Phase_1 Project Submission

Please fill out:

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- Student pace: part time
- Scheduled project review date/time: N/A
- Instructor name: Everlyne Asiko
- Blog post URL:N/A

PROBLEM STATEMENT

The project requires that we use exploratory data to review a set of movie data from a selected studio and use the findings as an insight into advising the head of Microsoft new moview studio on what films to create.

The Project will attempt to answer the Questions below.

Having reviewed the dataset provided, I decided to work with the IM.DB SQL database which contained a good amount of data for consideration. The following key pointers could be retrived from the data through data cleaning and analysis as shall be demonstarted hereafter.

The following key issues will be relevant in advising the M/S movie production director appropriately.

- Which are the top ten genre of movies in production by volume.
- Which are the highest rated movies in production.
- Is there any correlation between the production volume and the movie ratings.

DATA ANALYSIS PROCESS

In order to answer the subject question, we shasll use Data Analysis with Pandas in order to work hthrough the provided dataset. We shall go through the below key steps in our data analysis process.

1. Data exploration in Pandas
2. Data cleaning
3. Data analysis in Pandas

Data Exploration in Pandas

This process will involve the below key areas.

- Loading the data
- Checking the data and datatypes.
- Note any cleaning and/or engineering to be done

```
#importing necessary libraries for this analysis

import pandas as pd
import sqlite3
import numpy as np
import matplotlib.pyplot as plt
```

Loading the Data

Since we intend to use the SQL database we shall upload the databse file into this work book and connect to the SQL databse as demonstrated below.

We will then explore the tables in the SQL dataframe before deciding on which information will bne relevant for ouir intended analysis.

This will be demostrated in the next few code cells.

```
#connecting to the IM.DB SQL database

conn = sqlite3.connect('/content/im.db')
```

```
#Reading the table name component of the SQL database.

df = pd.read_sql("""SELECT name FROM sqlite_master WHERE type = 'table';""", conn)
df
```

	name
0	movie_basics
1	directors
2	known_for
3	movie_akas
4	movie_ratings
5	persons
6	principals
7	writers

```
#Reading the composition of moview basics into a dataframe.

pd.read_sql("SELECT * FROM movie_basics;", conn).head(10)
```

	movie_id	primary_title	original_title	start_year	runtime_minutes	
0	tt0063540	Sunghursh	Sunghursh	2013	175.0	A
1	tt0066787	One Day Before the Rainy Season	Ashad Ka Ek Din	2019	114.0	
2	tt0069049	The Other Side of the Wind	The Other Side of the Wind	2018	122.0	
3	tt0069204	Sabse Bada Sukh	Sabse Bada Sukh	2018	NaN	
4	tt0100275	The Wandering Soap Opera	La Telenovela Errante	2017	80.0	Com
5	tt0111414	A Thin Life	A Thin Life	2018	75.0	
6	tt0112502	Bigfoot	Bigfoot	2017	NaN	
7	tt0137204	Joe Finds Grace	Joe Finds Grace	2017	83.0	Adventure,

```
#Reading the composition of directors into a dataframe.
pd.read_sql("SELECT * FROM directors;", conn).head(10)
```

	movie_id	person_id
0	tt0285252	nm0899854
1	tt0462036	nm1940585
2	tt0835418	nm0151540
3	tt0835418	nm0151540
4	tt0878654	nm0089502
5	tt0878654	nm2291498
6	tt0878654	nm2292011
7	tt0879859	nm2416460
8	tt0996958	nm2286991
9	tt0996958	nm2286991

```
#Reading the composition of known_for into a dataframe.

pd.read_sql("SELECT * FROM known_for;", conn).head(10)
```

	person_id	movie_id
0	nm0061671	tt0837562
1	nm0061671	tt2398241
2	nm0061671	tt0844471
3	nm0061671	tt0118553
4	nm0061865	tt0896534
5	nm0061865	tt6791238
6	nm0061865	tt0287072
7	nm0061865	tt1682940
8	nm0062070	tt1470654
9	nm0062070	tt0363631

```
#Reading the composition of movie_akas into a dataframe.

pd.read_sql("SELECT * FROM movie_akas;", conn).head(10)
```

	movie_id	ordering	title	region	language	types	attributes	is_or

```
#Reading the composition of movie_ratings into a dataframe.

pd.read_sql("SELECT * FROM movie_ratings;", conn).head(10)
```

	movie_id	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
5	tt1069246	6.2	326
6	tt1094666	7.0	1613
7	tt1130982	6.4	571
8	tt1156528	7.2	265
9	tt1161457	4.2	148

```
#Reading the composition of persons into a dataframe.

pd.read_sql("SELECT * FROM persons;", conn).head(10)
```

