN	NaN	2010.000000	15.000000	NaN
25%	NaN	NaN	NaN	2012.000000	71.000000	NaN
50%	NaN	NaN	NaN	2014.000000	87.000000	NaN
75%	NaN	NaN	NaN	2017.000000	100.000000	NaN
max	NaN	NaN	NaN	2022.000000	1440.000000	NaN

Our dataset has data from the years 2010 to 2022 and contains 110,130 records with 6 attributes.

In [20]:
```
df2= pd.read_csv('./zippedData/imdb.title.ratings.csv.gz')
df2.head()
```

Out[20]:

	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 [21]:
```
df2.shape
```

Out[21]: (73856, 3)

In [22]:
```
df2.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
```

The data set imdb.title.ratings has 73856 records with 3 attributes. .info() method shows no missing values. Lets check using .describe() method to find out if there are any placeholders.

In [23]:
```
df2.describe()
```

Out[23]:

	averagerating	numvotes
count	73856.000000	7.385600e+04
mean	6.332729	3.523662e+03
std	1.474978	3.029402e+04
min	1.000000	5.000000e+00
25%	5.500000	1.400000e+01
50%	6.500000	4.900000e+01
75%	7.400000	2.820000e+02
max	10.000000	1.841066e+06

The column 'numvotes' seem to contain extreme data values (min = 5 while max = 1,841,066), we shall however not dwell on it as we are not using the column for our analysis today.

Now, lets load our third dataset tn.movie_budgets

In [24]:
```
df3= pd.read_csv('./zippedData/tn.movie_budgets.csv.gz')
df3.head()
```

Out[24]:

	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 [25]:
```
#remove the dollar sign in column indexes 6,7 & 8
df3['production_budget'] = df3['production_budget'].str.replace('$','').st
df3['domestic_gross'] = df3['domestic_gross'].str.replace('$','').str.repl
df3['worldwide_gross'] = df3['worldwide_gross'].str.replace('$','').str.re
```

In [26]:
```
df3.head()
```

Out[26]:

	id	release_date	movie	production_budget	domestic_gross	worldwide_gross
0	1	Dec 18, 2009	Avatar	425000000	760507625	2776345279
1	2	May 20, 2011	Pirates of the Caribbean: On Stranger Tides	410600000	241063875	1045663875
2	3	Jun 7, 2019	Dark Phoenix	350000000	42762350	149762350
3	4	May 1, 2015	Avengers: Age of Ultron	330600000	459005868	1403013963
4	5	Dec 15, 2017	Star Wars Ep. VIII: The Last Jedi	317000000	620181382	1316721747

In [27]:
```
df3.shape
```

Out[27]: (5782, 6)

In [28]:
```
df3.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
```

The data set tn.movie_budgets has 5782 records with 6 non-null attributes. Some attributes (production_budget, domestic_gross, worldwide_gross) are stored as objects instead of integers. We shall use the pd.to_numeric() function to convert the data type from string to integer.

In [29]:
```
#convert the columns to integers
df3['production_budget'] = pd.to_numeric(df3['production_budget'])
df3['domestic_gross'] = pd.to_numeric(df3['domestic_gross'])
df3['worldwide_gross'] = pd.to_numeric(df3['worldwide_gross'])
```

In [30]:
```
#confirm the data types have been converted
df3.dtypes
```

Out[30]:
```
id                   int64
release_date        object
movie               object
production_budget    int64
domestic_gross       int64
worldwide_gross      int64
dtype: object
```

In [31]:
```
df3.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   int64 
 4   domestic_gross     5782 non-null   int64 
 5   worldwide_gross    5782 non-null   int64 
dtypes: int64(4), object(2)
memory usage: 271.2+ KB
```

In [32]:
```
df3.describe(include = 'all')
```

Out[32]:

	id	release_date	movie	production_budget	domestic_gross	worldwide_g
count	5782.000000	5782	5782	5.782000e+03	5.782000e+03	5.782000e
unique	NaN	2418	5698	NaN	NaN	
top	NaN	Dec 31, 2014	King Kong	NaN	NaN	
freq	NaN	24	3	NaN	NaN	
mean	50.372363	NaN	NaN	3.158776e+07	4.187333e+07	9.148746e
std	28.821076	NaN	NaN	4.181208e+07	6.824060e+07	1.747200e
min	1.000000	NaN	NaN	1.100000e+03	0.000000e+00	0.000000e
25%	25.000000	NaN	NaN	5.000000e+06	1.429534e+06	4.125415e
50%	50.000000	NaN	NaN	1.700000e+07	1.722594e+07	2.798445e
75%	75.000000	NaN	NaN	4.000000e+07	5.234866e+07	9.764584e
max	100.000000	NaN	NaN	4.250000e+08	9.366622e+08	2.776345e

The minimum value for both domestic and worldwide gross is zero. Lets count the number of rows with zero to confirm that zero is not used as a placeholder for a missing value

In [33]:
```
len(df3[df3['domestic_gross'] <= 0])
```

Out[33]:
```
548
```

In [34]:
```
len(df3[df3['worldwide_gross'] <= 0])
```
Out[34]:
```
367
```

Ther are 548 records in domestic_gross (9.5%) and 367 (6.3%) records in worldwide_gross recorded as zero. These values appear to be placeholders. Lets replace them with the column means, since the percentange of the records to be replaced is low and may not affect our parameters greatly.

