Final Project Submission

Please fill out:

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- Student pace: full time
- Scheduled project review date/time:
- Instructor name:
- Blog post URL:

Microsoft's New Movie Studio

Overview

Microsoft has learnt that other big companies are creating video content and they want in on the fun too. However, they know nothing about creating movies. We are tasked with the responsibility of exploring the type of films currently doing best at box office and give actionable recommendations to Microsoft to venture into the film industry successfully.

The data method used in this project is exploratory data analysis, whereby we'll look into four different datasets and find relevant information that will help us provide clear recommendations.

Some of the results obtained from this analysis among others, show that the top 3 most profitable genres are Science Fiction & Fantasy, Action & Adventure, and Kids & family.

We therefore recommend Microsoft to create films along those genres as they are most likely to earn them more profits.

Business Problem

Microsoft is inspred to start creating movies like other big companies. However, Microsoft has no idea how to go about it.

We are therefore tasked with the responsibility of exploring the type of films doing best currently to help Microsoft venture into this industry successfully.

In order to objectively provide clear recommendations that will be beneficial to Microsoft, the following questions will act as a guide to drawing insights from our datasets.

```
 * Which film production studio made the highest total gross revenue in
box office.

 * Is there a relationship between the prduction budget and the revenue
made.
```

```
* How does the original language of a film affect its popularity.

* How is the trend of film runtime over the years.

* What is the correlation between critics' score and the people's score.

* What are the top ten most profitable genre.
```

Data Understanding

The for datasets we'll be working with here are 'bom.movie_gross.csv', 'tmdb.movies.csv', 'tn.movie_budgets.csv', and 'rotten_tomatoes_top_movies.csv'.

```
* The 'bom.movie_gross.csv' dataset is a box office dataset showing the
domestic and foreign gross revenues of each movie.

* The 'tmdb.movies.csv' dataset shows the original languages of different
movies and their percentage popularity.

* The 'tn.movie_budgets.csv' dataset shows production budgets and their
corresponding worldwide gross revenue.

*The 'rotten_tomatoes_top_movies.csv' dataset shows the box office
performance of each movie and their genres in USA.
```

These first three datasets can be found in a zipped file in GitHub, and the fourth dataset can be found in Kaggle.

These datasets will help us answer the questions above.

In [ ]:
```
# Your code here - remember to use markdown cells for comments as well!
```

In [ ]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
import sqlite3
```

1.

In this section, we find out which studio makes the most revenue by calculating the total gross revenue of a film per studio.

In [ ]:
```
# Loading our first dataset as bom_df
bom_df = pd.read_csv('bom.movie_gross.csv')
bom_df
```

Out[ ]:

	title	studio	domestic_gross	foreign_gross	year
0	Toy Story 3	BV	415000000.0	652000000	2010
1	Alice in Wonderland (2010)	BV	334200000.0	691300000	2010
2	Harry Potter and the Deathly Hallows Part 1	WB	296000000.0	664300000	2010
3	Inception	WB	292600000.0	535700000	2010
4	Shrek Forever After	P/DW	238700000.0	513900000	2010
...	...	...	...	...	...
3382	The Quake	Magn.	6200.0	NaN	2018
3383	Edward II (2018 re-release)	FM	4800.0	NaN	2018
3384	El Pacto	Sony	2500.0	NaN	2018
3385	The Swan	Synergetic	2400.0	NaN	2018
3386	An Actor Prepares	Grav.	1700.0	NaN	2018

3387 rows × 5 columns

Lets inspect our first dataset if there are missing values, and the datatype of each column. Then we drop the rows with missing values and convert the columns to our preferred data types.

In [ ]:

```
# inspecting our dataset
bom_df.info()
```

```
<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 [ ]:

```
# removing commas in the dataset
bom_df.replace(',','', regex=True, inplace=True)
```

In [ ]:

```
# dropping all the rows containing null values
bom_df.dropna(inplace=True)
```

In [ ]:

```
# converting the foreign_gross column from object dtype to float dtype
bom_df['foreign_gross'] = bom_df['foreign_gross'].astype(float)
```

In [ ]:

```
# confirming the changes
bom_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 2007 entries, 0 to 3353
Data columns (total 5 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
```

```
 0   title           2007 non-null   object
 1   studio          2007 non-null   object
 2   domestic_gross  2007 non-null   float64
 3   foreign_gross   2007 non-null   float64
 4   year            2007 non-null   int64
dtypes: float64(2), int64(1), object(2)
memory usage: 94.1+ KB
```

We now want to visualize the average amount of money made by a studio per film.