	person_id	primary_name	birth_year	death_year	prim
0	nm0061671	Mary Ellen Bauder	NaN	NaN	miscellaneous,production_r
1	nm0061865	Joseph Bauer	NaN	NaN	composer,music_department,s
2	nm0062070	Bruce Baum	NaN	NaN	miscella
3	nm0062195	Axel Baumann	NaN	NaN	camera_department,cinematograph
4	nm0062798	Pete Baxter	NaN	NaN	production_designer,art_departm
5	nm0062879	Ruel S. Bayani	NaN	NaN	director,production_manag
6	nm0063198	Bayou	NaN	NaN	
7	nm0063432	Stevie Be-Zet	NaN	NaN	com
8	nm0063618	Jeff Beal	1963.0	NaN	composer,music_depar

```
#Reading the composition of principals into a dataframe.

pd.read_sql("SELECT * FROM principals;", conn).head(10)
```

	movie_id	ordering	person_id	category	job	characters
0	tt0111414	1	nm0246005	actor	None	["The Man"]
1	tt0111414	2	nm0398271	director	None	None
2	tt0111414	3	nm3739909	producer	producer	None
3	tt0323808	10	nm0059247	editor	None	None

```
#Reading the composition of writers into a dataframe.

pd.read_sql("SELECT * FROM writers;", conn).head(10)
```

	movie_id	person_id
0	tt0285252	nm0899854
1	tt0438973	nm0175726
2	tt0438973	nm1802864
3	tt0462036	nm1940585
4	tt0835418	nm0310087
5	tt0835418	nm0841532
6	tt0878654	nm0284943
7	tt0878654	nm0284943
8	tt0878654	nm0284943
9	tt0996958	nm2286991

Joining data

Having reviewed the dataframes we shall join movie_basics with movie_ratings to come up with a new dataset for the purpose of this analysis.

```
#use SQL query to query the databse and join the tables.

sql_query = """
    SELECT *
    FROM movie_basics mv
    INNER JOIN movie_ratings mr ON mv.movie_id = mr.movie_id
    ;
"""

# Use pandas to read the query into a DataFrame
df = pd.read_sql(sql_query, conn)
df

# Save the DataFrame to a CSV file
df.to_csv('im_movies.csv', index=False)


#reading the contents of the new created database and dis[laying the first ten rows]

im_movies_df = pd.read_csv('/content/im_movies.csv')

im_movies_df.head(10)
```

	movie_id	primary_title	original_title	start_year	runtime_minutes	
0	tt0063540	Sunghursh	Sunghursh	2013	175.0	A
1	tt0066787	One Day Before the Rainy Season	Ashad Ka Ek Din	2019	114.0	
2	tt0069049	The Other Side of the Wind	The Other Side of the Wind	2018	122.0	
3	tt0069204	Sabse Bada Sukh	Sabse Bada Sukh	2018	NaN	
4	tt0100275	The Wandering Soap Opera	La Telenovela Errante	2017	80.0	Com
5	tt0112502	Bigfoot	Bigfoot	2017	NaN	
6	tt0137204	Joe Finds Grace	Joe Finds Grace	2017	83.0	Adventure,
7	tt0146592	Pál Adrienn	Pál Adrienn	2010	136.0	
8	tt0154039	So Much for Justice!	Oda az igazság	2010	100.0	
9	tt0159369	Cooper and Hemingway: The True Gen	Cooper and Hemingway: The True Gen	2013	180.0	

Data processing and Cleaning

In order to proceed with the analysis we will take the data thrpugh various data cleaning processes that will ensure the final dasta is accurate and verifiable for our use. This will ensure that our analysis has limited assumptions and is most accurate.

```
#checks for the overview of the data.

im_movies_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 73856 entries, 0 to 73855
Data columns (total 9 columns):
 #   Column           Non-Null Count  Dtype  
---  ------           --------------  -----  
 0   movie_id         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   movie_id.1       73856 non-null  object 
 7   averagerating    73856 non-null  float64
 8   numvotes         73856 non-null  int64  
dtypes: float64(2), int64(2), object(5)
memory usage: 5.1+ MB
```

```
#checks for statistical summary of the data.

im_movies_df.describe(include ='all')
```

	movie_id	primary_title	original_title	start_year	runtime_minutes	ge
count	73856	73856	73856	73856.000000	66236.000000	7:
unique	73856	69993	71097	NaN	NaN	
top	tt0063540	The Return	Broken	NaN	NaN	Dı
freq	1	11	9	NaN	NaN	1
mean	NaN	NaN	NaN	2014.276132	94.654040	
std	NaN	NaN	NaN	2.614807	208.574111	
min	NaN	NaN	NaN	2010.000000	3.000000	
25%	NaN	NaN	NaN	2012.000000	81.000000	
50%	NaN	NaN	NaN	2014.000000	91.000000	

Data Cleaning.