In [35]:
```
df3.loc[df3['domestic_gross'] <= 0,'domestic_gross'] = df3['domestic_gross
```

In [36]:
```
df3.loc[df3['worldwide_gross'] <= 0,'worldwide_gross'] = df3['worldwide_gr
```

In [37]:
```
df3.describe(include = 'all')
```
Out[37]:

	id	release_date	movie	production_budget	domestic_gross	worldwide_g
count	5782.000000	5782	5782	5.782000e+03	5.782000e+03	5.782000e
unique	NaN	2418	5698	NaN	NaN	
top	NaN	Dec 31, 2014	King Kong	NaN	NaN	
freq	NaN	24	3	NaN	NaN	
mean	50.372363	NaN	NaN	3.158776e+07	4.584195e+07	9.729443e
std	28.821076	NaN	NaN	4.181208e+07	6.689408e+07	1.730953e
min	1.000000	NaN	NaN	1.100000e+03	3.880000e+02	2.600000e
25%	25.000000	NaN	NaN	5.000000e+06	5.609102e+06	8.210838e
50%	50.000000	NaN	NaN	1.700000e+07	2.768800e+07	3.863768e
75%	75.000000	NaN	NaN	4.000000e+07	5.234866e+07	9.764584e
max	100.000000	NaN	NaN	4.250000e+08	9.366622e+08	2.776345e

Merging Datasets

We shall merge data sets imdb.title.basics and imdb.title.ratings to enable us analyze the relationship between genres, runtime in minutes and movie popularity denoted by average rating. We will use the merge method to combine df1 and df2. Afterwards we shall join the tn.movies.budgets to analyze the cost of production and revenue by Genre.

In [38]:
```
df = pd.merge(df1,df2)
df.head()
```

Out[38]:

	tconst	primary_title	original_title	start_year	runtime_minutes	ge
0	tt0063540	Sunghursh	Sunghursh	2013	175.0	Action,Crime,Dr
1	tt0066787	One Day Before the Rainy Season	Ashad Ka Ek Din	2019	114.0	Biography,Dr
2	tt0069049	The Other Side of the Wind	The Other Side of the Wind	2018	122.0	Dr
3	tt0100275	The Wandering Soap Opera	La Telenovela Errante	2017	80.0	Comedy,Drama,Far
4	tt0137204	Joe Finds Grace	Joe Finds Grace	2017	83.0	Adventure,Animation,Con