In [ ]:
```
# creating a new column 'total_gross_(in millions)' which is the sum of domestic and fo
bom_df['total_gross_in_millions'] = (bom_df['domestic_gross']/1000000) + (bom_df['forei
bom_df.head(2)
```

Out[ ]:

	title	studio	domestic_gross	foreign_gross	year	total_gross_in_millions
0	Toy Story 3	BV	415000000.0	652000000.0	2010	1067.0
1	Alice in Wonderland (2010)	BV	334200000.0	691300000.0	2010	1025.5

In [ ]:
```
# dropping columns that we do not need
bom_df = bom_df.drop(columns = ['title', 'domestic_gross', 'foreign_gross', 'year'])
```

In [ ]:
```
# grouping the dataset by the studio, and calculate the mean of the total income for th
columns = ['studio', 'total_gross_in_millions']
bom_df = bom_df.groupby('studio')['total_gross_in_millions'].mean()
bom_df = bom_df.reset_index()
bom_df
```

Out[ ]:

	studio	total_gross_in_millions
0	3D	16.000000
1	A24	26.258895
2	AF	2.327500
3	AGF	0.176800
4	AR	58.050000
...	...	...
167	WOW	0.049400
168	Wein.	59.360909
169	Yash	49.205750
170	Zee	1.671000
171	Zeit.	4.405840

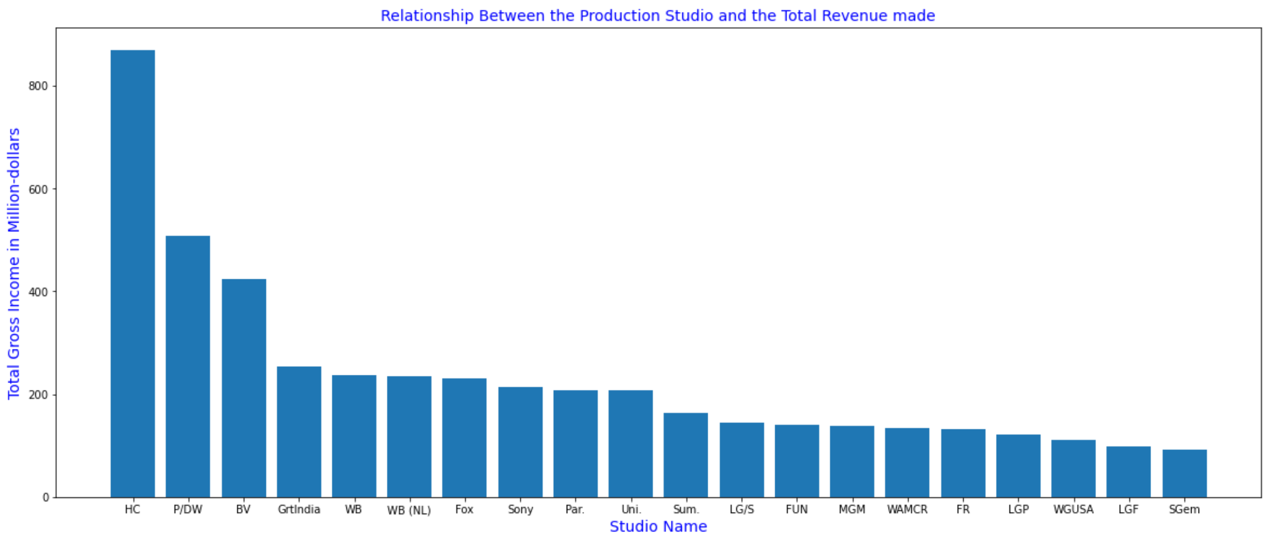
172 rows × 2 columns

In [ ]:
```
# sorting the sum of the total gross income from the highest
bom_df = bom_df.sort_values('total_gross_in_millions', ascending=False)
# select the top 20 studios
bom_df1 =bom_df.head(20)
```

In [ ]:
```
# plotting a barplot for the top 20 films in box office and the studio of production
fig, ax = plt.subplots(figsize=(20,8))

plt.style.use('ggplot')
plt.bar( x= bom_df1['studio'], height= bom_df1['total_gross_in_millions'])

plt.xlabel('Studio Name',color = 'blue', fontsize=14)
plt.ylabel('Total Gross Income in Million-dollars',color = 'blue', fontsize=14)
plt.title('Relationship Between the Production Studio and the Total Revenue made', colo
plt.show()
```



From the above barplot, we can look at the average of the total gross revenue that each of the top 20 studios have made over the years from 2010 to 2018 per film produced. The top 5 five studios are HC, P/DW, BV, GrtIndia, and WB.

2.

In this section, our aim is to find out whether the original language of a film affects its popularity for films produced since the year 2000.

In [ ]:
```
#loading our second dataset as tmdb_df
tmdb_df = pd.read_csv('tmdb.movies.csv', index_col=0)
tmdb_df.head()
```

Out[ ]:

	genre_ids	id	original_language	original_title	popularity	release_date	title	vote_average
0	[12, 14, 10751]	12444	en	Harry Potter and the Deathly Hallows: Part 1	33.533	2010-11-19	Harry Potter and the Deathly Hallows: Part 1	7.7
1	[14, 12, 16, 10751]	10191	en	How to Train Your Dragon	28.734	2010-03-26	How to Train Your Dragon	7.7
2	[12, 28, 878]	10138	en	Iron Man 2	28.515	2010-05-07	Iron Man 2	6.8

	genre_ids	id	original_language	original_title	popularity	release_date	title	vote_average
3	[16, 35, 10751]	862	en	Toy Story	28.005	1995-11-22	Toy Story	7.9
4	[28, 878, 12]	27205	en	Inception	27.920	2010-07-16	Inception	8.3

In [ ]:
```
#converting the release date column to datetime dtype
tmdb_df['release_date'] = pd.to_datetime(tmdb_df['release_date'], format = '%Y/%m/%d')
```