Having had an overview of the data layout, we will proceed to some cleanig. Our focus will be majorly on the column 'genres' as it will be the basis of our analysis going forward.

```
#check count of missing values

im_movies_df.isna().sum()
```

```
movie_id              0
primary_title         0
original_title        0
start_year            0
runtime_minutes    7620
genres              804
movie_id.1            0
averagerating         0
numvotes              0
dtype: int64
```

```
#check percentage of missing items on eaxch column.

percent_missing = im_movies_df.isna().sum() / len(im_movies_df) * 100

print(percent_missing)
```

```
movie_id            0.000000
primary_title       0.000000
original_title      0.000000
start_year          0.000000
runtime_minutes    10.317374
genres              1.088605
movie_id.1          0.000000
averagerating       0.000000
numvotes            0.000000
dtype: float64
```

Action on missing data.

From the above summary of missing values on each column, looking at our column of interest, we can see that there is a 1% data missing in the genres data. We shall opt to drop the rows with missing data because this is a small portion of data and it will not change our outcomes by a large margin.

```
#drop rows where genre is missing.
im_movies_df = im_movies_df.dropna(subset=['genres'])


#display new im_movies_df after dropping some rows from the datfame on the genres column.

im_movies_df
```

	movie_id	primary_title	original_title	start_year	runtime_minutes	
0	tt0063540	Sunghursh	Sunghursh	2013	175.0	A
1	tt0066787	One Day Before the Rainy Season	Ashad Ka Ek Din	2019	114.0	
2	tt0069049	The Other Side of the Wind	The Other Side of the Wind	2018	122.0	
3	tt0069204	Sabse Bada Sukh	Sabse Bada Sukh	2018	NaN	
4	tt0100275	The Wandering Soap Opera	La Telenovela Errante	2017	80.0	Come
...	...	...	...	...	...	
73850	tt9913056	Swarm Season	Swarm Season	2019	86.0	
73851	tt9913084	Diabolik sono io	Diabolik sono io	2019	75.0	
73852	tt9914286	Sokagin Çocuklari	Sokagin Çocuklari	2019	98.0	
73853	tt9914642	Albatross	Albatross	2017	NaN	
73855	tt9916160	Drømmeland	Drømmeland	2019	72.0	

73052 rows × 9 columns

```
#check the info for the new dataframe.

im_movies_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 73052 entries, 0 to 73855
Data columns (total 9 columns):
 #   Column           Non-Null Count  Dtype  
---  ------           --------------  -----  
 0   movie_id         73052 non-null  object 
 1   primary_title    73052 non-null  object 
 2   original_title   73052 non-null  object 
 3   start_year       73052 non-null  int64  
 4   runtime_minutes  65720 non-null  float64
 5   genres           73052 non-null  object 
 6   movie_id.1       73052 non-null  object 
 7   averagerating    73052 non-null  float64
 8   numvotes         73052 non-null  int64  
dtypes: float64(2), int64(2), object(5)
memory usage: 5.6+ MB
```

```
# check for duplicates

duplicate_rows = im_movies_df[im_movies_df.duplicated()]

duplicate_rows
```

```
#no duplicate rows
```

movie_id	primary_title	original_title	start_year	runtime_minutes	genres	mo

Clearly there are no duplicate values in our dataframe and we will assume thateach of the movies used in our analysis are uniq.

Data analysis in Pandas

```
#top ten genre of movies being produced by volume of production

top_10_im_movies__genre_df = im_movies_df['genres'].value_counts().head(10)

top_10_im_movies__genre_df
```

```
Drama                   11612
Documentary             10313
Comedy                   5613
Horror                   2692
Comedy,Drama             2617
Thriller                 1555
Drama,Romance            1510
Comedy,Romance           1236
Comedy,Drama,Romance     1208
Horror,Thriller          1004
Name: genres, dtype: int64
```

We can make an assumption that the market quota is represented by the volume of each genre in production. A further analysis will try to show the top ten movies in terms of volumes produced with a graphical representation of the same.