In [39]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 65642 entries, 0 to 65641
Data columns (total 8 columns):
 #   Column           Non-Null Count  Dtype  
---  ------           --------------  -----  
 0   tconst           65642 non-null  object 
 1   primary_title    65642 non-null  object 
 2   original_title   65642 non-null  object 
 3   start_year       65642 non-null  int64  
 4   runtime_minutes  65642 non-null  float64
 5   genres           65642 non-null  object 
 6   averagerating    65642 non-null  float64
 7   numvotes         65642 non-null  int64  
dtypes: float64(2), int64(2), object(4)
memory usage: 4.5+ MB
```

In [40]:
```
dup_df = df.duplicated().any()
dup_df
```

Out[40]: False

In [41]:
```
from pandas import Series, DataFrame
```

In [42]:
```
#We notice some rows that have more than one movie genre, lets separate
s = df['genres'].str.split(',').apply(Series, 1).stack()
s.index = s.index.droplevel(-1)
s.name = 'genres'
del df['genres']
df = df.join(s)
```

In [43]:
```
df.head()
```

Out[43]:

	tconst	primary_title	original_title	start_year	runtime_minutes	averagerating	numvot
0	tt0063540	Sunghursh	Sunghursh	2013	175.0	7.0	
0	tt0063540	Sunghursh	Sunghursh	2013	175.0	7.0	
0	tt0063540	Sunghursh	Sunghursh	2013	175.0	7.0	
1	tt0066787	One Day Before the Rainy Season	Ashad Ka Ek Din	2019	114.0	7.2	
1	tt0066787	One Day Before the Rainy Season	Ashad Ka Ek Din	2019	114.0	7.2	

In [44]:
```
#Lets check the shape of our new dataset
df.shape
```

Out[44]: (118297, 8)

Exploratory Data Analysis & Data Visualization

First, we will check overall descriptive statistics of the numerical columns and also whether there is any correlation between the numerical columns

In [45]:
```
df.describe()
```

Out[45]:

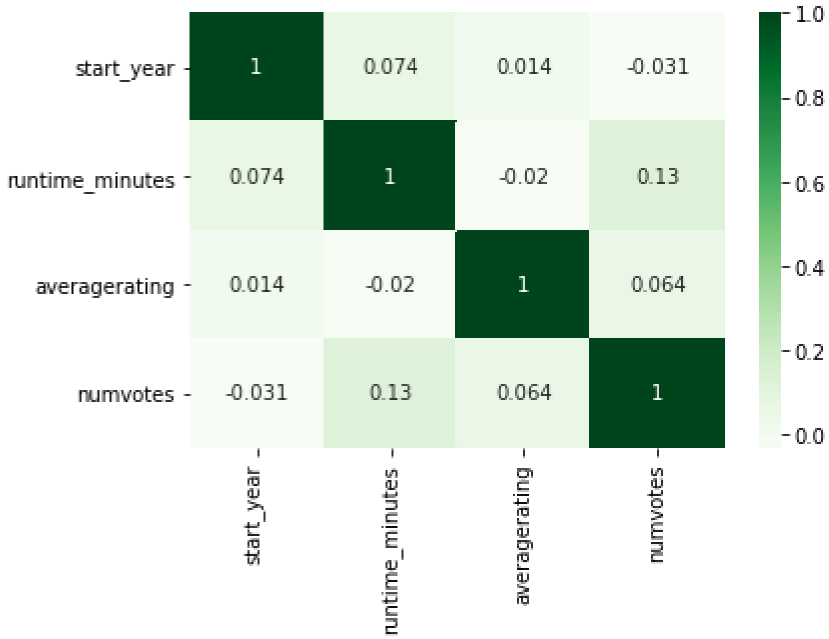
	start_year	runtime_minutes	averagerating	numvotes
count	118297.000000	118297.000000	118297.000000	1.182970e+05
mean	2014.196269	94.635992	6.293012	5.793603e+03
std	2.561618	24.570481	1.445889	3.966349e+04
min	2010.000000	15.000000	1.000000	5.000000e+00
25%	2012.000000	82.000000	5.400000	1.800000e+01
50%	2014.000000	92.000000	6.400000	7.900000e+01
75%	2016.000000	105.000000	7.300000	5.120000e+02
max	2019.000000	1440.000000	10.000000	1.841066e+06

In [46]:
```
df[df['runtime_minutes'] >1000]
```

Out[46]:

	tconst	primary_title	original_title	start_year	runtime_minutes	averagerating	nu
13816	tt2008009	The Clock	The Clock	2010	1440.0	8.9	
63628	tt8677246	Bullfighting Memories	Bullfighting Memories	2017	1100.0	8.6	
63628	tt8677246	Bullfighting Memories	Bullfighting Memories	2017	1100.0	8.6	

In [47]:
```
#lets display correlation using heatmap
sns.heatmap(df.corr(),annot = True, cmap='Greens');
```



Even tough there seems to be some correlation among attributes, there are not strongly correlated.

Total Films Per Genre

Next, we shall investigate the popular genre amongst film producers. To do this, lets find the total counts of films by genre.

In [48]:
```
#Lets investigate the total film count per genre over the years
Film_Genre = df['genres'].value_counts()
Film_Genre
```

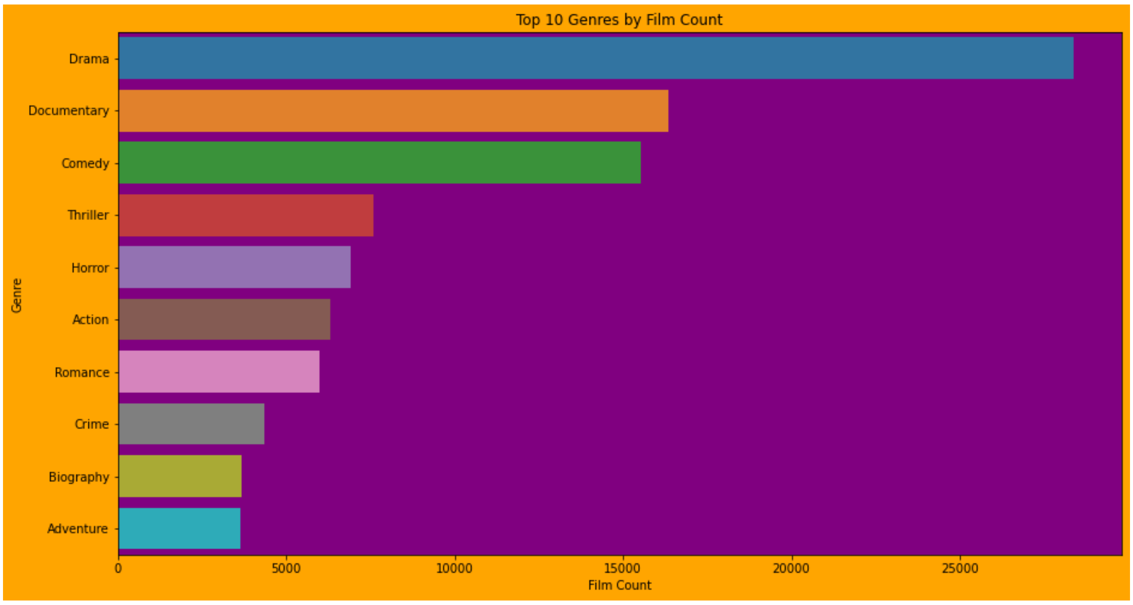
Out[48]:
```
Drama          28382
Documentary    16348
Comedy         15510
Thriller        7583
Horror          6917
Action          6296
Romance         5975
Crime           4338
Biography       3676
Adventure       3619
Family          3228
Mystery         2888
History         2698
Sci-Fi          2048
Fantasy         1968
Music           1841
Animation       1609
Sport           1095
War              793
Musical          637
News             574
Western          256
Reality-TV        13
Adult              2
Game-Show          2
Short              1
Name: genres, dtype: int64
```

The Drama genre is the most popular film genre amongst film producers. It had the highest film count, followed by Documentary then comedy. Below is a barplot visualization of the top 10 genres by film count.

In [49]:

```
plt.figure(facecolor = "orange",figsize = (15, 8))

ax= sns.barplot(
    x = Film_Genre.head(10).values,
    y = Film_Genre.head(10).index
)
ax.set(xlabel='Film Count',
       ylabel='Genre',
       title='Top 10 Genres by Film Count')
ax.set_facecolor("purple")
plt.style.use('ggplot')
plt.show()
```



Average Rating by Genre

In [50]:

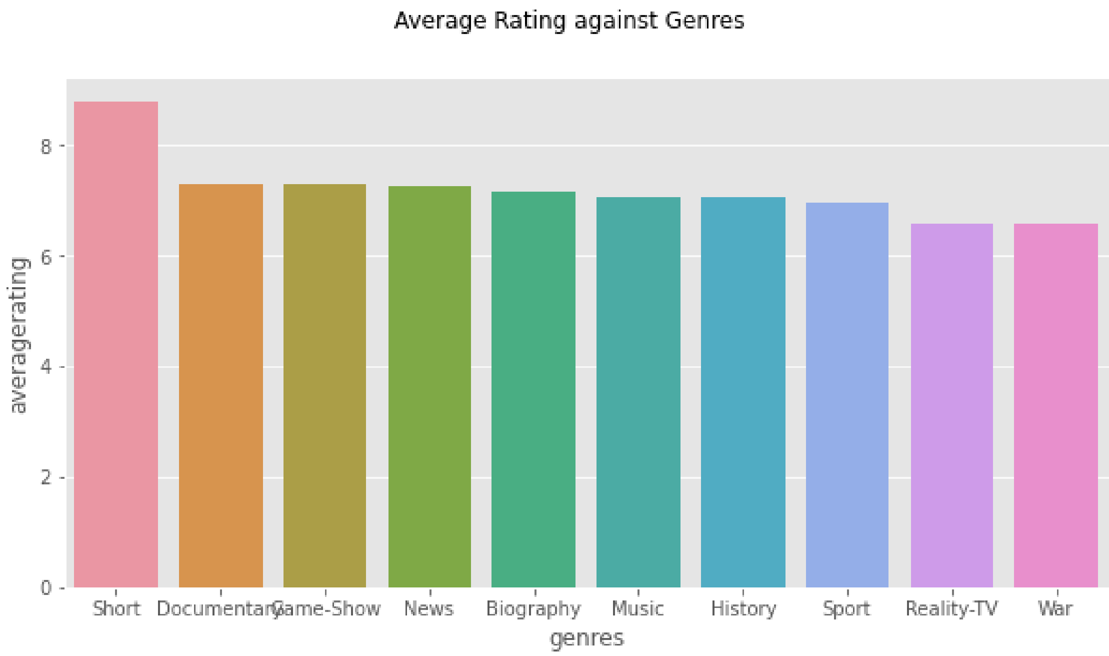
```
import warnings
warnings.filterwarnings('ignore')
```

In [51]:
```
#find the average rating by Genre
rating = df.groupby('genres')['genres','averagerating'].mean()
rating = rating.sort_values(by='averagerating',ascending=False)
rating = rating.head(10)
rating
```

Out[51]:

genres	averagerating
Short	8.800000
Documentary	7.317256
Game-Show	7.300000
News	7.278571
Biography	7.169070
Music	7.070288
History	7.048443
Sport	6.962466
Reality-TV	6.600000
War	6.572131

In [52]:
```
#plot a bar graph for the top 10 rating by Genre
plt.figure(figsize=(10,5))
sns.barplot(rating.head(10).index,rating['averagerating'])
plt.suptitle('Average Rating against Genres')
plt.show()
```



The most produced genre did not necessarily get the best rating. Out the three genres with highest film, only documentaries had a higher rating.

Correlation between Runtime and Rating

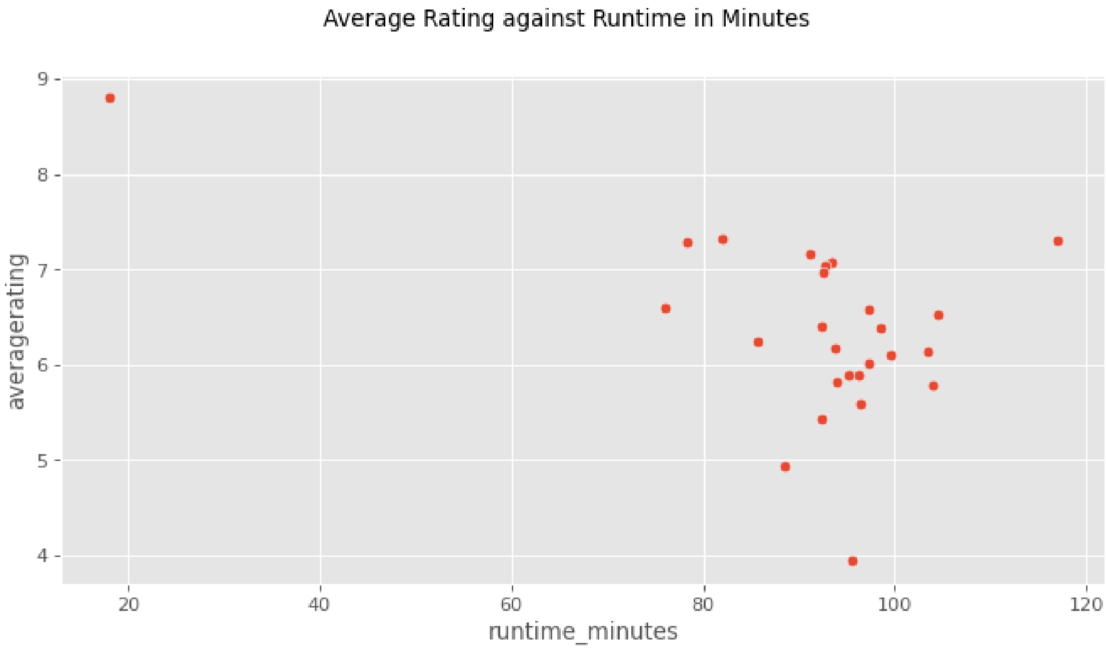
We will use a scatter plot to visualize the correlation between runtime and rating

In [53]:
```
# find the average rating and average runtime by genre
s_df = df.groupby('genres')['runtime_minutes','averagerating'].mean()
s_df = s_df.sort_values(by='runtime_minutes',ascending=False)
s_df
```

Out[53]:

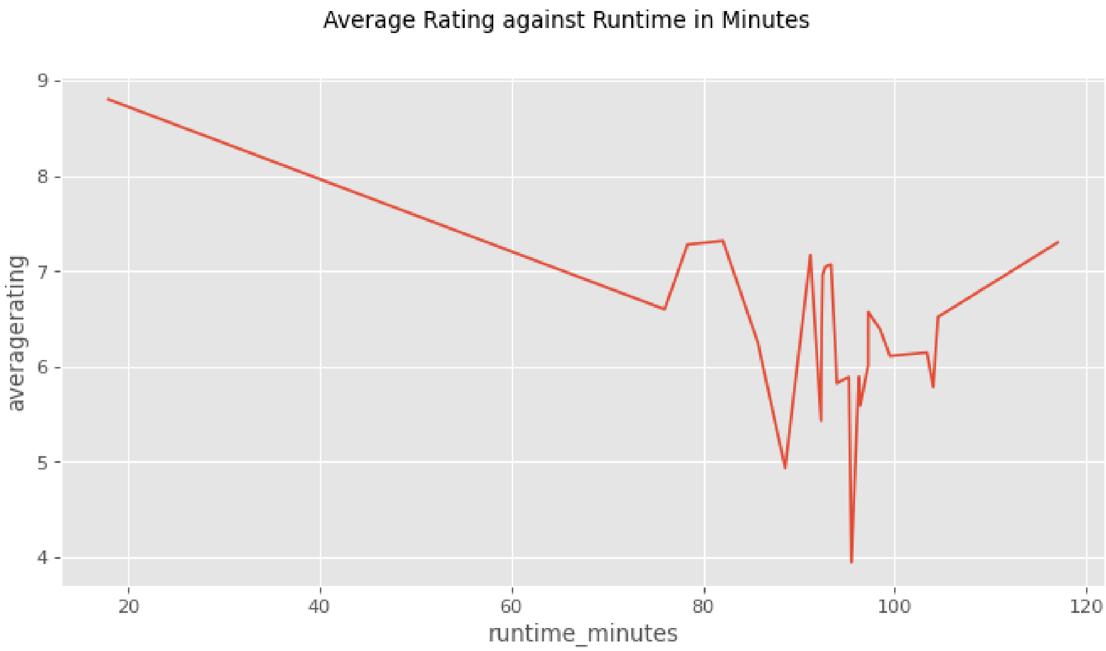
genres	runtime_minutes	averagerating
Game-Show	117.000000	7.300000
Musical	104.527473	6.519937
Action	104.018107	5.784133
Romance	103.365690	6.147464
Crime	99.509912	6.110742
Drama	98.472165	6.391142
War	97.242119	6.572131
Comedy	97.234881	6.013701
Thriller	96.414084	5.592140
Fantasy	96.257622	5.894055
Adult	95.500000	3.950000
Mystery	95.224377	5.890789
Western	93.960938	5.824219
Adventure	93.818734	6.178281
Music	93.359587	7.070288
History	92.789844	7.048443
Sport	92.488584	6.962466
Family	92.386927	6.398823
Sci-Fi	92.326660	5.431494
Biography	91.213819	7.169070
Horror	88.575828	4.934538
Animation	85.742076	6.246364
Documentary	82.090470	7.317256
News	78.391986	7.278571
Reality-TV	76.000000	6.600000
Short	18.000000	8.800000

In [54]:
```
plt.figure(figsize=(10,5), dpi = 80)
sns.scatterplot(x='runtime_minutes',y='averagerating',data=s_df)
plt.suptitle('Average Rating against Runtime in Minutes')
plt.show()
```