In [ ]:
```
tmdb_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 26517 entries, 0 to 26516
Data columns (total 9 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   genre_ids          26517 non-null  object
 1   id                 26517 non-null  int64
 2   original_language  26517 non-null  object
 3   original_title     26517 non-null  object
 4   popularity         26517 non-null  float64
 5   release_date       26517 non-null  datetime64[ns]
 6   title              26517 non-null  object
 7   vote_average       26517 non-null  float64
 8   vote_count         26517 non-null  int64
dtypes: datetime64[ns](1), float64(2), int64(2), object(4)
memory usage: 2.0+ MB
```

In [ ]:
```
#sorting data from the oldest film to the most recent
tmdb_df.sort_values(by='release_date', inplace = True)
tmdb_df
```

Out[ ]:

	genre_ids	id	original_language	original_title	popularity	release_date	title	vote_ave
14335	[18, 10752]	143	en	All Quiet on the Western Front	9.583	1930-04-29	All Quiet on the Western Front	
21758	[27, 53]	43148	en	The Vampire Bat	2.292	1933-01-21	The Vampire Bat	
3580	[35, 18, 10749]	263768	fr	Le Bonheur	1.653	1936-02-27	Le Bonheur	
26345	[]	316707	en	How Walt Disney Cartoons Are Made	0.600	1939-01-19	How Walt Disney Cartoons Are Made	
11192	[18, 36, 10749]	887	en	The Best Years of Our Lives	9.647	1946-12-25	The Best Years of Our Lives	
...	...	...	...	...	...	...	...	
24819	[18]	481880	en	Trial by Fire	4.480	2019-05-17	Trial by Fire	

	genre_ids	id	original_language	original_title	popularity	release_date	title	vote_ave
24003	[18, 9648, 53]	411144	en	We Have Always Lived in the Castle	14.028	2019-05-17	We Have Always Lived in the Castle	
24892	[99]	541577	en	This Changes Everything	3.955	2019-06-28	This Changes Everything	
24265	[10749, 18]	428836	en	Ophelia	8.715	2019-06-28	Ophelia	
26057	[27, 80, 80, 80, 80, 80, 80]	570704	en	Murdery Christmas	0.840	2020-12-25	Murdery Christmas	

26517 rows × 9 columns

In [ ]:

```
#fitering the dataframe to remain with data from the year 2000
tmdb_df1 = tmdb_df[(tmdb_df['release_date'] >= '2000-01-01')]
tmdb_df1
```

Out[ ]:

	genre_ids	id	original_language	original_title	popularity	release_date	title	vote_ave
6610	[10402, 99]	59991	en	Horowitz in Moscow	0.947	2000-04-04	Horowitz in Moscow	
5352	[80, 18, 878, 53]	10559	en	Frequency	8.833	2000-04-28	Frequency	
5783	[16, 10751, 35]	21036	ja	パンダコパンダ	3.416	2000-07-25	Panda! Go Panda!	
2594	[18, 10402]	786	en	Almost Famous	11.022	2000-09-15	Almost Famous	
58	[18]	705	en	All About Eve	13.163	2000-10-06	All About Eve	
...	...	...	...	...	...	...	...	...
24819	[18]	481880	en	Trial by Fire	4.480	2019-05-17	Trial by Fire	
24003	[18, 9648, 53]	411144	en	We Have Always Lived in the Castle	14.028	2019-05-17	We Have Always Lived in the Castle	
24892	[99]	541577	en	This Changes Everything	3.955	2019-06-28	This Changes Everything	
24265	[10749, 18]	428836	en	Ophelia	8.715	2019-06-28	Ophelia	
26057	[27, 80, 80, 80,	570704	en	Murdery Christmas	0.840	2020-12-25	Murdery Christmas	

genre_ids	id	original_language	original_title	popularity	release_date	title	vote_ave
80, 80]							

26398 rows × 9 columns

In [ ]:
```
tmdb_df1['original_language'].value_counts()
```

Out[ ]:
```
en    23196
fr      506
es      455
ru      297
ja      259
       ...
hy        1
af        1
bo        1
xh        1
ha        1
Name: original_language, Length: 76, dtype: int64
```

In [ ]:
```
#grouping by original language and calculating the popularity mean per original languag
tmdb_df1 = tmdb_df1.groupby('original_language')['popularity'].mean()
tmdb_df1 = tmdb_df1.reset_index()
tmdb_df1
```

Out[ ]:

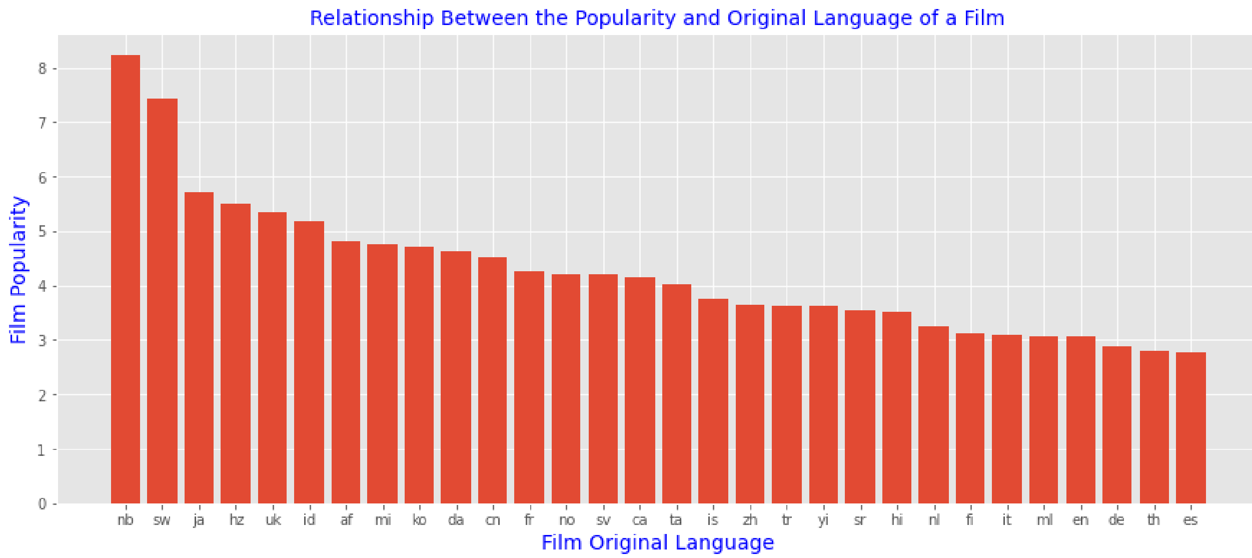
	original_language	popularity
0	ab	0.977800
1	af	4.814000
2	ar	2.707484
3	bg	1.047500
4	bn	1.160000
...	...	...
71	vi	1.158429
72	xh	1.564000
73	xx	0.914167
74	yi	3.614000
75	zh	3.645927

76 rows × 2 columns

In [ ]:
```
#sort the mean of the total gross income from the highest
tmdb_df1 = tmdb_df1.sort_values('popularity', ascending=False)
# select the top 20 studios
tmdb_df2 = tmdb_df1.head(30)
```

In [ ]:
```
#plotting a barplot for the top 30 common languages and their popularity
fig, ax = plt.subplots(figsize=(15,6))
plt.bar( x= tmdb_df2['original_language'], height= tmdb_df2['popularity'])
```

```
plt.xlabel('Film Original Language',color = 'blue', fontsize=14)
plt.ylabel('Film Popularity',color = 'blue', fontsize=14)
plt.title('Relationship Between the Popularity and Original Language of a Film', color
plt.show()
```



Based on the above visualization, we can see that the original language in which a film is produced does not affects its popularity. However, from our data, we can see that most films are originally created in English. This implies that the language in which a film is originally created in does not guarantee its popularity.

3.

In this section, we explore the relationship between the production budget and the worldwide gross, and also find out the type of correlation between them.

In [ ]:
```
budgets_df = pd.read_csv('tn.movie_budgets.csv', index_col=0)
budgets_df.head()
```

Out[ ]:

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

In [ ]:
```
# inspecting our dataframe for missing values and the columns' datatypes
budgets_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 5782 entries, 1 to 82
Data columns (total 5 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   release_date       5782 non-null   object
```

```
 1   movie              5782 non-null   object
 2   production_budget  5782 non-null   object
 3   domestic_gross     5782 non-null   object
 4   worldwide_gross    5782 non-null   object
dtypes: object(5)
memory usage: 271.0+ KB
```

In [ ]:
```
# checking for duplicated values
budgets_df.duplicated().sum()
```

Out[ ]:
```
0
```

In [ ]:
```
# removing special characters from specific columns and changing datatype from object t
budgets_df['worldwide_gross'] = budgets_df['worldwide_gross'].str.replace('\$|,','', re
budgets_df['production_budget'] = budgets_df['production_budget'].str.replace('\$|,',''
```

In [ ]:
```
#confirming changes
budgets_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 5782 entries, 1 to 82
Data columns (total 5 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   release_date       5782 non-null   object
 1   movie              5782 non-null   object
 2   production_budget  5782 non-null   float64
 3   domestic_gross     5782 non-null   object
 4   worldwide_gross    5782 non-null   float64
dtypes: float64(2), object(3)
memory usage: 271.0+ KB
```