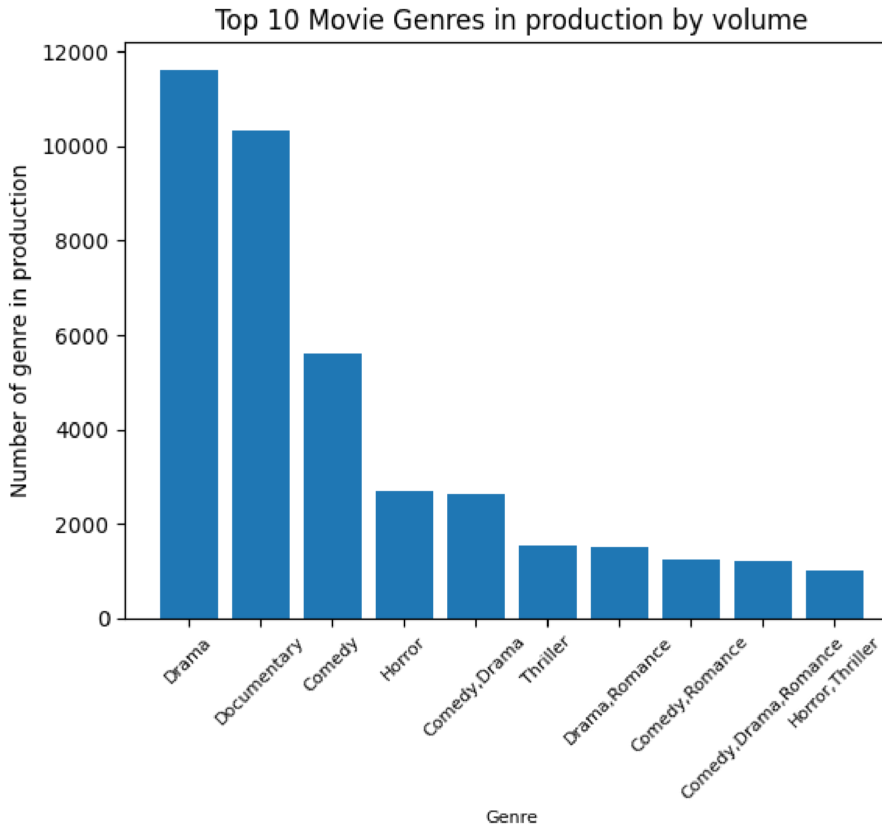
```
#to come up with a list of top ten movies in production and the repective numbers of the same.

top_10_im_movies_genre_df = list(im_movies_df['genres'].value_counts().nlargest(10).index)

top_10_im_movies_genre_df

top_10_im_movies_genre_df_counts = list(im_movies_df['genres'].value_counts().nlargest(10))

# Convert the counts to integers
top_10_im_movies_genre_df_counts= [int(count) for count in top_10_im_movies_genre_df_counts]
top_10_im_movies_genre_df_counts


#print the numbers for the movies in production.

print("genres:", top_10_im_movies_genre_df)
print("Counts:", top_10_im_movies_genre_df_counts)
```

```
genres: ['Drama', 'Documentary', 'Comedy', 'Horror', 'Comedy,Drama', 'Thriller', 'Drama,Romance', 'Comedy,Romance'
Counts: [11612, 10313, 5613, 2692, 2617, 1555, 1510, 1236, 1208, 1004]
```

```
#plot bar graph for top ten moview genres in production.


fig, ax = plt.subplots()

ax.bar(top_10_im_movies_genre_df, top_10_im_movies_genre_df_counts)

ax.tick_params(axis='x', labelsize=8, rotation=45)
```

```
ax.set_title("Top 10 Movie Genres in production by volume")
ax.set_xlabel('Genre', fontsize=8)
ax.set_ylabel('Number of genre in production')
```

```
Text(0, 0.5, 'Number of genre in production')
```



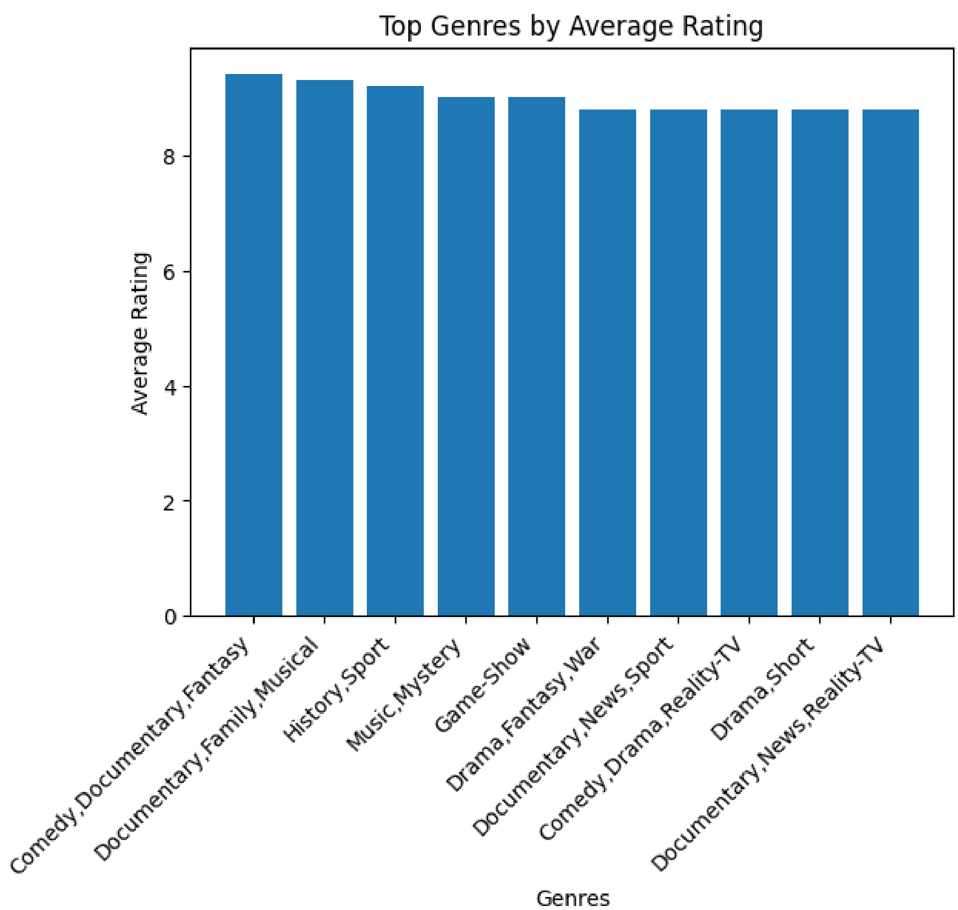
Top rated movie genres.