From the above scatter plot, the average rating does not necessarily depend on runtime. The plot shows weak negative correlation. Lets use a line graph to show that there is no linear relationship between runtime and average rating.

In [55]:
```
plt.figure(figsize=(10,5),dpi = 80)
sns.lineplot(s_df['runtime_minutes'],s_df['averagerating'])
plt.suptitle('Average Rating against Runtime in Minutes')
plt.show()
```



Classify Movies Based on Ratings [Good,Better

In [56]:
```
def rating(averagerating):
    if averagerating>=7.0:
        return 'Excellent'
    elif averagerating>=6.0:
        return 'Good'
    else:
        return 'Average'
df['rating_cat'] = df['averagerating'].apply(rating)
```

In [57]:
```
df.head()
```

Out[57]:

	tconst	primary_title	original_title	start_year	runtime_minutes	averagerating	numvot
0	tt0063540	Sunghursh	Sunghursh	2013	175.0	7.0	
0	tt0063540	Sunghursh	Sunghursh	2013	175.0	7.0	
0	tt0063540	Sunghursh	Sunghursh	2013	175.0	7.0	
1	tt0066787	One Day Before the Rainy Season	Ashad Ka Ek Din	2019	114.0	7.2	
1	tt0066787	One Day Before the Rainy Season	Ashad Ka Ek Din	2019	114.0	7.2	

Cost analysis by Genre

Now, lets join our tn.movies.budgets as df3 data and analyze the cost of production and revenue by genre.

In [58]:
```
data = pd.merge(df, df3, left_on = 'primary_title', right_on = 'movie' )
data.head()
```

Out[58]:

	tconst	primary_title	original_title	start_year	runtime_minutes	averagerating	numvot
0	tt0249516	Foodfight!	Foodfight!	2012	91.0	1.9	82
1	tt0249516	Foodfight!	Foodfight!	2012	91.0	1.9	82
2	tt0249516	Foodfight!	Foodfight!	2012	91.0	1.9	82
3	tt0337692	On the Road	On the Road	2012	124.0	6.1	378
4	tt0337692	On the Road	On the Road	2012	124.0	6.1	378

In [59]:

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 6287 entries, 0 to 6286
Data columns (total 15 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   tconst             6287 non-null   object 
 1   primary_title      6287 non-null   object 
 2   original_title     6287 non-null   object 
 3   start_year         6287 non-null   int64  
 4   runtime_minutes    6287 non-null   float64
 5   averagerating      6287 non-null   float64
 6   numvotes           6287 non-null   int64  
 7   genres             6287 non-null   object 
 8   rating_cat         6287 non-null   object 
 9   id                 6287 non-null   int64  
 10  release_date       6287 non-null   object 
 11  movie              6287 non-null   object 
 12  production_budget  6287 non-null   int64  
 13  domestic_gross     6287 non-null   float64
 14  worldwide_gross    6287 non-null   float64
dtypes: float64(4), int64(4), object(7)
memory usage: 785.9+ KB
```