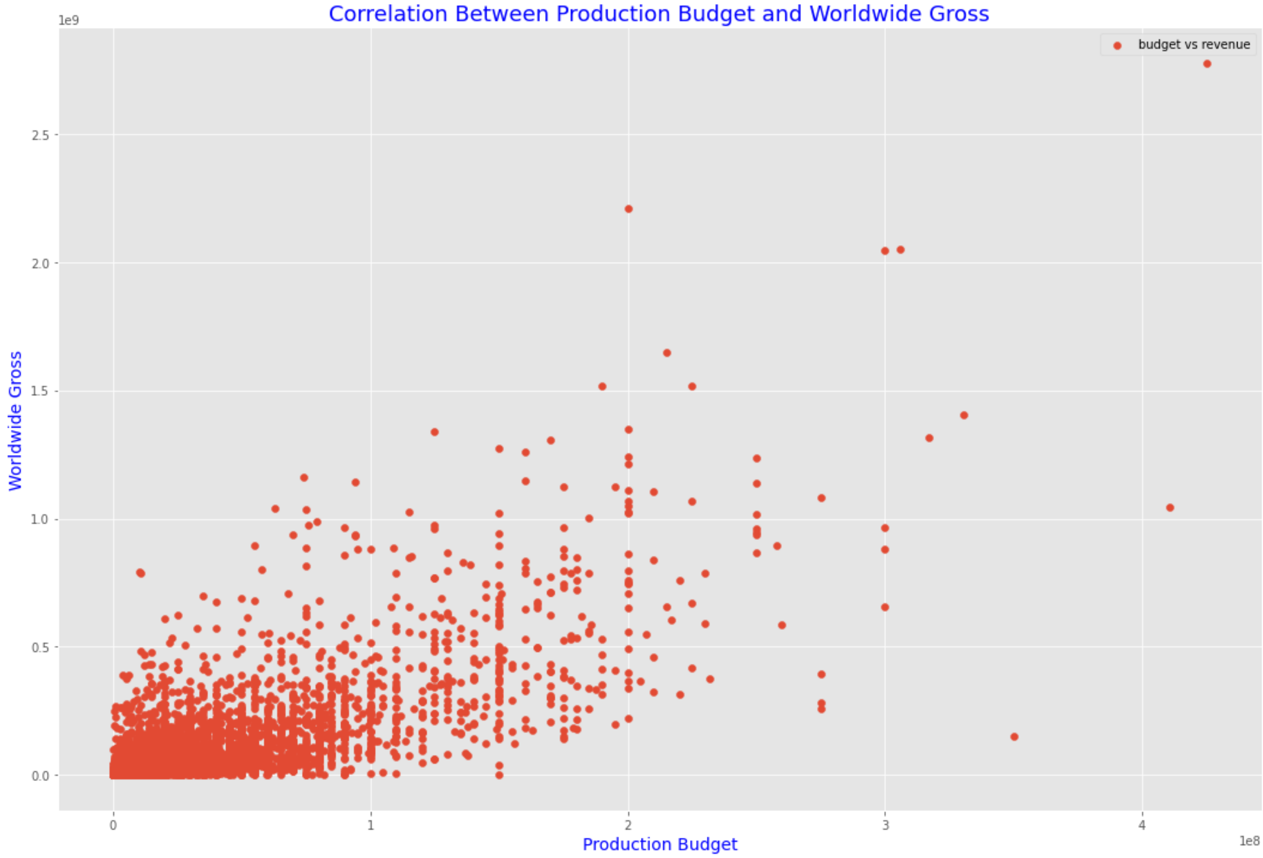
In [ ]:
```
#calculating the correlation between production budget and worlwide gross
correlation = budgets_df["production_budget"].corr(budgets_df["worldwide_gross"])
correlation
```

Out[ ]:
```
0.7483059765694753
```

In [ ]:
```
#scatter plot between production budget and worldwide gross
fig, ax = plt.subplots(figsize=(18,12))
plt.style.use('ggplot')
plt.scatter(x=budgets_df['production_budget'], y=budgets_df['worldwide_gross'], label =

plt.xlabel('Production Budget', color = 'blue', fontsize=14)
plt.ylabel('Worldwide Gross', color = 'blue', fontsize=14)
plt.title('Correlation Between Production Budget and Worldwide Gross', color = 'blue',

plt.legend()
plt.show();
```



From the scatter plot above, we can see that the correlation between the production budget and the worldwide gross revenue is positive. The scatter plot confirms the value obtained before of 0.748, which is a strong positive correlation.

4.

This part explores the relationship between critic score and people score, the trend of film runtime over the years, and the most profitable genres.

In [ ]:
```
rotten_df = pd.read_csv('rotten_tomatoes_top_movies.csv', index_col=0)
rotten_df.head(2)
```

Out[ ]:

	title	year	synopsis	critic_score	people_score	consensus	total_reviews	total_ratings	ty
0	Black Panther	2018	After the death of his father, T'Challa return...	96	79.0	Black Panther elevates superhero cinema to thr...	519	50,000+	Action Adventu
1	Avengers: Endgame	2019	Adrift in space with no food or water, Tony St...	94	90.0	Exciting, entertaining, and emotionally impact...	538	50,000+	Action Adventu

2 rows × 25 columns

In [ ]:
```
rotten_df = rotten_df.loc[:, [ 'year', 'critic_score', 'people_score', 'type', 'genre',
rotten_df.head(10)
```

Out[ ]:

	year	critic_score	people_score	type	genre	box_office_(gross_usa)	runtime
0	2018	96	79.0	Action & Adventure	adventure, action, fantasy	$700.2M	2h 14m
1	2019	94	90.0	Action & Adventure	sci fi, adventure, action, fantasy	$858.4M	3h 1m
2	2018	97	88.0	Action & Adventure	action, mystery and thriller, adventure	$220.1M	2h 27m
3	2015	97	86.0	Action & Adventure	adventure, action	$153.6M	2h
4	2018	97	93.0	Action & Adventure	action, adventure, fantasy, comedy, kids and f...	$190.2M	1h 57m
5	2017	93	83.0	Action & Adventure	adventure, fantasy, action	$412.8M	2h 21m
6	2017	92	81.0	Action & Adventure	drama, history, war	$188.0M	1h 47m
7	2017	97	94.0	Action & Adventure	comedy, music, animation, kids and family, adv...	$210.5M	1h 49m
8	2017	93	87.0	Action & Adventure	comedy, fantasy, sci fi, action, adventure	$315.0M	2h 10m
9	2017	93	90.0	Action & Adventure	adventure, action, fantasy	$226.3M	2h 17m