The next step of this analysis will focus on the highest rated genre of movies under production. we shall used pandas to comes with the top ten rated movies and give their specific rating.

```
#Top ten highest movie rating by genre.

genre_ratings = im_movies_df.groupby('genres')['averagerating'].mean()

# sort the resulting series object by rating in descending order and select the top genres with the highest ratings
top_genres_by_rating = genre_ratings.sort_values(ascending=False).head(10)

top_genres_by_rating
```

```
genres
Comedy,Documentary,Fantasy     9.4
Documentary,Family,Musical     9.3
History,Sport                  9.2
Music,Mystery                  9.0
Game-Show                      9.0
Drama,Fantasy,War              8.8
Documentary,News,Sport         8.8
Comedy,Drama,Reality-TV        8.8
Drama,Short                    8.8
Documentary,News,Reality-TV    8.8
Name: averagerating, dtype: float64
```

```
fig, ax = plt.subplots()

# create a bar chart with the genre names on the x-axis and their average ratings on the y-axis
ax.bar(top_genres_by_rating.index, top_genres_by_rating.values)

# set the title and axis labels
ax.set_title('Top Genres by Average Rating')
ax.set_xlabel('Genres')
ax.set_ylabel('Average Rating')

# rotate the x-axis labels for readability
plt.xticks(rotation=45, ha='right')

# display the plot
plt.show()
```



To find the Highest grossing movies in the database.

We will merge the dataframe we will combine a third datfrasme with the movies grossing amounts and subsequently do a further analysis on the datafrasme.

```
#importing the budget data to apply in the subsequent analysis.

tn_movie_budget_df = pd.read_csv('/content/tn.movie_budgets.csv.gz')

tn_movie_budget_df.head(10)
```

	id	release_date	movie	production_budget	domestic_gross	worldwide_gros
0	1	Dec 18, 2009	Avatar	$425,000,000	$760,507,625	$2,776,345,27
1	2	May 20, 2011	Pirates of the Caribbean: On Stranger Tides	$410,600,000	$241,063,875	$1,045,663,87
2	3	Jun 7, 2019	Dark Phoenix	$350,000,000	$42,762,350	$149,762,35
3	4	May 1, 2015	Avengers: Age of Ultron	$330,600,000	$459,005,868	$1,403,013,96

```
#Merging the dataframes along the movie names.

im_movies_df_tn_movie_budget_df = pd.merge(im_movies_df, tn_movie_budget_df, left_on='primary_title', right_on='movie')

im_movies_df_tn_movie_budget_df
```

	movie_id	primary_title	original_title	start_year	runtime_minutes	genres	movie_id.1	av
0	tt0249516	Foodfight!	Foodfight!	2012	91.0	Action,Animation,Comedy	tt0249516	
1	tt0337692	On the Road	On the Road	2012	124.0	Adventure,Drama,Romance	tt0337692	
2	tt4339118	On the Road	On the Road	2014	89.0	Drama	tt4339118	
3	tt5647250	On the Road	On the Road	2016	121.0	Drama	tt5647250	
4	tt0359950	The Secret Life of Walter Mitty	The Secret Life of Walter Mitty	2013	114.0	Adventure,Comedy,Drama	tt0359950	
...	...	...	...	...	...	...	...	
2862	tt8680254	Richard III	Richard III	2016	NaN	Drama	tt8680254	
2863	tt8824064	Heroes	Heroes	2019	88.0	Documentary	tt8824064	
2864	tt8976772	Push	Push	2019	92.0	Documentary	tt8976772	
2865	tt9024106	Unplanned	Unplanned	2019	106.0	Biography,Drama	tt9024106	
2866	tt9248762	The Terrorist	The Terrorist	2018	NaN	Thriller	tt9248762	