Our dataset has 6287 records with 15 attributes. We shall drop the columns that we do not require in our analysis.

In [60]:

```
data.drop(['primary_title','numvotes','id','movie'], axis = 1)
```

Out[60]:

	tconst	original_title	start_year	runtime_minutes	averagerating	genres	ratin
0	tt0249516	Foodfight!	2012	91.0	1.9	Action	Av
1	tt0249516	Foodfight!	2012	91.0	1.9	Animation	Av
2	tt0249516	Foodfight!	2012	91.0	1.9	Comedy	Av
3	tt0337692	On the Road	2012	124.0	6.1	Adventure	
4	tt0337692	On the Road	2012	124.0	6.1	Drama	
...	...	...	...	...	...	...	
6282	tt8941440	Virus	2019	152.0	8.6	Drama	Ex
6283	tt8941440	Virus	2019	152.0	8.6	Thriller	Ex
6284	tt8976772	Push	2019	92.0	7.3	Documentary	Ex
6285	tt9024106	Unplanned	2019	106.0	6.3	Biography	
6286	tt9024106	Unplanned	2019	106.0	6.3	Drama	

6287 rows × 11 columns

From the above dataframe, we shall create a dataframe with average rating, production budget, domestic gross and world wide gross by genre

In [61]:
```
genre_cost = data.groupby(
    'genres')['genres','averagerating','production_budget','domestic_gross
    .sort_values(by = 'averagerating', ascending=True)
genre_cost = genre_cost.reset_index('genres')
genre_cost
```

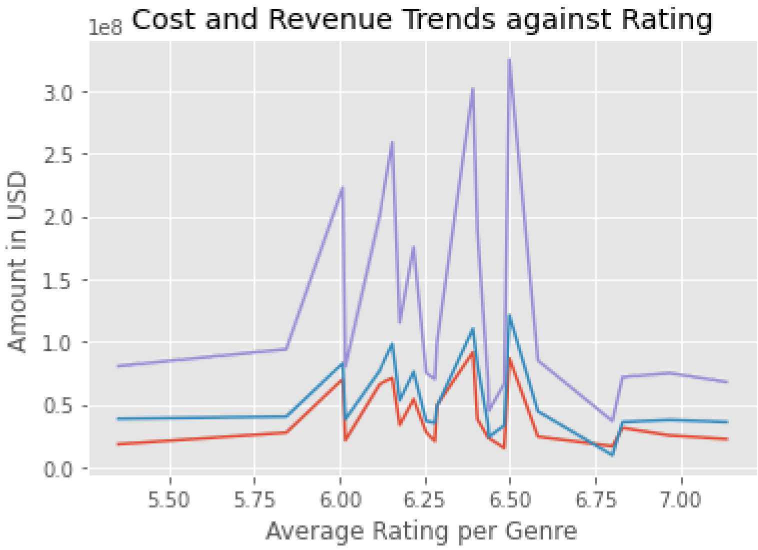
Out[61]:

	genres	averagerating	production_budget	domestic_gross	worldwide_gross
0	Horror	5.351977	1.817108e+07	3.848260e+07	8.044402e+07
1	Thriller	5.843408	2.736711e+07	4.012727e+07	9.391977e+07
2	Fantasy	6.008721	7.007436e+07	8.266031e+07	2.229422e+08
3	Mystery	6.016742	2.137133e+07	3.806949e+07	8.006978e+07
4	Action	6.117292	6.605217e+07	7.691180e+07	2.005426e+08
5	Sci-Fi	6.155500	7.100522e+07	9.838018e+07	2.591188e+08
6	Comedy	6.177358	3.363656e+07	5.330739e+07	1.153136e+08
7	Family	6.217986	5.403068e+07	7.591595e+07	1.754672e+08
8	Crime	6.254875	2.767853e+07	3.672209e+07	7.530296e+07
9	Romance	6.280126	2.055426e+07	3.515228e+07	7.002700e+07
10	Western	6.286667	4.945333e+07	4.858995e+07	1.000667e+08
11	Adventure	6.391441	9.158111e+07	1.102689e+08	3.019046e+08
12	Musical	6.404762	3.819048e+07	8.197708e+07	1.886826e+08
13	Drama	6.435605	2.366643e+07	3.435408e+07	6.960996e+07
14	War	6.438462	2.310256e+07	2.396878e+07	4.492101e+07
15	Music	6.483333	1.509611e+07	3.324993e+07	6.666269e+07
16	Animation	6.498425	8.679362e+07	1.209691e+08	3.251581e+08
17	Sport	6.581967	2.420697e+07	4.435020e+07	8.503264e+07
18	News	6.800000	1.660000e+07	9.403741e+06	3.668208e+07
19	History	6.829577	3.119592e+07	3.580427e+07	7.167731e+07
20	Biography	6.967876	2.515310e+07	3.748472e+07	7.489481e+07
21	Documentary	7.134197	2.228313e+07	3.582550e+07	6.775706e+07