In [ ]:
```
rotten_df.duplicated().sum()
```

Out[ ]: 0

In [ ]:
```
print(rotten_df.shape)
print()
print(rotten_df.info())
```

```
(1610, 7)

<class 'pandas.core.frame.DataFrame'>
Int64Index: 1610 entries, 0 to 1609
Data columns (total 7 columns):
 #   Column                Non-Null Count  Dtype  
---  ------                --------------  -----  
 0   year                  1610 non-null   int64  
 1   critic_score          1610 non-null   int64  
 2   people_score          1609 non-null   float64
 3   type                  1610 non-null   object 
 4   genre                 1603 non-null   object 
 5   box_office_(gross_usa)  1102 non-null   object 
 6   runtime               1603 non-null   object 
dtypes: float64(1), int64(2), object(4)
memory usage: 100.6+ KB
None
```

In [ ]:
```
#dropping rows with missing values
rotten_df = rotten_df.dropna()
rotten_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1101 entries, 0 to 1609
Data columns (total 7 columns):
 #   Column                Non-Null Count  Dtype  
---  ------                --------------  -----  
 0   year                  1101 non-null   int64  
 1   critic_score          1101 non-null   int64  
 2   people_score          1101 non-null   float64
 3   type                  1101 non-null   object 
 4   genre                 1101 non-null   object 
 5   box_office_(gross_usa)  1101 non-null   object 
 6   runtime               1101 non-null   object 
dtypes: float64(1), int64(2), object(4)
memory usage: 68.8+ KB
```

In [ ]:
```
rotten_df['type'].nunique()
```

Out[ ]:
```
17
```

In [ ]:
```
rotten_df['genre'].nunique()
```

Out[ ]:
```
229
```

In [ ]:
```
# removing special characters and alphabets from box office column and converting the d
rotten_df['box_office_(gross_usa)'] = rotten_df['box_office_(gross_usa)'].str.replace('
```

In [ ]:
```
#converting the runtime column to minutes only
rotten_df['runtime'] = pd.to_timedelta(rotten_df['runtime'])
### Convert 'timeColumn' to minutes only.
rotten_df['runtime_min'] = rotten_df['runtime'].dt.total_seconds() / 60
rotten_df.head(2)
```

Out[ ]:

	year	critic_score	people_score	type	genre	box_office_(gross_usa)	runtime	runtime_min
0	2018	96	79.0	Action & Adventure	adventure, action, fantasy	700.2	0 days 02:14:00	134.0
1	2019	94	90.0	Action & Adventure	sci fi, adventure, action, fantasy	858.4	0 days 03:01:00	181.0

In [ ]:

```
#sorting by order of years
rotten_df = rotten_df.sort_values('year', ascending=True)
rotten_df
```

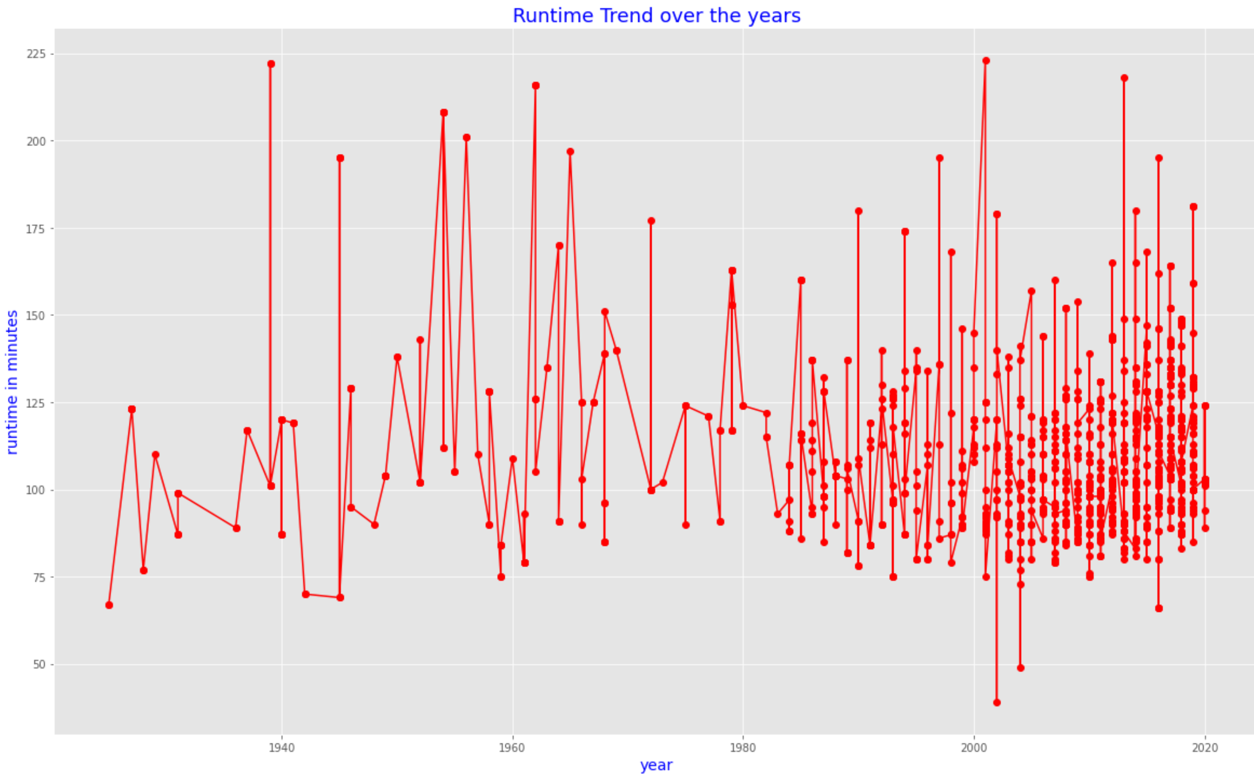
Out[ ]:

	year	critic_score	people_score	type	genre	box_office_(gross_usa)	runtime	runtime_
213	1925	100	86.0	Art House & International	mystery and thriller, drama, history	51.0	0 days 01:07:00	
352	1925	100	86.0	Classics	mystery and thriller, drama, history	51.0	0 days 01:07:00	
21	1927	97	92.0	Action & Adventure	drama, sci fi	1.2	0 days 02:03:00	1
328	1927	97	92.0	Classics	drama, sci fi	1.2	0 days 02:03:00	1
1222	1927	97	92.0	Science Fiction & Fantasy	drama, sci fi	1.2	0 days 02:03:00	1
...	...	...	...	...	...	...	...	
1273	2020	88	95.0	Science Fiction & Fantasy	adventure, animation, fantasy, comedy, kids an...	60.4	0 days 01:43:00	1
1092	2020	93	59.0	Mystery & Suspense	horror, mystery and thriller, sci fi	745.8	0 days 01:42:00	1
778	2020	92	63.0	Horror	horror, mystery and thriller	157.0	0 days 01:34:00	
833	2020	88	95.0	Kids & Family	adventure, animation, fantasy,	60.4	0 days 01:43:00	1

	year	critic_score	people_score	type	genre	box_office_(gross_usa)	runtime	runtime_
					comedy, kids an...			
1220	2020	91	88.0	Science Fiction & Fantasy	mystery and thriller, horror	64.3	0 days 02:04:00	1

1101 rows × 8 columns

In [ ]:
```
#plotting a line graph to show the trend of how runtime has changed over the years
fig, ax = plt.subplots(figsize=(20,12))
plt.plot(rotten_df['year'], rotten_df['runtime_min'], color='red', marker='o')
plt.title('Runtime Trend over the years', fontsize=18, color = 'blue')
plt.xlabel('year', fontsize=14, color = 'blue')
plt.ylabel('runtime in minutes', fontsize=14, color = 'blue')
plt.grid(True)
plt.show()
```



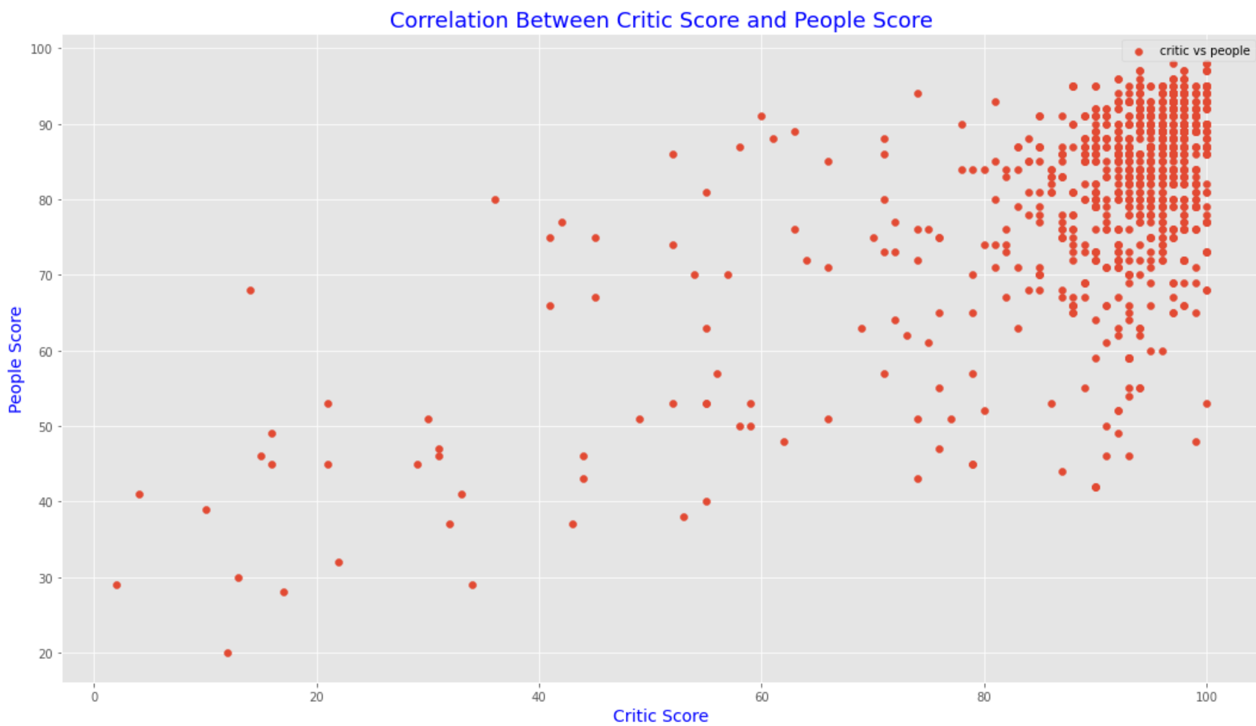
From the above line graph, we can conclude that the runtime of films has no significant difference since most films lie between 75 and 150 minutes. We can also note that the there has been an increase in the production of films in the recent past compared to half a century ago.