2867 rows × 15 columns

```
#checks for the overview of the data.

im_movies_df_tn_movie_budget_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 2867 entries, 0 to 2866
Data columns (total 15 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   movie_id         2867 non-null   object
 1   primary_title    2867 non-null   object
```

```
 2   original_title     2867 non-null   object
 3   start_year         2867 non-null   int64
 4   runtime_minutes    2752 non-null   float64
 5   genres             2867 non-null   object
 6   movie_id.1         2867 non-null   object
 7   averagerating      2867 non-null   float64
 8   numvotes           2867 non-null   int64
 9   id                 2867 non-null   int64
 10  release_date       2867 non-null   object
 11  movie              2867 non-null   object
 12  production_budget  2867 non-null   object
 13  domestic_gross     2867 non-null   object
 14  worldwide_gross    2867 non-null   object
dtypes: float64(2), int64(3), object(10)
memory usage: 358.4+ KB
```

```
#checks for statistical summary of the data.

im_movies_df_tn_movie_budget_df.describe(include ='all')
```

	movie_id	primary_title	original_title	start_year	runtime_minutes	genres	movie_id.1	averagerating	
count	2867	2867	2867	2867.000000	2752.000000	2867	2867	2867.000000	2
unique	2745	2126	2302	NaN	NaN	311	2745	NaN	
top	tt2093100	Home	The Gift	NaN	NaN	Drama	tt2093100	NaN	
freq	3	24	14	NaN	NaN	319	3	NaN	
mean	NaN	NaN	NaN	2013.916638	102.972020	NaN	NaN	6.249111	6
std	NaN	NaN	NaN	2.547187	20.786121	NaN	NaN	1.185953	1
min	NaN	NaN	NaN	2010.000000	3.000000	NaN	NaN	1.600000	5
25%	NaN	NaN	NaN	2012.000000	90.000000	NaN	NaN	5.600000	1
50%	NaN	NaN	NaN	2014.000000	101.000000	NaN	NaN	6.400000	7
75%	NaN	NaN	NaN	2016.000000	113.250000	NaN	NaN	7.100000	7
max	NaN	NaN	NaN	2019.000000	280.000000	NaN	NaN	9.300000	1

Data Cleaning.

Having had an overview of the data layout, we will proceed to some cleanig. we reaslise the production budget, the domestic gross and the world wide gross amounts are in dollars and have the dollar sign added. We are thus unable to do any statistical analysis on the data. We are thus bound to do a further cleanin gon the data to make it workable. The next few codes willbe used to carry out data cleaning.

```
#stripping the data of the dollar sugn character.

def remove_character(data, cols, characters):
    """simple function to remove characters"""
    # loop through the columns
    for col in cols:
        data[col] = data[col].str.strip(characters)

    return data.head()


remove_character(im_movies_df_tn_movie_budget_df, ['production_budget', 'domestic_gross','worldwide_gross'], '$')
```

	movie_id	primary_title	original_title	start_year	runtime_minutes	genres	movie_id.1	avera
0	tt0249516	Foodfight!	Foodfight!	2012	91.0	Action,Animation,Comedy	tt0249516	
1	tt0337692	On the Road	On the Road	2012	124.0	Adventure,Drama,Romance	tt0337692	
2	tt4339118	On the Road	On the Road	2014	89.0	Drama	tt4339118	
3	tt5647250	On the Road	On the Road	2016	121.0	Drama	tt5647250	
4	tt0359950	The Secret Life of Walter Mitty	The Secret Life of Walter Mitty	2013	114.0	Adventure,Comedy,Drama	tt0359950	

Stripping the financial data of coma characters.