In [62]:
```
x = genre_cost['averagerating']
y1 = genre_cost['production_budget']
y2 = genre_cost['domestic_gross']
y3 = genre_cost['worldwide_gross']

ax1 = plt.plot(x, y1)
plt.plot(x, y2)
plt.plot(x, y3)

plt.xlabel('Average Rating per Genre')
plt.ylabel('Amount in USD')
plt.title('Cost and Revenue Trends against Rating')
color=('DarkBlue','c','crimson')
plt.figure(figsize=(10, 8));
plt.show()
```




```
<Figure size 720x576 with 0 Axes>
```

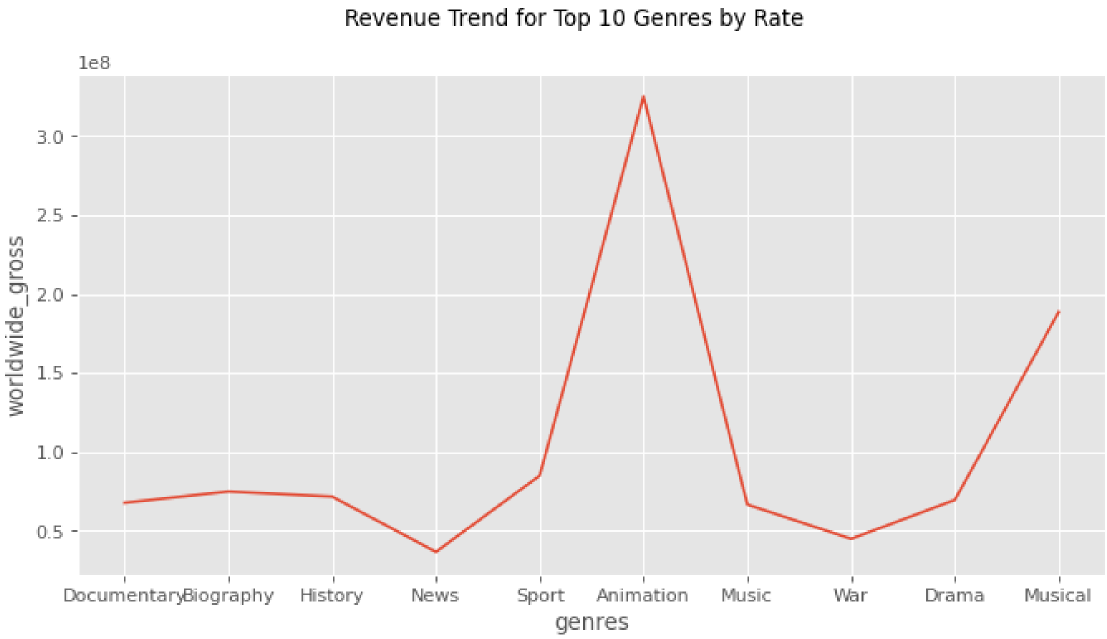
From the above graph, there is no direct relationship between average rating and the cost of production and revenue. The cost and both revenues seem to be higher between rating 6 and 6.5, which is rated good. Further, the three parameters have the same trend in respect to rating.

Revenue Trends for Top 10 Rated Genres

Lets examine a plot of top 10 Genres by rating and confirm whether high rating translates to high revenue. We shall use worldwide gross income for this analysis

In [63]:
```
#Lets re-sort our cost by genre data in descending order
genre_cost = data.groupby(
    'genres')['genres','averagerating','production_budget','domestic_gross
    .sort_values(by = 'averagerating', ascending=False)
genre_cost = genre_cost.reset_index('genres')
```