In [ ]:
```
#plotting the correlation between critic score and people score
fig, ax = plt.subplots(figsize=(18,10))

plt.scatter(x=rotten_df['critic_score'], y=rotten_df['people_score'], label = 'critic v

plt.xlabel('Critic Score', color = 'blue', fontsize=14)
plt.ylabel('People Score', color = 'blue', fontsize=14)
plt.title('Correlation Between Critic Score and People Score', color = 'blue', fontsize
```

```
plt.legend()
plt.show();
```



From the above scatter plot, we can see that the correlation between critic score and people score is positive. This implies that the measure used by critics to rate a film is almost similar to that of the people.

In [ ]:
```
#grouping columns by type
columns = ['type', 'box_office_(gross_usa)']
rotten_df = rotten_df.groupby('type')['box_office_(gross_usa)'].mean()
rotten_df = rotten_df.reset_index()
rotten_df
```

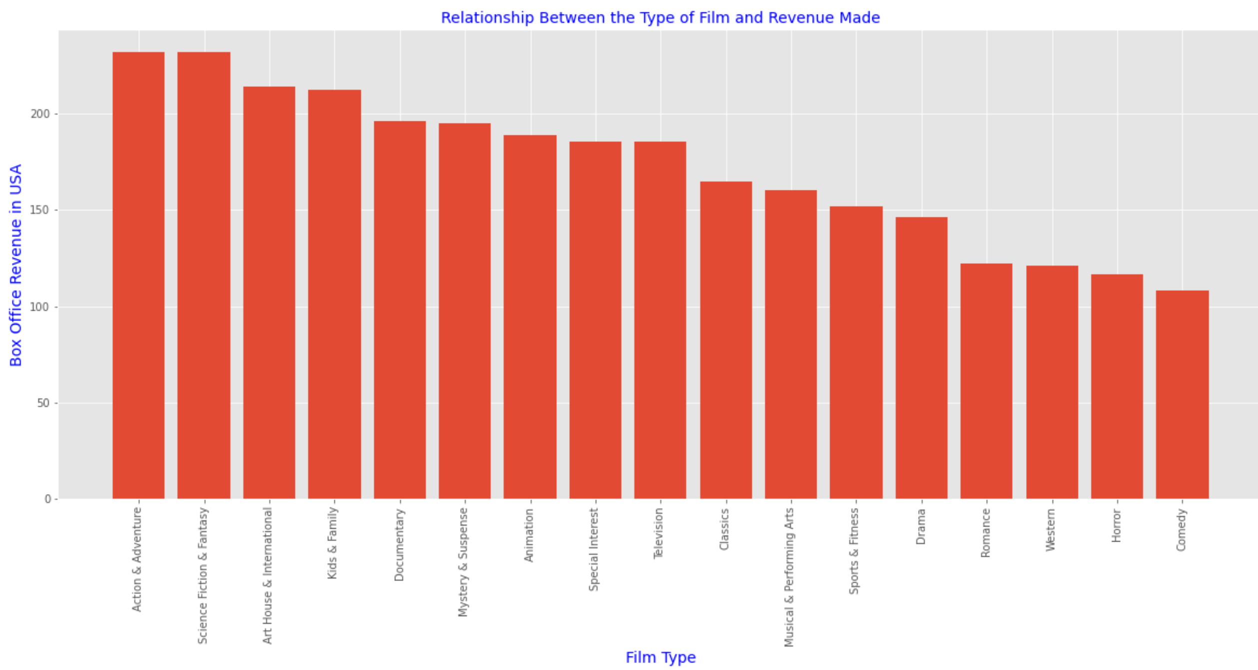
Out[ ]:

	type	box_office_(gross_usa)
0	Action & Adventure	232.085135
1	Animation	189.090141
2	Art House & International	213.960563
3	Classics	164.719231
4	Comedy	108.247692
5	Documentary	195.943478
6	Drama	146.496053
7	Horror	116.603922
8	Kids & Family	212.179747
9	Musical & Performing Arts	160.161111
10	Mystery & Suspense	194.918519
11	Romance	122.309836
12	Science Fiction & Fantasy	231.934177

	type	box_office_(gross_usa)
13	Special Interest	185.443820
14	Sports & Fitness	152.045161
15	Television	185.366667
16	Western	120.835088

In [ ]:
```
#sorting the sum of the total gross income from the highest
rotten_df = rotten_df.sort_values('box_office_(gross_usa)', ascending=False)
```

In [ ]:
```
#plotting a barplot for the film type and the box office profits
fig, ax = plt.subplots(figsize=(20,8))
plt.bar( x= rotten_df['type'], height= rotten_df['box_office_(gross_usa)'])
plt.xlabel('Film Type',color = 'blue', fontsize=14)
plt.ylabel('Box Office Revenue in USA',color = 'blue', fontsize=14)
plt.title('Relationship Between the Type of Film and Revenue Made', color = 'blue', fon
plt.xticks(rotation='vertical')
plt.show()
```



The above bar plot represents the different types or genres of films and their corresponding profits in USA. We see that the most profitable genres include Science Fiction & Fantasy, Action & Adventure, Kids & family, among other profitable genres.