The next step will be to to strip the data of comma characters to allow for further statistical examination.

```
#stripping the data of the comas
im_movies_df_tn_movie_budget_df['production_budget'] = im_movies_df_tn_movie_budget_df['production_budget' ].str.replace
```

```
#stripping the data of the comas

im_movies_df_tn_movie_budget_df['domestic_gross'] = im_movies_df_tn_movie_budget_df['domestic_gross' ].str.replace(',',
```

```
#stripping the data of the comas

im_movies_df_tn_movie_budget_df['worldwide_gross'] = im_movies_df_tn_movie_budget_df['worldwide_gross' ].str.replace(','
```

```
#checks for the overview of the data.

im_movies_df_tn_movie_budget_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 2867 entries, 0 to 2866
Data columns (total 15 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   movie_id           2867 non-null   object
 1   primary_title      2867 non-null   object
 2   original_title     2867 non-null   object
```

```
 3   start_year         2867 non-null   int64
 4   runtime_minutes    2752 non-null   float64
 5   genres             2867 non-null   object
 6   movie_id.1         2867 non-null   object
 7   averagerating      2867 non-null   float64
 8   numvotes           2867 non-null   int64
 9   id                 2867 non-null   int64
 10  release_date       2867 non-null   object
 11  movie              2867 non-null   object
 12  production_budget  2867 non-null   object
 13  domestic_gross     2867 non-null   object
 14  worldwide_gross    2867 non-null   object
dtypes: float64(2), int64(3), object(10)
memory usage: 358.4+ KB
```

Changing the data into float from string objects

The data stripped of comas leave string object characyers, the next step is to change these strings values to float values.

```
im_movies_df_tn_movie_budget_df['production_budget'] = im_movies_df_tn_movie_budget_df['production_budget'].str.strip().
```

```
im_movies_df_tn_movie_budget_df['domestic_gross'] = im_movies_df_tn_movie_budget_df['domestic_gross'].str.strip().astype
```

```
im_movies_df_tn_movie_budget_df['worldwide_gross'] = im_movies_df_tn_movie_budget_df['worldwide_gross'].str.strip().asty
```

```
#checks for the overview of the data afterchanging them to float character.

im_movies_df_tn_movie_budget_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 2867 entries, 0 to 2866
Data columns (total 15 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   movie_id           2867 non-null   object
 1   primary_title      2867 non-null   object
 2   original_title     2867 non-null   object
 3   start_year         2867 non-null   int64
 4   runtime_minutes    2752 non-null   float64
 5   genres             2867 non-null   object
 6   movie_id.1         2867 non-null   object
 7   averagerating      2867 non-null   float64
 8   numvotes           2867 non-null   int64
 9   id                 2867 non-null   int64
 10  release_date       2867 non-null   object
 11  movie              2867 non-null   object
 12  production_budget  2867 non-null   float64
 13  domestic_gross     2867 non-null   float64
 14  worldwide_gross    2867 non-null   float64
dtypes: float64(5), int64(3), object(7)
memory usage: 358.4+ KB
```

Domestic and Worldwide gross summation and profit margins.

The next steps of the analysis takes into account the total profits made locally and abroad from the movie sales, ultimaltely we need to be able to check the highest grossing movies by their genress.

```
#summation of domestic and wolrdwide movie gross sales

im_movies_df_tn_movie_budget_df['domestic_worldwide_gross'] = im_movies_df_tn_movie_budget_df.apply(lambda x: x['domesti


# the profit margins which is the difference between the gross sales and the production cost

im_movies_df_tn_movie_budget_df['profit_margins'] = im_movies_df_tn_movie_budget_df.apply(lambda x: x['domestic_worldwid


#checks for the overview of the data with the additional columns

im_movies_df_tn_movie_budget_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 2867 entries, 0 to 2866
Data columns (total 17 columns):
 #   Column                    Non-Null Count  Dtype  
---  ------                    --------------  -----  
 0   movie_id                  2867 non-null   object 
 1   primary_title             2867 non-null   object 
 2   original_title            2867 non-null   object 
 3   start_year                2867 non-null   int64  
 4   runtime_minutes           2752 non-null   float64
 5   genres                    2867 non-null   object 
 6   movie_id.1                2867 non-null   object 
 7   averagerating             2867 non-null   float64
 8   numvotes                  2867 non-null   int64  
 9   id                        2867 non-null   int64  
 10  release_date              2867 non-null   object 
 11  movie                     2867 non-null   object 
 12  production_budget         2867 non-null   float64
 13  domestic_gross            2867 non-null   float64
 14  worldwide_gross           2867 non-null   float64
 15  domestic_worldwide_gross  2867 non-null   float64
 16  profit_margins            2867 non-null   float64
dtypes: float64(7), int64(3), object(7)
memory usage: 403.2+ KB
```

```
#mean profitmargins by movie  genre.

profit_margins_df = im_movies_df_tn_movie_budget_df.groupby("genres")["profit_margins"].agg("mean").astype(float)

profit_margins_df
```