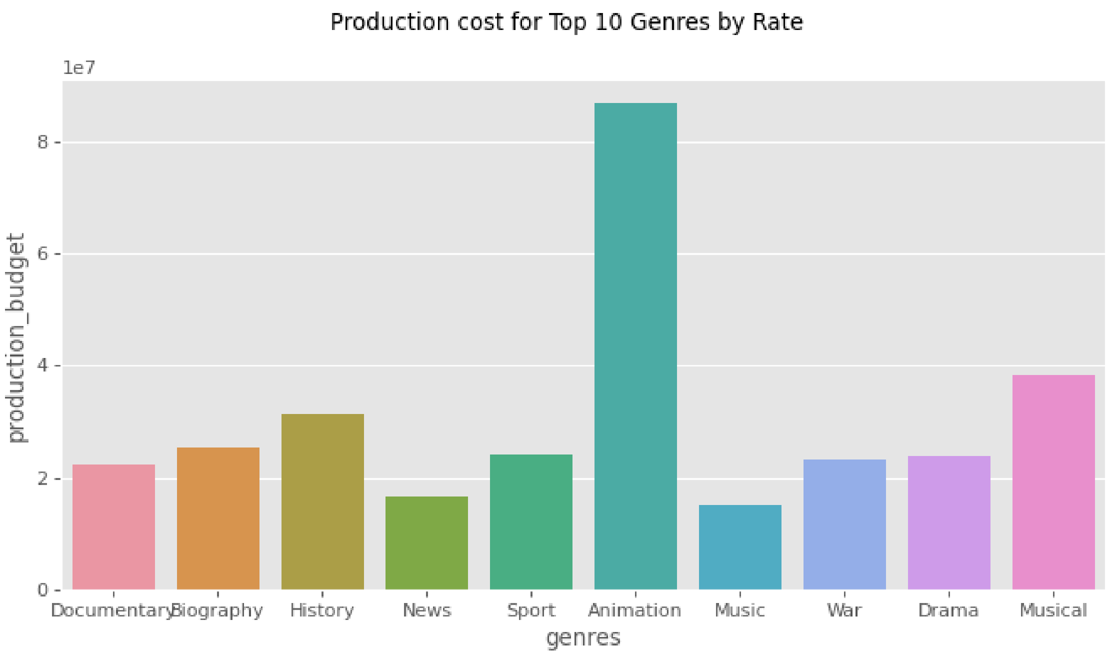
In [64]:
```
plt.figure(figsize=(10,5), dpi = 80)
sns.lineplot(genre_cost.head(10)['genres'],genre_cost.head(10)['worldwide_
plt.suptitle('Revenue Trend for Top 10 Genres by Rate')
plt.show()
```



There is no linear relationship between revenue and rating

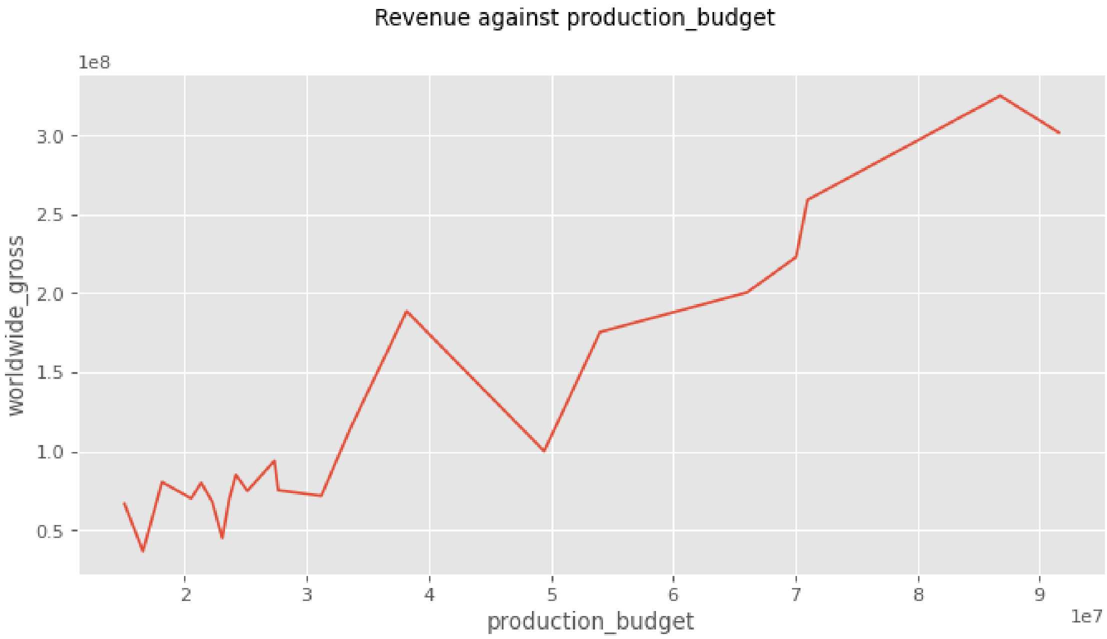
Production cost for Top 10 rated Genres

In [65]:
```
#lets examine the cost of production for top 10 genres by rating
plt.figure(figsize=(10,5), dpi = 80)
sns.barplot(genre_cost.head(10)['genres'],genre_cost.head(10)['production_
plt.suptitle('Production cost for Top 10 Genres by Rate')
plt.show()
```



The cost of production is relatively lower for highly rated Genres

In [66]:
```
plt.figure(figsize=(10,5), dpi = 80)
sns.lineplot(x=genre_cost['production_budget'],y=genre_cost['worldwide_gro
plt.suptitle('Revenue against production_budget')
plt.show()
```



The revenue increases as cost of production increases

Observations

The top three genres produced by Film producers are: • Drama • Documentary • Comedy.

There is no strong correlation between rating and runtime.

Films rated good are generally costly to produce than those rated excellent and average.

There is no linear relationship between film rating and gross revenue.

The genre Documentary performed better in all the analyses.

Conclusion

Microsoft movie studio should consider producing films that are most popular by production numbers.

Microsoft to consider films rating when choosing film genres to produce. Films rated excellent are genarally produced at lower cost.

Revenue increased with cost of production. This implies that there is no significant change in profits as cost of production reduces. Hence,

Generally, I would recomend Microsoft movie studio to produce documentaries. The genre showed good results in all the analysed parameters, which implies that it has the potential of selling better and generating higher Returns on Investment.

Further Research

Further analysis to be done to determine the relationship between diffent movie genres and Return on investment

References

https://www.kaggle.com (https://www.kaggle.com)

https://codingnomads.co/blog (https://codingnomads.co/blog)