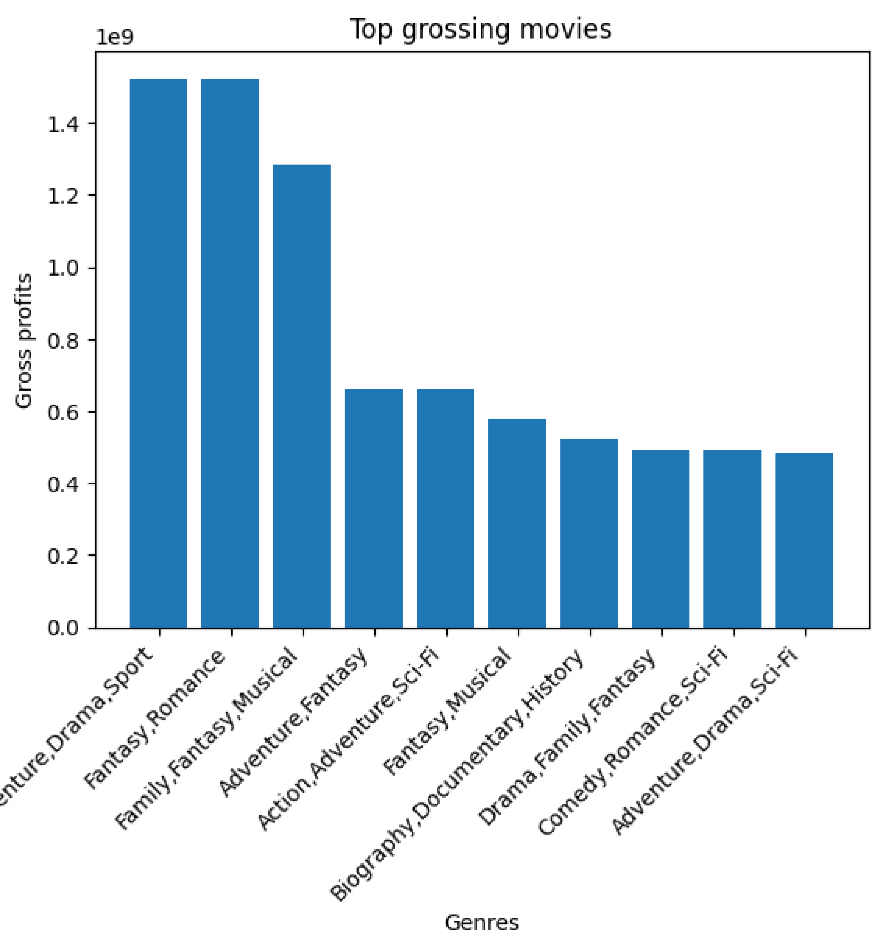
```
genres
Action                        6.836908e+07
Action,Adventure             -3.561111e+06
Action,Adventure,Animation    4.789828e+08
Action,Adventure,Biography    1.737994e+08
Action,Adventure,Comedy       3.524199e+08
                                  ...     
Sci-Fi,Thriller               2.277576e+07
Sport                        -7.943943e+06
Thriller                      6.925048e+07
War                           2.039821e+07
Western                      -1.912819e+06
Name: profit_margins, Length: 311, dtype: float64
```

```
#sorting the profit margins by the top ten grossing movie genre.

top_10_profit_margins_df = profit_margins_df.sort_values(ascending=False)[:10]
top_10_profit_margins_df.astype(float)
```

```
genres
Adventure,Drama,Sport            1.523208e+09
Fantasy,Romance                  1.523208e+09
Family,Fantasy,Musical           1.283851e+09
Adventure,Fantasy                6.624354e+08
```

```
Action,Adventure,Sci-Fi          6.588433e+08
Fantasy,Musical                  5.783411e+08
Biography,Documentary,History    5.206793e+08
Drama,Family,Fantasy             4.931971e+08
Comedy,Romance,Sci-Fi            4.919102e+08
Adventure,Drama,Sci-Fi           4.823675e+08
Name: profit_margins, dtype: float64
```

```
#plotting a bar graph with the top ten grossing movies by genre.

fig, ax = plt.subplots()

# create a bar chart with the genre names on the x-axis and their average ratings on the y-axis
ax.bar(top_10_profit_margins_df.index, top_10_profit_margins_df.values)

# set the title and axis labels
ax.set_title('Top grossing movies')
ax.set_xlabel('Genres')
ax.set_ylabel('Gross profits')

# rotate the x-axis labels for readability
plt.xticks(rotation=45, ha='right')

# display the plot
plt.show()
```



SUMMARY AND CONCLUSIONS

From the analysis we were able to pick out the following fsacts around the movies in the given dataset.

- The three top genres in production are drama, documentary and comedy. In the event that the movie house intends to reach to the largest audience, these three genres would be a good place to get started.
- On the highest rsted movies, the clear outcome from that analysis will be deebunked in the next conclusion that the highest rating movies are not necessaily the ones that rack in the most profits or the highest viewership.
- We were also able to pick out the highest grossing movies. The top three being

1. Adventure, drama, sport
2. Fantasy,romance
3. Family, fantasy, musical

These would be the top three recommendations to the production house were we to realise the highest profit margins.

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